A Phase Difference Based Cooperative Spectrum Sensing Scheme for Cognitive Radio Network

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Abstract. The increasing scarcity of spectrum resources is one of the most challenging issues to cognitive radio systems in 5G era. Traditional schemes fail to gain the balance between accuracy and complexity, which are the two of the most significant parameters to evaluate the performance of the spectrum sensing. In this paper, in order to improve the sensing accuracy and reduce the computation complexity, we propose a novel cooperative spectrum sensing scheme based on phase difference is proposed. By using the mean of Phase Difference (PD) as the test statistics, the proposed PD mean detection is formulated for efficient spectrum sensing and its performance is analyzed under Rayleigh fading channel and Gaussian noise, which has a low complexity of $O(K)$ and is immune to the noise uncertainty in contrast to the energy detection scheme. Moreover, to improve performance of the sensing scheme based on phase difference by a single CR, we consider the cooperative scenario with multiple CR nodes. Simulation verifies that our scheme obtains 3–4 dB gains comparing with energy detection.

Keywords: Cognitive radio · Spectrum sensing · Means Phase difference · Fading · Cooperative sensing

1 Introduction

In 4G era, the mobile telecommunication pursues 1 Gb/s for fixed or low mobility and 100 Mb/s for high mobility with regard to user data rate, but this has not been satisfied due to the dramatically increasing numbers of mobile devices nowadays. With the approaching of the 5G which is being promoted by various organization, the mobile telecommunication needs more frequency to satisfied those needs. But with the spectrum resources become more and more scarce, some measurement shows the average utilization rate of current spectrum below 3 GHz is merely 5.2%, which unveils that the spectrum resources are heavily under utilized [1]. To improve the spectrum utilization greatly, we can allow a secondary user to access licensed band when the primary user (PU) is absent. In 3GPP Release 13, Long Term Evolution-Unlicensed (LTE-U) [2] is newly

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proposed to struggle for performance in unlicensed bands. LTE-U adopts carrier aggregation (CA) technology and operates on unlicensed frequency bands in 5 GHz, aiming to achieve higher data rate by eliminating interference from the industrial, scientific, and medical (ISM) bands. Therefore, Cognitive Radio (CR) is playing a key role in working out the circumstance of scarce spectrum and promoting the 5G. Cognitive radio, as an agile radio technology, has been proposed to promote the efficient use of the spectrum [3]. Cognitive radio is booming technology which has the capacity to deal with the stringent requirement and scarcity of the radio spectrum. The evolution of this technology has revealed a phenomenon that the design of wireless systems will consider more and more about the ability of radio spectrum sensing, self-adaptation, and dynamic spectrum sharing. The above considerations are nothing more than to achieve higher spectral efficiency. Cooperative communications and networking is another new communication technology paradigm that allows distributed terminals in a wireless network to collaborate through some distributed transmission or signal processing so as to realize a new form of space diversity to combat the detrimental effects of fading channels.

The essence of cognitive radio technology is that the SU (secondary user) share the spectrum with the primary user (PU) and will not interference the PU. Thus it is crucial to obtain the status of PU for CR in a way. As an essential way to obtain the status of PU, spectrum sensing is the basis for efficient spectrum utilization in CR [4]. Energy detection (ED) [5], matched filtering [6] and cyclostationary detection [7] are three most widely used spectrum sensing methods. All of these methods have their own advantages and disadvantages [8]. The Matched Filtering scheme maximizes the SNR of the received signal and needs less time to achieve high processing gain but the prior information must be known. Energy detection can be implemented without prior information but it has poor performance under low SNR environment. Cyclostationary Detection still has better sensing performance under low SNR circumstance but this scheme needs high algorithm complexity and prior information still needs. Traditional spectrum sensing schemes fail to resolve the contradiction between accuracy and complexity. And they focus on the amplitude of signal, which is extremely sensitive to the noise uncertainty and multi-path fading such as Rayleigh fading. Therefore, it is important to design a new scheme to sense the spectrum.

In [9–11], Pawula and Adachi derived the distribution of phase difference (PD) of the noise-perturbed signal. These promote us to use the phase difference of received signal to design the spectrum sensing scheme. Through careful analysis, it is noticed that there is an obvious difference in the PD's distributions between Gaussian noise and noise-perturbed signal. Besides, this difference still exist in Rayleigh Fading channel and we will prove this regular by formulas. We take advantage this PD's character and set test statistics in order to sense the status of PU with low complexity. All the scheme above implemented by one CR, but a signal CR will face more problems such as blocking by buildings thus this paper will let more CRs to join the scheme to further improve the accuracy.

The rest of this paper is organized as follows. Section 2 introduces the system model and the definition of PD, analyzes the distribution of signal's PD. Section 3 formulates the test statistics and analyzes the scheme's performance for a signal CR, the last part of this section put more attention on analyzing the performance of cooperative detection for multi CRs. Simulation analysis is provided in Sect. 4. Finally, the paper is concluded in Sect. 5.

2 System Model and Phase Difference

2.1 System Model

The spectrum sensing problem can be considered as a binary hypothesis test problem and two hypotheses can be formulated as follows:

$$\begin{array}{lll} H_0^i : r_i(n) = w_i(n) & n = 1, 2, ..., N & i = 1, 2, ...N_c \\ H_1^i : r_i(n) = w_i(n) + h_i s(n) & n = 1, 2, ..., N & i = 1, 2, ...N_c \end{array} \quad (1)$$

where $r_i(n)$ is the nth sample of received signal from the ith CR, h_i is the instantaneous channel gain between PU and the ith CR, $w(n)$ is the Additive White Gaussian Noise (AWGN) samples and $s(n)$ is the PU signal. H_0^i is the hypothesis stating that only noise is present and PU is absent, while H_1^i indicates that PU is present and all the hypothesis are made from the ith CR decision. N represents the length of signal samples and also denotes that our scheme handles finite length samples. N_c represents the number of CRs. In the ideal situation, the ith CR will make false alarm decision H_1^i when the PU is present, while make the opposite decision H_0^i when the PU is not present by our scheme. However, the CRs sometimes make wrong decisions because of the AWGN and Rayleigh fading. Therefore, to evaluate the performance of our scheme, we made P_d^i presents the detection probability and P_f^i presents false alarm probability for the ith CR, P_d^i and P_f^i can be formulated as follows:

$$\begin{array}{l} P_d^i = P(H_1^i|H_1) \\ P_f^i = P(H_1^i|H_0) \end{array} \quad (2)$$

P_d^i represents the detection probability that the ith CR makes correctly decision when the PU is presents and larger P_d^i indicates that the CRs has little interference to PU. P_f^i represents the probability that the ith CR makes wrong decision when the PU is not present and lower P_f^i indicates more access opportunity. So an excellent scheme means lower P_f and higher P_d. However, there is a trade-off between P_f and P_d for most sensing schemes, which makes it impossible to improve P_d and reduce P_f at the same time. Thus receiver operating characteristic (ROC) curve (P_f vs P_d) is usually used as the performance metric of sensing schemes. Next, we will discuss the phase difference on the case of single CR. Moreover, the case of more CRs is same as the case of signal CR, thus the following discussion is under one CR case.

2.2 Definition of Phase Difference

The received signal can be formulated as follows:

$$r(n) = [s(nT)e^{j2\pi f_c nT}]h(nT) + w(nT) \tag{3}$$

where, T is the sampling interval, and $s(nT)$ is the instantaneous value of PU signal, f_c represents the residual carrier frequency after down conversion, $h(nT)$ is channel impulse responses, $w(nT)$ is Gaussian noise. The phase θ of received data sample, $r(n)$ can be calculated through following formula:

$$\begin{aligned} \theta'_n &= \begin{cases} \arctan(\dfrac{\mathrm{Im}(r(n))}{\mathrm{Re}(r(n))}) & (Re(r(n) \geq 0) \\ (\arctan(\dfrac{\mathrm{Im}(r(n))}{\mathrm{Re}(r(n))}) + \pi) & (Re(r(n) < 0) \end{cases} \\ \theta_n &= \theta'_n \; mod \; 2\pi \end{aligned} \tag{4}$$

where, $Re(r(n))$ and $Im(r(n))$ represent the real and imaginary part respectively of the received data sample. Where needs paying special attention is that we introduce the modulo 2π operation to ensure phase θ_n is in the range of $[0, 2\pi]$. Then, the phase difference φ_n between two adjacent samples is defined as follows:

$$\varphi_n = (\theta_{n+1} - \theta_n) \; mod \; 2\pi \tag{5}$$

2.3 PD Distribution of Gaussian Noise

We all know that the instantaneous phase θ_n of Gaussian noise follows a uniform distribution in $[0, 2\pi]$, which means $\theta_n \sim U(0, 2\pi)$. According to the nature of Gaussian noise, the two adjacent phases are completely irrelevant and in other words, the two adjacent phases are completely independently identically distributed. Thus, $\varphi'_n = \theta_{n+1} - \theta_n$ follow a triangular distribution from -2π to 2π which can be expressed as:

$$P_{\varphi'_n} = \begin{cases} \dfrac{1}{2\pi} + \dfrac{\varphi'_n}{4\pi^2} & -2\pi \leq \varphi'_n < 0 \\ \dfrac{1}{2\pi} - \dfrac{\varphi'_n}{4\pi^2} & 0 \leq \varphi'_n \leq 2\pi \end{cases} \tag{6}$$

Considering that the φ'_n is in the range of $[0, 2\pi]$, then we make $\varphi_n = \varphi'_n \bmod (2\pi)$. When the φ'_n is in the range $[-2\pi, 0]$, $\varphi_n = \varphi'_n \bmod (2\pi)$. So the distribution of the φ_n can be expressed as follows:

$$P_{\varphi_n} = P_{\varphi'_n}(\varphi_n) + P_{\varphi'_n}(\varphi_n - 2\pi) = \tfrac{1}{2\pi} \tag{7}$$

We can conclude that the PD φ_n of Gaussian noise complying with a uniformly distributed in $[0, 2\pi]$ based the above analysis. Therefore, according to the nature of uniformly distributed, it is easy to obtain the mean and variance value of PD of Gaussian noise by the following formula and the mean and variance are π and $\frac{\pi^2}{3}$ respectively.

$$\mu_{\varphi} = \int_0^{2\pi} \varphi P_{\varphi} d\varphi \tag{8}$$

$$\sigma_{\varphi}^2 = \int_0^{2\pi} (\varphi - \mu_{\varphi})^2 P_{\varphi} d\varphi \tag{9}$$

There is no signal component in our analysis under this circumstance, i.e. hypothesis H_0 and all the results are about noise. Then, in the next section, we will pay more attention to the PD distribution of signal perturbed by Gaussian noise. Besides, that problem will be discussed in two different channel conditions, the first channel condition is AWGN channel without fading, and kind channel condition is AWGN channel with Rayleigh fading which is more in line with the actual scenarios.

2.4 PD Distribution of Signal Perturbed by Gaussian Noise (AWGN Channel)

Regard to the noise-perturbed signal, papers [9–11] has already derived formulas that illustrate the characteristics of PD distribution. Thus, in this paper, we are not doing a detailed derivation for that and the formula of CDF is as following:

$$F_{\varphi_n}(\varphi_n) = \frac{1}{4\pi} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} e^{-E} \left[\frac{W \sin(\Delta\omega)}{E} + \xi \right] dt \tag{10}$$

where

$$E = U - V \sin t - W \cos \Delta\omega \cos t \tag{11}$$

$$U = (SNR_{n+1} - SNR_n)/2 \tag{12}$$

$$V = (SNR_{n+1} + SNR_n)/2 \tag{13}$$

$$W = \sqrt{SNR_{n+1} SNR_n} = \sqrt{U^2 - V^2} \tag{14}$$

$$\xi = \frac{\alpha \sin \varphi_n - \beta \cos \varphi_n}{1 - (\alpha \cos \varphi_n + \beta \sin \varphi_n) \cos t} \tag{15}$$

$$\Delta\omega = \phi_n - \varphi_n \tag{16}$$

in which, SNR_n and SNR_{n+1} are the instantaneous SNR of the nth and the $n+1$th sampling point respectively, φ_n is phase difference between the nth sampling point and the $n+1$th sampling point of PU signal without noise and Rayleigh fading. It's worthy to noted that $\alpha + \beta j$ represents the complex correlation of the sum of Rayleigh fading signal and noise and $\xi = 0$ because of AWGN channel. Continuous wave only be considered here, so the SNR_n will be equal to SNR_{n+1}, and we can assume the $SNR_{n+1} = SNR_n = \gamma$. And then, after substituting and derivation of CDF, the formula of PDF is as follows:

$$P_{\varphi_n}(\varphi_n) = [1 + 2\gamma - \gamma(1 - \cos \Delta\omega \cos t)] e^{-\gamma(1 - \cos \Delta\omega \cos t)} \tag{17}$$

2.5 PD Distribution of Signal Perturbed by Gaussian Noise and Rayleigh Fading

In this section, we consider the PU signal's PD distribution which perturbed by Gaussian noise and Rayleigh fading. Thus, the complex correlation of the sum of Rayleigh fading signal and noise cannot be neglect and it can be expressed as $\alpha + \beta j$. Similarly, only continuous wave be considered, so we can still assume the $SNR_{n+1} = SNR_n = \gamma$. According to the condition $\alpha + \beta j$ and $SNR_{n+1} = SNR_n = \gamma$, we can obtain the following formula:

$$\alpha + \beta j = \sqrt{\alpha^2 + \beta^2} e^{j\phi_n} = \tfrac{\gamma e^{j\phi_n}}{\gamma + 1} \tag{18}$$

As our spectrum detect scheme work under low SNR condition, so the term approximate to constant one. Thus, the CDF of PD distribution can be expressed as following:

$$\begin{aligned} &F_{\varphi_n}(\varphi_n) \\ &= \frac{1}{4\pi} \int_{-\pi/2}^{\pi/2} [\frac{\sin \varDelta\omega}{1 - \cos \varDelta\omega \cos t} + \frac{\gamma \sin \varDelta\omega}{\gamma(1 - \cos \varDelta\omega \cos t) + 1}] dt \\ &= \frac{\sin \varDelta\omega}{\pi \left|\sin \varDelta\omega\right|} \arctan \left| \cot \frac{\varDelta\omega}{2} \right| \\ &+ \frac{\sin \varDelta\omega}{\pi \sqrt{(1 + 1/\gamma)^2 - \cos^2 \varDelta\omega}} \arctan \sqrt{\frac{(\gamma + 1) + \gamma \cos \varDelta\omega}{(\gamma + 1) - \gamma \cos \varDelta\omega}} \end{aligned} \tag{19}$$

and the distribution of $\varDelta\omega$ can be described as following:

$$F_{\varDelta\omega}(\varDelta\omega) = \begin{cases} F_{\varphi_n}(\varDelta\omega) - F_{\varphi_n}(-\pi) & \varDelta\omega \le 0 \\ F_{\varphi_n}(\varDelta\omega) - F_{\varphi_n}(-\pi) + 1 & \varDelta\omega > 0 \end{cases} \tag{20}$$

After transformation of the terms *arctan*, a simplified form of $F_{\varDelta\omega}(\varDelta\omega)$ can be expressed by following formula:

$$F_{\varDelta\omega}(\varDelta\omega) = 1/2 + \varDelta\omega/2\pi + \tfrac{\sin \varDelta\omega T(\varDelta\omega)}{2\pi Q(\varDelta\omega)} \tag{21}$$

where

$$T(\varDelta\omega) = \frac{\pi}{2} + \arcsin \frac{\gamma \cos \varDelta\omega}{\gamma + 1} \tag{22}$$

$$Q(\varDelta\omega) = \sqrt{(1 + \frac{1}{\gamma})^2 - \cos^2 \varDelta\omega} \tag{23}$$

and as $\varDelta\omega = \phi_n - \varphi_n$, so

$$f_{\varphi_n}(\varphi_n) = f_{\varDelta\omega}(\phi_n - \varphi_n) = F'_{\varDelta\omega}(\phi_n - \varphi_n) \tag{24}$$

Thus, after the derivation, the PDF of PD can be represents by following:

$$
\begin{aligned}
f_{\varphi_n}(\varphi_n) = & \frac{1}{2\pi} + \frac{\cos \Delta\omega T(\Delta\omega)}{2\pi Q(\Delta\omega)} \\
& - \frac{\cos \Delta\omega \sin^2 \Delta\omega T(\Delta\omega)}{2Q(\Delta\omega)} \\
& - \frac{\gamma \sin^2 \Delta\omega}{2\pi(\gamma+1)Q(\Delta\omega)\sqrt{1-\frac{\gamma^2\cos^2\Delta\omega}{(\gamma+1)^2}}}
\end{aligned}
\tag{25}
$$

3 Test Statistics and Cooperative Sensing

3.1 Test Statistics

After the derivation above, we can easily obtain the conclusion that the mean and variance of signal perturbed by noise are very different from the Gaussian noise. Thus, every CR can take advantage those characteristic to sense the status of PU. So, in this paper, we design a scheme that every CR makes the mean of PD as test statistics and the mean of PD is:

$$
S_\theta^i = \frac{1}{N}\sum_{i=1}^{N} \varphi_n^i \tag{26}
$$

where the S_θ^i is test statistic calculated by the ith CR, N represents the number of PDs, and the φ_n^i is the PD between the nth sampling point and the $(n+1)$th sampling point of the receive signal from ith CR, calculated by formula (3) (4) (5). When the mean of PD S_θ^i falls in the range of $\left[\pi - \varphi_0^i, \pi - \varphi_0^i\right]$, the ith CR will make the decision that the PU in not present and the ith CR's decision model is expressed as follows:

$$
D_i = \begin{cases} H_0^i & \left|S_\theta^i - \pi\right| \le \varphi_0^i \\ H_1^i & \left|S_\theta^i - \pi\right| > \varphi_0^i \end{cases} \tag{27}
$$

where, D_i is the ith CR's decision and φ_0^i is the decision threshold.

3.2 Threshold Setting

If the number of φ_n^i is large enough, the test statistics S_θ^i can be approximated as a Gaussian distribution according to the central limit theorem, whose mean and variance are π and $\frac{\pi^2}{3N}$ respectively. Thus, the PDF of test statistics S_θ^i can be expressed as follows:

$$
f(S_\theta^i|H_0) = \frac{1}{\sqrt{2\pi^3/3N}} e^{-\frac{(S_\theta^i-\pi)^2}{2\pi^2/3N}} \tag{28}
$$

We can easily obtain the false alarm probability P_f^i by following formula:

$$\begin{aligned} P_f^i &= 1 - \int\limits_{\pi-\varphi_0^i}^{\pi+\varphi_0^i} \frac{1}{\sqrt{2\pi^3/3N}} e^{-\frac{(S_\theta^i-\pi)^2}{2\pi^2/3N}} dS_\theta^i \\ &= erfc(\frac{S_\theta^i}{\sqrt{2\pi^2/3N}}) \end{aligned} \tag{29}$$

In practice, the threshold is usually chosen according to a fixed false alarm probability, which can be expressed as follows:

$$\varphi_0^i = \sqrt{2\pi^2/3N} erfc^{-1}(P_f) \tag{30}$$

As the case the PU is presents, we can easily obtain the value of mean μ_i and the variance σ_i^2 by formulas (17) or (25). For the case H_1, according to the central limit theorem, the PDF of test statistics S_θ^i can be expressed as follows:

$$f(S_\theta^i|H_1) = \frac{1}{\sqrt{2\pi\sigma_i^2/N}} e^{-\frac{(S_\theta^i-\mu_i)^2}{2\sigma_i^2/N}} \tag{31}$$

Thus, the detection probability P_d^i of the ith CR can be expressed as follows:

$$\begin{aligned} P_d^i &= 1 - \int\limits_{\pi-\varphi_0^i}^{\pi+\varphi_0^i} \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(S_\theta^i-\mu^i)^2}{2\sigma_i^2}} dS_\theta^i \\ &= erfc(\frac{S_\theta^i}{\sqrt{2\sigma_i^2}}) \end{aligned} \tag{32}$$

3.3 Cooperative Sensing

In an actual scenario, the hidden terminal problem which occurs when the CR is sheltered by giant buildings especially in urban area and that become an urgent issue to tackle. In this case, the CR cannot detect the existence of PU, and will access the spectrum which the PU is occupying. Thus certainly caused a series severe interference to the PU. In our sensing scheme, we deploy more CRs to collaborate [12]. The cooperative spectrum structure is illustrated in the Fig. 1, the overall process works like this: Firstly, every CR performs their local spectrum sensing scheme based on PD independently and make a local decision on whether the PU is present or not. And then, every CR forward their local decisions to the fusion center. Finally, the fusion center fuses the all CR's decisions by fusion algorithm and makes the final decision of the status of PU. There are mainly two fusion algorithms, which are decision fusion and data fusion respectively. In decision fusion case, fusion center receive all one-bit binary decisions from CRs, and fused together according to an OR logic. Instead,

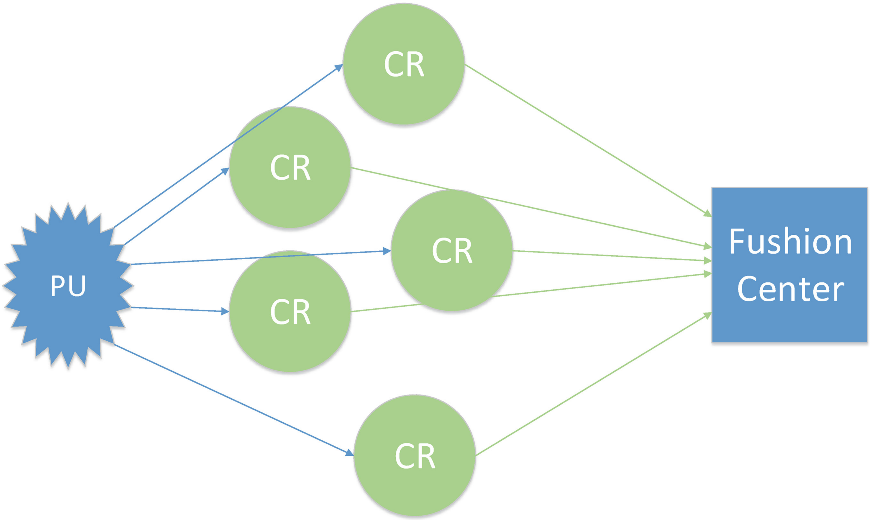

Fig. 1. Cooperative spectrum sensing structure

in data fusion case, fusion center not receive one-bit binary decisions but receive the observation value from all CRs. In our scheme, decision fusion algorithm is employed as CRs transmit less amount of data [13,14]. In this paper, we use the number 0 to denote the decision H_0^i and number 1 to denote the decision H_1^i from the ith CR. So the decision from the ith CR D_i has only two values, 0 or 1, which can be expressed by $D_i \in \{0, 1\}$. On one side of the fusion center, all decisions from the CRs are fused together according to the following logic:

$$D = \sum_{i=1}^{K} D_i \begin{cases} \geq n, H_1 \\ < n, H_0 \end{cases} \tag{33}$$

where, H_1 and H_0 represent the final decision of status of PU from the fusion center. If the fusion center makes the decision, i.e. H_1, there must be at least n out of K CRs making decision H_1^i and transmit 1s to the fusion center, vice versa. It is worthy to noted that when the n is set to be 1, this logic can be seen as OR rule and this logic rule can be seen as AND logic rule when the n is K. Under the circumstance of OR rule, the fusion center makes the decision that the PU is presence when at least one CR make the local decision H_1.

The OR logic can be seen as a kind of conservative logic when the CR access the spectrum and OR logic will lower the interference to the PU because of higher P_d. For the AND logic rule, it can be seen as more radical logic and improve the utilization ratio of spectrum, but at the cost of higher collision probability with the PU. In this paper, we discuss only two basic fusion algorithms, there are also many more fusion algorithms that can be studied and different algorithms are suitable for different actual scenes. The final detection probability P_d and false alarm probability P_f of cooperative spectrum sensing based on the OR rule is presented by following formulas:

$$P_d = 1 - \prod_{i=1}^{K} (1 - P_d^i) \tag{34}$$

$$P_f = 1 - \prod_{i=1}^{K} (1 - P_f^i) \tag{35}$$

All the CRs can be considered in the same radio condition, thus they have same test statistics distribute. So here replaces the P_d^i and P_f^i by formula (32) and formula (29) respectively and makes $S_\theta^i = S_\theta$, $\sigma_i = \sigma$, $\mu^i = \mu$. The final P_d and P_f can be expressed by following formulas:

$$P_d = 1 - (1 - erfc(\frac{S_\theta}{\sqrt{2\sigma^2}}))^K \tag{36}$$

$$P_f = 1 - (1 - erfc(\frac{S_\theta}{\sqrt{2\pi^2/3N}}))^K \tag{37}$$

And for the AND logic rule, the final detection probability P_d and false alarm probability P_f of cooperative spectrum sensing can be expressed by following formulas:

$$P_d = \prod_{i=1}^{K} P_d^i = (erfc(\frac{S_\theta}{\sqrt{2\sigma^2}}))^K \tag{38}$$

$$P_f = \prod_{i=1}^{K} P_f^i = (erfc(\frac{S_\theta}{\sqrt{2\pi^2/3N}}))^K \tag{39}$$

3.4 Performance Analysis

According to the nature of our scheme, only $N + 1$ sampling points need to be store for every CR and the computational complexity is $O(N)$. To be contrasted with the other more sophisticated schemes such as sensing scheme based on cyclostationary feature, our sensing cost every CR's lower computing resource.

4 Simulation Analysis

In this section, the method of Monte Carlo Simulation is applied in our simulation to offset the random error, thus improving the accuracy of our simulation and simulation times is set to 1000. According to the analysis above, the performance of our scheme is related to many factors, such as the length of sample points, the number of CRs, the fusion logic rules and channel condition. All of the simulations are implemented under the Rayleigh fading channel condition as it is more similar to the practical radio environment.

Figure 2 compares the detection probability P_d of our scheme with the detection probability P_d that of scheme by energy detection for several basic modulation signals, when the $N = 1000$, $P_f = 0.01$ and the number of CR is set to $8(K = 8)$. With the SNR increasing, detection probability P_d is also increasing, so those curves are accord with the general regular. We can observe that our scheme obtains 3–4 dB gains when the P_d is above 90% comparing with the scheme based on energy detection. The overlapping of curves in most parts prove that our scheme is robust to modulation mode which is similarly as energy detection. The curves in small parts are not overlapping and detection probability of sine wave signal is higher than signals modulated by other modulation in those parts, that is because the phase of sine wave signal is more continuous than the others.

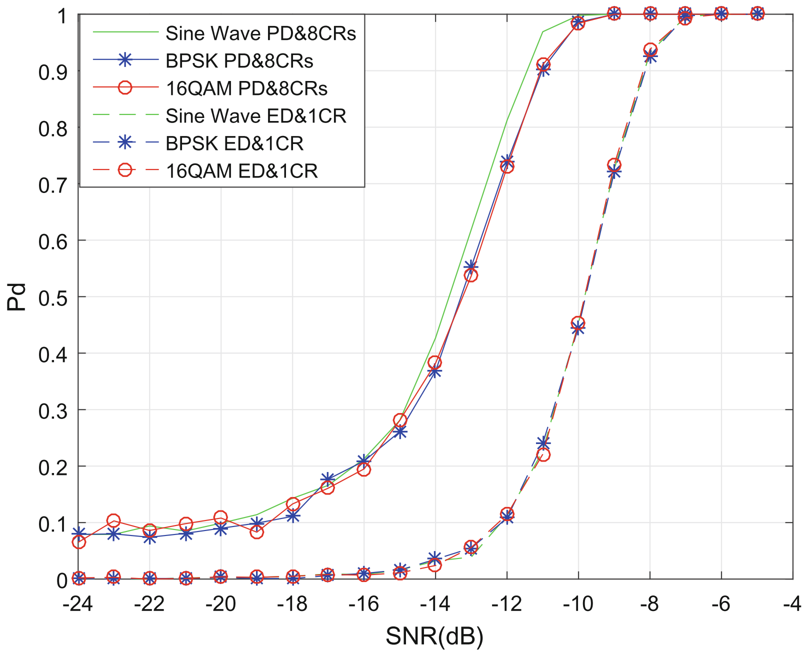

Fig. 2. Detection probability for different ways of modulation

Figure 3 shows the detection probability versus signal length N, when the P_f is set to 0.01 and the number of CRs is set to 8. According to the Fig. 3, we can obtained the regular that when three curves reached the same level of P_d, the curve whose length of sample data is longer needs the lower SNR. This regular can be explained by the reason that the length of sample data is longer, the test statistics, i.e. the mean of PD will converge to mathematical expectation according to the law of large numbers.

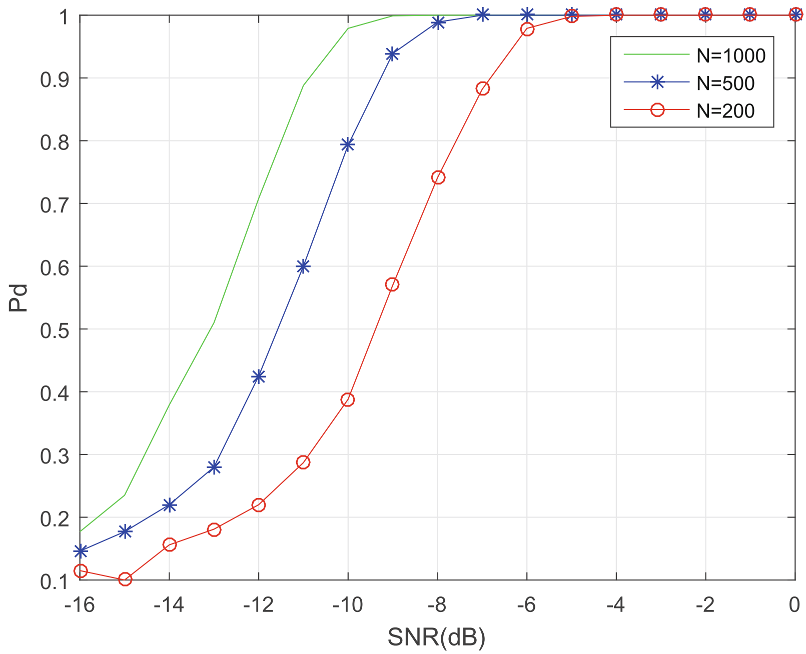

Fig. 3. Detection probability Pd for different length of sampling points

Figure 4 shows the relation between the number of CRs represented by K and detection probability. We can get that with the number of CRs increasing, the detection probability P_d is increasing too when all the curves are in the same SNR condition. That can be explained by formula (34), the detection probability P_d is less to 1, so the larger K become, the larger P_d becomes.

Figure 5 shows the receiver operating characteristic (ROC) curves which describe the relation between detection probability P_d and false alarm probability P_f under the condition that $K = 8$, $N = 1000$. That lists the performance results of cooperative spectrum sensing for different fusion rules and the case of ED over Rayleigh fading channels with the $SNR = -14\,\text{dB}$. With the false alarm probability P_f increasing, detection probability P_d of three curves increase too, but in the area of lower P_f, the P_d of our scheme based on OR fusion logic rule increases sharply. So the OR rule is the better rule than the AND rule, and our scheme based on OR fusion logic rule have the best performance than others.

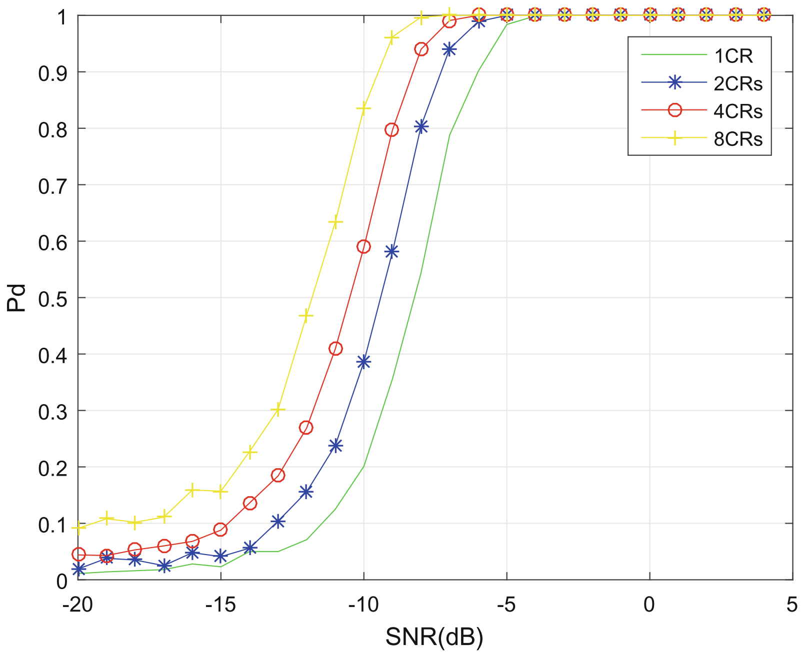

Fig. 4. Detection probability Pd for different number of CRs

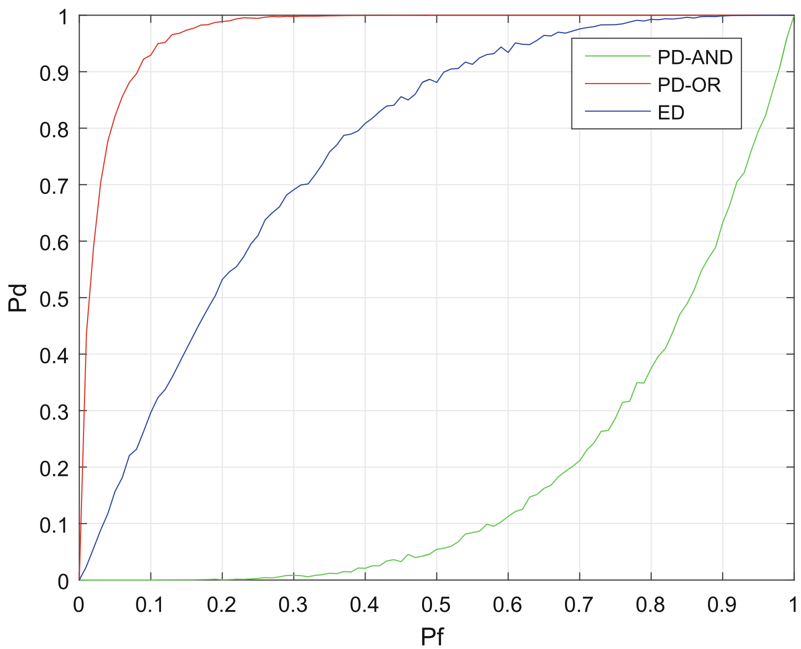

Fig. 5. ROC curves at $-14\,\mathrm{dB}$

5 Conclusion

In this paper we proposed a novel cooperative spectrum scheme based on phase difference which can improve the spectrum sensing performance compared with traditional sensing scheme. Firstly, we analyze the distributions of the phase difference between two adjacent samples under the condition of Gaussian noise, the signal perturbed by noise and the signal perturbed by Rayleigh fade, and find that the mean and variance of those signal are very different as the their distributions are very different. On that basis, we select the mean of PD as test statistics, which follows Gaussian distribution and needs lower computer resource. According to the analysing above, we obtain the threshold of detection. Cooperative spectrum sensing was then considered and shown to be a powerful method for dealing with the hidden terminal problem. Simulation shows that our scheme has best performance compared to energy detection under the Rayleigh Faded channel and OR rules has better performance than AND performance.

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