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COOPERATIVE SPECTRUM SENSING ALGORITHM BASED ON PHASE COMPENSATION IN COGNITIVE RADIO CLOUD NETWORKS

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Abstract. *Cognitive radio is an effective way to improve the utilization of spectrum resource. This paper focused on the spectrum sensing in cognitive radio cloud networks and proposed a cooperative spectrum sensing algorithm based on phase compensation to improve the spectrum sensing performance. In the algorithm, the received signals in the sensing nodes are sent to the cloud, compensated in phase and combined into one signal. Then, the combined signal is used to test the hypothesis, whether the primary user is present. It uses all available information of all sensing nodes and improves the performance of spectrum detection effectively. The simulation results show that the proposed algorithm has 2-4 dB advantage in signal-to-noise ratio over other algorithms.*
Keywords: Cognitive radio, Spectrum sensing, Phase compensation, Cloud computing

1. **Introduction.** With the development of wireless data service, the non-replicating spectrum resources become more and more scarce. And, the contradiction between the growing demand for spectrum resources and the available spectrum resources becomes more and more serious [1].

Cognitive radio (CR) can effectively alleviate the problems and catches a lot of attention in the world [2,3]. The main idea of CR is to access spectrum opportunistically and dynamically [4]. In CR networks, SUs should periodically detect the spectrum in order to avoid the interference to PUs when the SU is accessing the spectrum. If the detected spectrum is idle, the SU will continue to access the spectrum. If the detected spectrum is busy, the SU will immediately exit the spectrum to avoid interference to the PU [5,6].

Spectrum sensing has been studied in many ways. A BP based cooperative compressed spectrum sensing algorithm was proposed [7]. It can effectively achieve cooperation in heterogeneous environments and improve performance of compressed spectrum sensing under a low sampling rate and low signal-to-noise ratio (SNR). Chen et al. proposed a cooperative spectrum sensing algorithm to improve the performance of asynchronous cooperative sensing [8]. Shen et al. proposed a signal set cardinality and contiguity based wideband spectrum sensing scheme [9]. The proposed scheme can work without the prior knowledge of the noise power and the primary user signal, and is robust against the noise uncertainty. A spectrum sensing frame based on the level of interference is proposed to maximize the throughput under the condition of limited interference [10]. The weighted algorithms, such as the reliability-based cooperative spectrum sensing (CSS) algorithm [11], weighted cooperative spectrum sensing algorithm (WCSA) [12], detection probability-based weighted (DPW) [13], and average weighted (AW) algorithm [14], are often used to improve the spectrum sensing performance.

The cloud computing brings some new ideas to sense spectrum cooperatively [15,16]. Kumar and Lu introduced the cloud computing into cognitive radio networks [17]. It has been proved that the scheme can reduce the computational complexity and energy consumption. It not only improves the real-time performance of the network, but also improves the life of mobile device in the network. Chang et al. proposed novel channel estimation and noise-plus-interference estimation methodologies [18]. It significantly improves the system capacity and bit error rate. Similarly, Chen et al. studied the cloud based cognitive radio spectrum access strategy and proposed the optimal spectrum access operation strategy to maximize the transmission efficiency of the secondary network [19].

In this paper, we use the cloud computing to sense the spectrum and propose a cloud computing cooperative spectrum sensing (CCCSS) algorithm, which is based on phase compensation. In this algorithm, all received signals in the sensing nodes are sent to the cloud. In the cloud, the phase errors between the signals are compensated. And then all compensated signals are combined into one signal. Finally, the combined signal is used to detect whether the PU is present. It showed that the proposed algorithm has 2-4 dB advantage in signal-to-noise ratio over other algorithms.

The remainder of the paper is organized as follows. Section 2 proposes the system model of networks. The CCCSS algorithm is described in Section 3. Simulation results are shown in Section 4. Finally, Section 5 gives some conclusions.

2. **System Model.** Suppose there are one PU and N SUs in the cognitive radio cloud network, as shown in Figure 1. All received signals in sensing nodes are sent to the cloud, compensated in phase and combined into one signal to detect whether the PU is present. There are two hypotheses, H_1 and H_0. H_1 represents the hypothesis in which there is a PU present, and H_0 represents the hypothesis in which there is no any PU present. The spectrum sensing in the cloud network can be modeled as a binary hypothesis testing

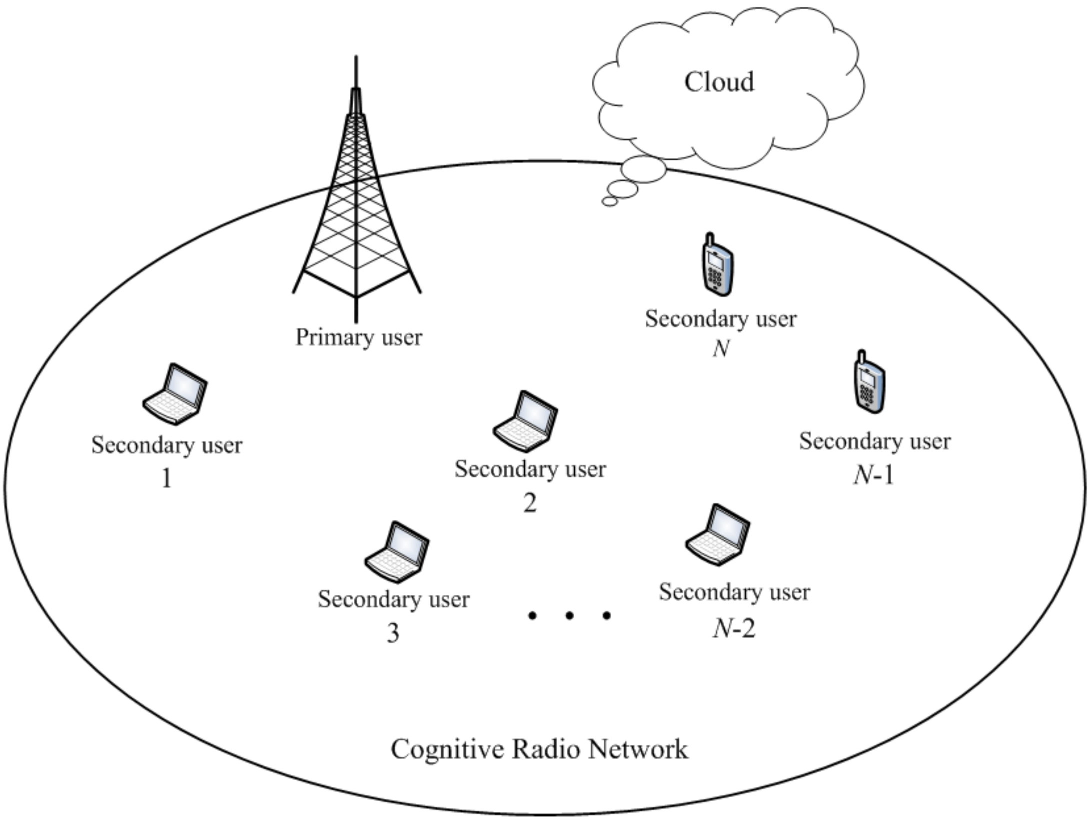

Figure 1. System model of cognitive radio network

problem as follows

$$\begin{cases} H_1 : Ts = \sum_{i=1}^{N} s_i(t) = \sum_{i=1}^{N} h_i \cdot x(t - t_i) + \sum_{i=1}^{N} n_i(t) \\ H_0 : Ts = \sum_{i=1}^{N} s_i(t) = \sum_{i=1}^{N} n_i(t) \end{cases} \tag{1}$$

where Ts is the spectrum sensing statistic in cloud, $s_i(t)$ and $n_i(t)$ are the received signal and additive Gauss white noise (AGWN) from ith ($i = 1, \ldots, N$) sensing node in the cloud respectively, h_i is the corresponding channel gain, t_i is the corresponding transmission delay, and $x(t)$ is the primary signal transited.

3. **Cloud Computing Cooperative Spectrum Sensing Algorithm.** Obviously, the delay of each received signal in sensing nodes is not same with each other, and the phase of each received signal is different each other. In order to get the largest gain spectrum sensing statistic to achieve the most accurate spectrum detection, all received signals should be compensated. Therefore, the cooperative spectrum sensing in cloud networks can be divided into three stages, the phase compensation, signals combining and spectrum decision, as shown in Figure 2. In the first stage, we select the signal with the most energy as the reference signal from all the received signals, then transform it with Hilbert transformer. In the second stage we compensate the phase errors between the reference signal and the other received signals to obtain the largest diversity gain. In the last stage all compensated signals and the reference signal are combined to a signal, which is detected to decide whether the PU is present.

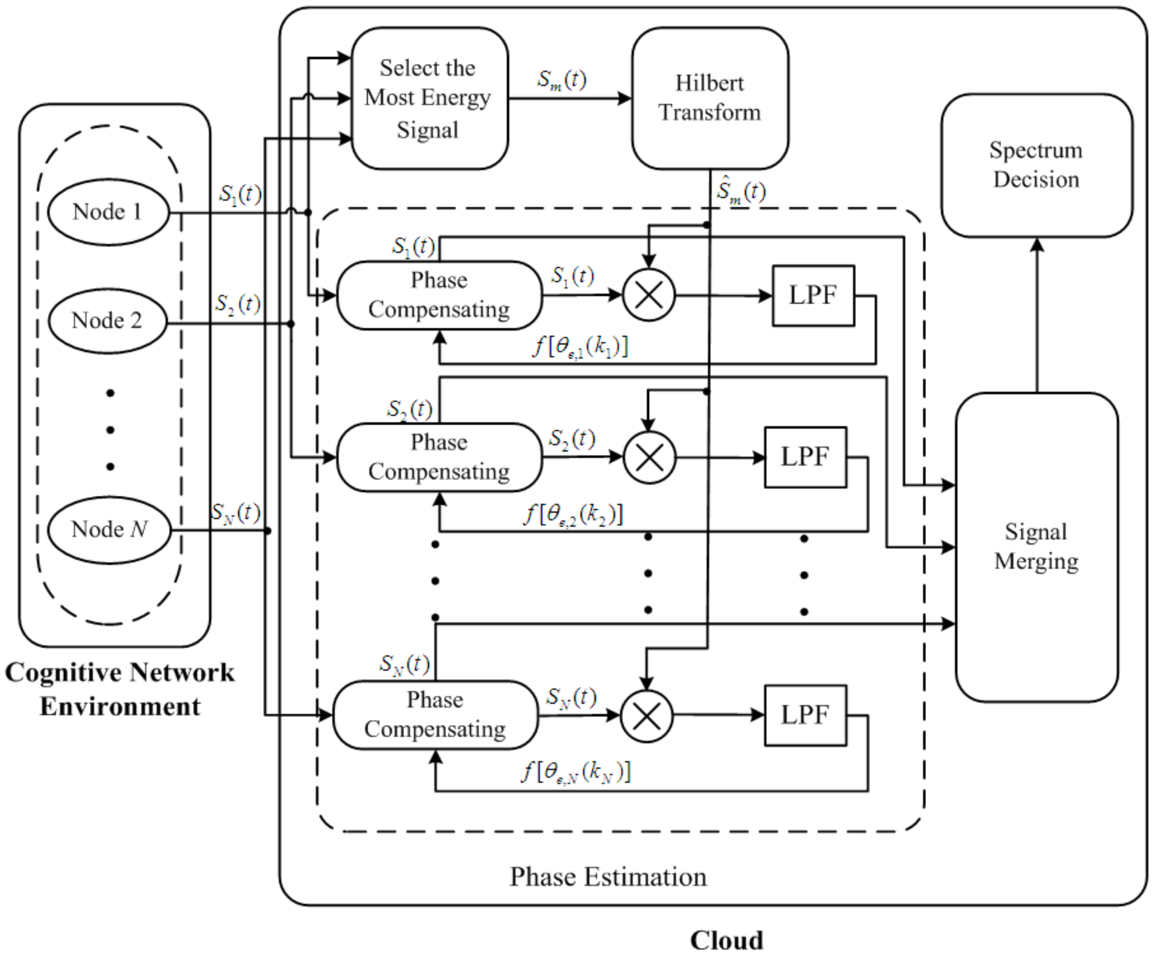

FIGURE 2. Diagram of spectrum sensing in cloud

Generally, the transmitted signal of the PU can be given by

$$x(t) = p(t) \cdot \cos(\omega_c t) \tag{2}$$

where $p(t)$ is a narrowband signal, ω_c is the carrier frequency. If we ignore the AGWN in the channel, the received signal from ith sensing node in the cloud is given by

$$s_i(t) = h_i \cdot x(t - t_i) = h_i \cdot p(t - t_i) \cos[\omega_c(t - t_i)] \tag{3}$$

Considering $p(t)$ is the narrowband signal, the effect of multipath delay on $p(t)$ can be ignored. Therefore, the received signals in the cloud can be described as follows

$$s_i(t) = h_i \cdot p(t) \cos(\omega_c t - \omega_c t_i) = h_i \cdot p(t) \cos(\omega_c t + \theta_i) \tag{4}$$

where θ_i is the carrier phase of $s_i(t)$.

Assume that $s_m(t)$ is the signal with the most energy and is taken as the reference signal. The Hilbert transform of $s_m(t)$ can be given by

$$\hat{s}_m(t) = h_m \cdot \hat{p}(t) \cdot \sin(\omega_c t + \theta_m) \tag{5}$$

where

$$\hat{p}(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{p(t)}{t - \tau} d\tau = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{p(t - \tau)}{\tau} d\tau = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{p(t + \tau)}{\tau} d\tau \tag{6}$$

Multiply $\hat{s}_m(t)$ and the other received signals $s_i(t)$ $(i \neq m)$ and then obtain

$$\begin{aligned} \hat{s}_m(t) \cdot s_i(t) &= h_m \cdot \hat{p}(t) \cdot \sin(\omega_c t + \theta_m) \cdot h_i \cdot p(t) \cdot \cos(\omega_c t + \theta_i) \\ &= h_m \cdot h_i \cdot \hat{p}(t) \cdot p(t) \cdot \sin(\omega_c t + \theta_m) \cdot \cos(\omega_c t + \theta_i) \end{aligned} \tag{7}$$

Let

$$X = h_m \cdot h_i \cdot \hat{p}(t) \cdot p(t) \tag{8}$$

and

$$\theta_{e,i} = \theta_m - \theta_i \tag{9}$$

Equation (7) can be simplified as follows

$$\begin{aligned} \hat{s}_m(t) \cdot s_i(t) &= X \cdot \sin(\omega_c t + \theta_m) \cdot \cos(\omega_c t + \theta_i) \\ &= \frac{1}{2} X \cdot [\sin(2\omega_c t + \theta_m + \theta_i) + \sin(\theta_m - \theta_i)] \\ &= \frac{1}{2} X \cdot [\sin(2\omega_c t + \theta_m + \theta_i) + \sin(\theta_{e,i})] \end{aligned} \tag{10}$$

Filtering the high frequency component, we get

$$f(\theta_{e,i}) = \frac{1}{2} X \sin(\theta_{e,i}) \tag{11}$$

It is evident that the output of the low-pass filter, $f(\theta_{e,i})$, is proportional to the phase errors, $\theta_{e,i}$ when $-\pi < \theta_{e,i} < \pi$. That is to say we can use $f(\theta_{e,i})$ to adjust the phases of received signals. Then, we get the cooperative spectrum sensing algorithm as follows.

Algorithm 1: Cloud computing cooperative spectrum sensing algorithm

1) Select the most energy signal from all received signals as the reference signal, $s_m(t)$.

2) Transform $s_m(t)$ with Hilbert transformer and get $\hat{s}_m(t)$.

3) Multiply $\hat{s}_m(t)$ and $s_i(t)$ $(i \neq m)$, and then filter it, we get the phase error control signal of the kth iteration, $f[\theta_{e,i}(k_i)]$.

4) Update phase of the ith signal as follows

$$\theta_i(k_i) = \theta_i(k_i - 1) + \nabla \bullet f[\theta_{e,i}(k_i)] \quad (i = 1, \ldots, N) \tag{12}$$

where ∇ is the iterative step size.

5) If the absolute value of $f[\theta_{e,i}(k_i)]$ is less than the given threshold, the phase updating is ended and the phase compensation is completed. Otherwise, go back to Step 3 until the absolute value of $f[\theta_{e,i}(k_i)]$ is less than the given threshold.

6) Combine all signals, include the reference signal and compensated signals, into one signal, and then send it to the spectrum detector.

7) Spectrum decision. The cloud detected the combined signal to decide whether the PU is present. If the PU is present, the channel is busy, SUs cannot use the channel. If the PU is absent, the channel is idle, SUs can use the channel to transmit their data.

8) End.

4. **Simulation Results and Analyses.** In this section, we present some simulation results of the CCCSS algorithm, and compare with others. In the simulation we have one PU and 8 SUs. The PU signal is a phase shift keying (PSK) signal with the baud rate which is 5000 Bauds and carrier frequency which is 10 MHz. The sampling frequency is 100 MHz. We use the maximum and minimum eigenvalue spectrum detection algorithm to detect the signal [20].

Figure 3 quantifies the convergence of the phase errors between the received signals and the reference signal. All the phase errors converge to zero within 13 iterations. It means that the CCCSS algorithm converges very fast and can meet the requirement of real-time spectrum sensing in cognitive radio networks.

Figure 4 shows the detection probabilities of the five different spectrum sensing algorithms. With the increase of SNR, the detection probabilities of all algorithms are increased, but the detection probability of the CCCSS algorithm proposed in this paper is higher than others. When the detection probability is about 0.98, the SNRs in the CCCSS, CSS and DPW algorithms should be −16 dB, −14.3 dB, −13.2 dB respectively, and the SNRs in the WCSA and AW algorithms should be larger than −12 dB respectively That is to say, the CCCSS algorithm has 1.7 dB margins at least in SNR over others.

Figure 5 compares the false alarm probabilities of the five algorithms. As the increase of SNR, the false alarm probabilities of all algorithms are reduced. However, the false alarm probability of the CCCSS algorithm is always smaller than others. When SNR = −16 dB, the false alarm probability of CCCSS algorithm is about 0.028. The SNRs in CSS, WCSA and DPW algorithms should be −13.7 dB, −13 dB, −12.14 dB respectively if they want to achieve the same false alarm probability. The CCCSS algorithm has 2.3 dB gain at least in SNR over others.

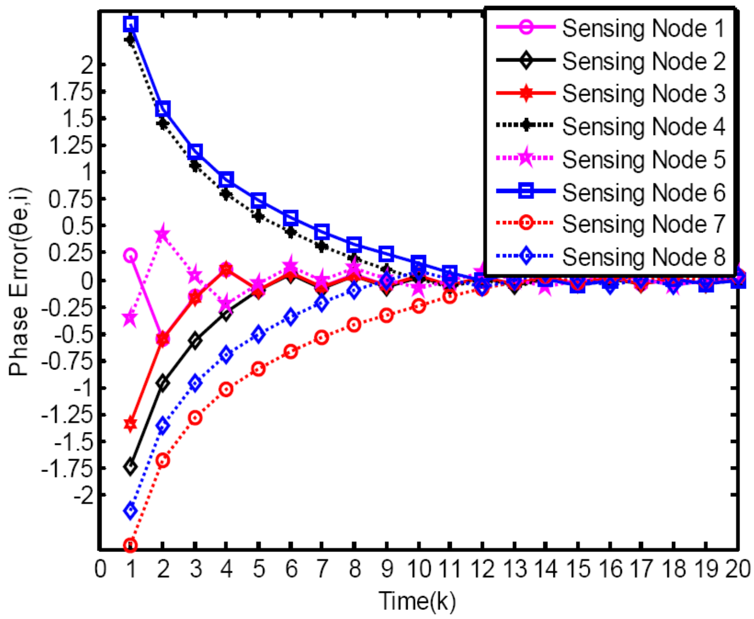

FIGURE 3. Convergence of different phase errors

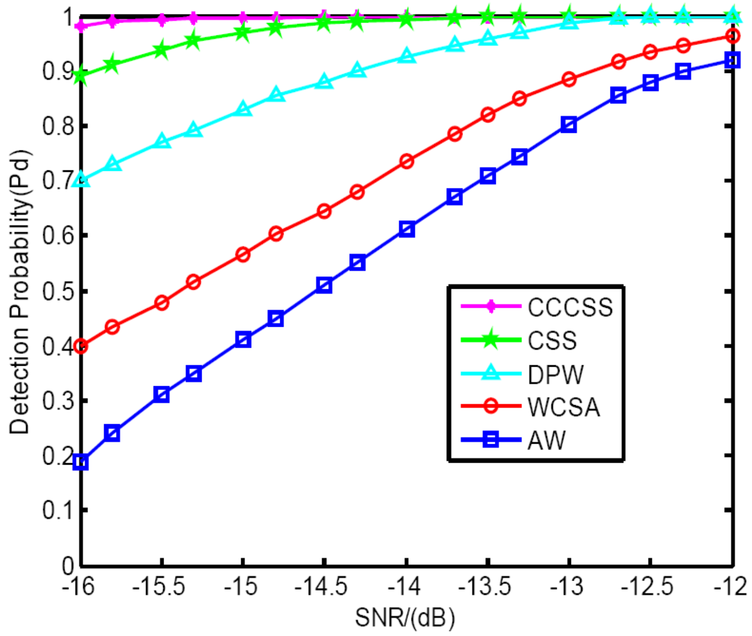

Figure 4. Comparison of detection probabilities

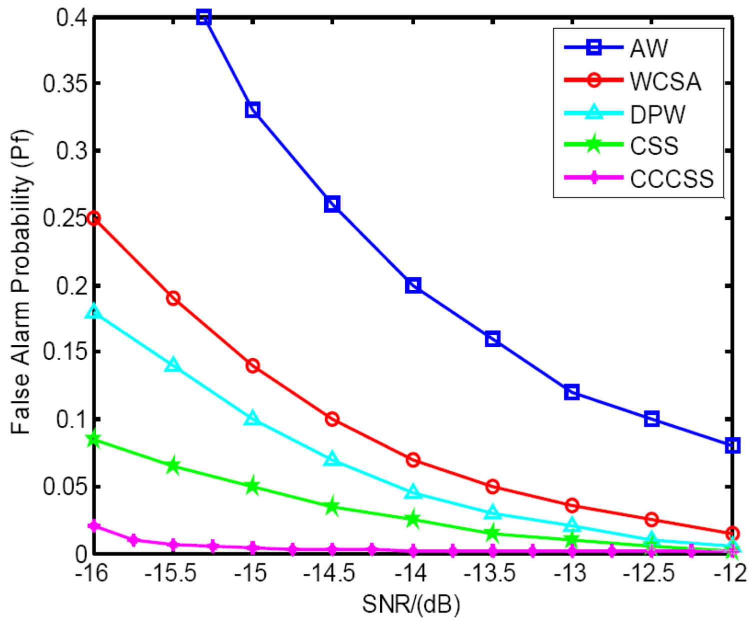

Figure 5. Comparison of false alarm probabilities

Figure 6 and Figure 7 give the comparison of detection and false alarm probabilities of the CCCSS algorithm under the different numbers of node. It can be seen that with the increase of the number of sensing nodes, the performance of CCCSS algorithm is improved more and more obviously.

Figure 8 and Figure 9 show detection and false alarm probabilities of the CCCSS algorithm under different kinds of PU signal. It is easily seen that the performance for detecting any kind of signal is almost the same. That is to say the CCCSS algorithm can be used to detect any kind of signal.

5. **Conclusions.** In order to improve the performance of multi-user cooperative spectrum sensing in cognitive radio cloud networks, a cooperative spectrum sensing algorithm based on phase compensation is proposed in this paper. In this algorithm, all the sensing nodes

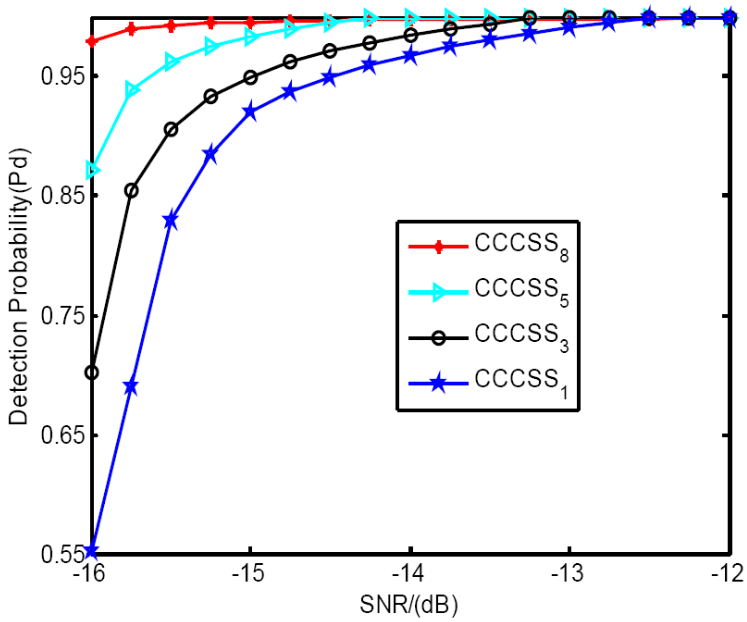

Figure 6. Comparison of detection probabilities for different number of sensing nodes

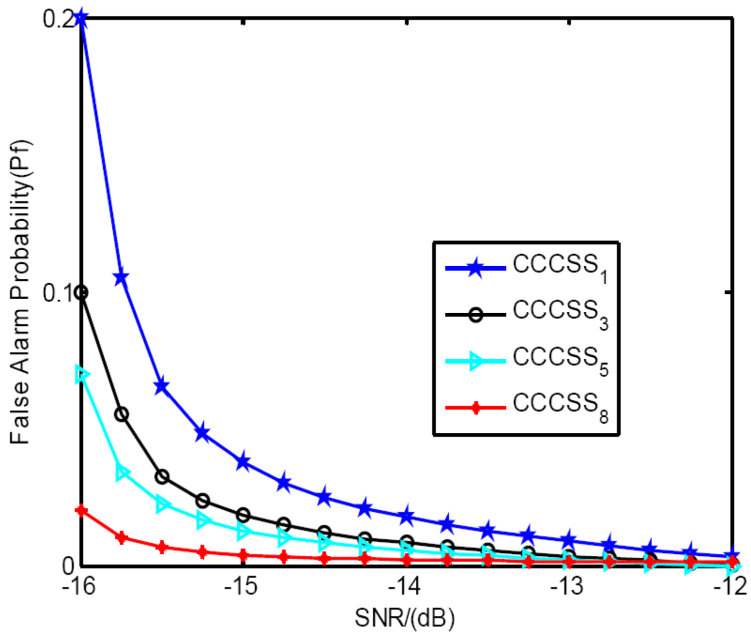

Figure 7. Comparison of false alarm probabilities for different numbers of sensing nodes

send their received signals to the cloud. In the cloud, the phase errors between the signals are compensated, and then all compensated signals are combined into one signal to be detected whether the PU is present. It can improve the spectrum detection performance effectively. Simulation results show that the CCCSS algorithm has 1.7 dB gains in SNR over other algorithms at least. In the further work we will analyze the effect of the phase compensator on detecting wideband signals.

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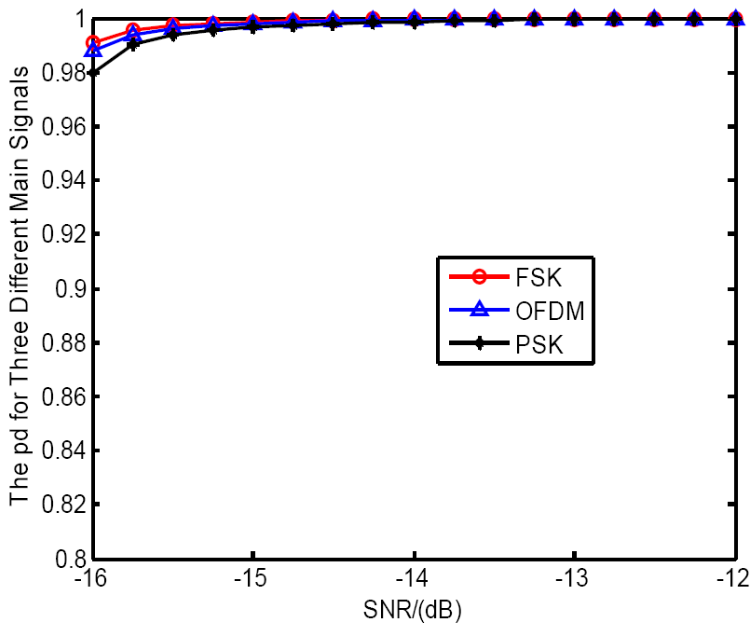

FIGURE 8. Comparison of detection probability of three signals

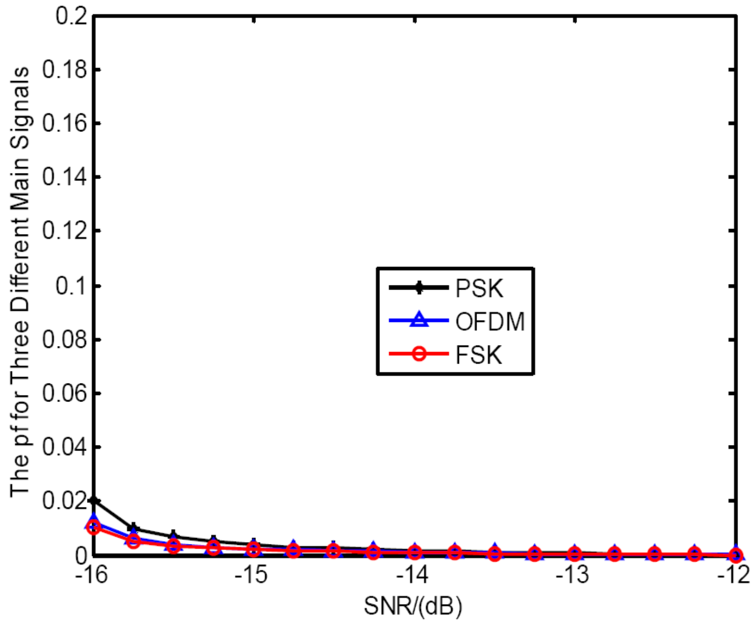

FIGURE 9. Comparison of false alarm probabilities of three signals

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