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Research Article

Cooperative Spectrum Sensing Algorithm to Overcome Noise Fluctuations Based on Energy Detection in Sensing Systems

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In sensing systems, nodes must be able to rapidly detect whether a signal from a primary transmitter is present in a certain spectrum. However, traditional energy-detection algorithms are poorly adapted to treating noisy signals. In this paper, we investigate how rapid energy detection and detection sensitivity are related to detection duration and average power fluctuation in noise. The results indicate that detection performance and detection sensitivity decrease quickly with increasing average power fluctuation in noise and are worse in situations with low signal-to-noise ratio. First, we present a dynamic threshold algorithm based on energy detection to suppress the influence of noise fluctuation and improve the sensing sensitivity. Then, we present a new energy-detection algorithm based on cooperation between nodes. Simulations show that the proposed scheme improves the resistance to average power fluctuation in noise for short detection timescales and provides sensitive detection that improves with increasing numbers of cooperative detectors. In other words, the proposed scheme enhances the ability to overcome noise and improves spectrum sensing performance.

1. Introduction

Spectrum sensing for cognitive radio involves a cognitive user that can detect signals in real time and provide feedback when an authorized user sends a signal. Spectrum sensing strongly affects the accuracy of communication between the authorized user and the cognitive user, and a good spectrum sensing algorithm is robust against noise (i.e., produces minimal disruption of authorized users). Therefore, which sensing scheme to use in situations with a low signal-to-noise ratio (SNR) is an important topic [1, 2]. Most programs now are based on energy detection, which is sensitive to noise, so small fluctuations in noise power may cause a sharp decline in energy detection. Most energy-detection schemes are based on constant noise power [3–8], although some research is available on nonconstant noise power [9–15]. In fact, constant noise power [3–8] is not possible because of background noise, which includes thermal noise, quantization noise, noise due to power leakage through nonideal filters [16], interference between authorized users, and cognitive interference between users and other components [17, 18]. Thus, noise on detection timescales cannot be constant; instead, the average noise power fluctuates.

In this paper, we study the relationship between average power fluctuation in noise, detection sensitivity, and detection duration. With zero average power fluctuation in noise, a given detection performance is achieved in theory when the noise power is constant, provided sufficiently long detection time and that the signal can be detected by cognitive radio at low SNR. Thus, a second user provides high detection sensitivity. However, with nonzero average power fluctuation in noise, even given sufficiently long detection duration, the ability of the cognitive user to detect the SNR is limited and the detection sensitivity decreases dramatically. If the SNR detected by the cognitive user is below the detection sensitivity, no authorized users will be detected in the given band, even if blessed with an infinitely long detection time. In this case, the cognitive user inevitably interferes with the signals of the authorized users. The average power fluctuation in noise decreases the detection performance and detection sensitivity, so a sensing scheme is required that is robust against fluctuations in noise. Toward this end, we present herein a cooperative spectrum sensing algorithm that provides increased sensing performance as the number of collaborative users increases. The algorithm improves robustness against noise fluctuations while providing the same detection performance, thereby improving the detection sensitivity.

2. Energy-Detection Model

Assume that the signal is independent of the noise and that random processes are stationary and ergodic unless otherwise specified. The problem of signal detection in additive Gaussian noise can be formulated as a binary hypothesis-testing problem with the following hypotheses:

$$\begin{cases} \mathscr{H}_0 : Y(n) = W(n), & n = 1, 2, \cdots, N, \\ \mathscr{H}_1 : Y(n) = X(n) + W(n), & n = 1, 2, \cdots, N, \end{cases} \quad (1)$$

where $Y(n)$, $X(n)$, and $W(n)$ are the signal received at the cognitive radio nodes, the transmitted signal at the primary nodes, and white noise samples, respectively; $\mathscr{H}_1$ ($\mathscr{H}_0$) indicate that the licensed user is present (not present). Noise samples $W(n)$ come from an additive white Gaussian noise process with power spectral density σ_n^2, [i.e., $W(n) \sim \mathscr{N}(0, \sigma_n^2)$.].

We assume no deterministic knowledge about the signal $X(n)$ other than the average power of the signal. In this case, the optimal detector is an energy detector or a radiometer [11], and the test statistic is given by

$$D(Y) = \frac{1}{N}\sum_{n=0}^{N-1} Y^2(n) \underset{\mathscr{H}_0}{\overset{\mathscr{H}_1}{\gtrless}} \gamma, \quad (2)$$

where $D(Y)$ is the decision variable, γ is the decision threshold, and N is the number of samples. If the noise variance is known with zero noise uncertainty, the central limit theorem gives the following approximations [9, 11]:

$$\begin{cases} D(Y)|\mathscr{H}_0 \sim \mathscr{N}\left(\sigma_n^2, \dfrac{2}{N}\sigma_n^4\right), \\ D(Y)|\mathscr{H}_1 \sim \mathscr{N}\left(P + \sigma_n^2, \dfrac{2}{N}\left(P + \sigma_n^2\right)^2\right), \end{cases} \quad (3)$$

where $P = (\sum_{n=1}^{N} |X(n)|^2)/N$ is the average signal power and σ_n^2 is the noise variance.

3. Energy Detection with Single Node

With these approximations, one obtains the following detection probability P_D and false alarm probability P_{FA} [9, 11]:

$$P_D = \mathrm{prob}(D(Y) > \gamma|\mathscr{H}_1) = Q\left(\frac{\gamma - \left(P + \sigma_n^2\right)}{\sqrt{2/N}(P + \sigma_n^2)}\right), \quad (4)$$

$$P_{\mathrm{FA}} = \mathrm{prob}(D(Y) > \gamma|\mathscr{H}_0) = Q\left(\frac{\gamma - \sigma_n^2}{\sqrt{2/N}\sigma_n^2}\right), \quad (5)$$

where $Q(\cdot)$ is the standard Gaussian complementary cumulative distribution function and P_D, P_{FA}, and P_{MD} are the detection probability, false alarm probability, and missed detection probability, respectively.

The relationship between target variables (i.e., detection probability P_D, false alarm probability P_{FA}, missed detection probability P_{MD}, and sample number N, with the latter giving the detection duration) is deduced for a given SNR.

To simplify the problem, we discuss the energy-detection algorithm based on the average noise power without uncertainty. Using Eqs. (4) and (5) to eliminate the decision-threshold variable γ gives

$$N = 2\left[Q^{-1}(P_{\mathrm{FA}}) - Q^{-1}(P_D)(1 + \mathrm{SNR})\right]^2 \mathrm{SNR}^{-2}, \quad (6)$$

where $Q^{-1}(\cdot)$ is the inverse standard Gaussian complementary cumulative distribution function, and $\mathrm{SNR} = P/\sigma_n^2$ is the signal-to-noise ratio.

Now consider the case with uncertainty in the noise model. The variance of noise with uncertainty can be included in a single interval $\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]$, where ρ is the noise uncertainty factor and ρ is close to 1; that is, $\rho > 1$ and $\rho \approx 1$. Thus, Eqs. (4) and (5) take the form

$$P_D = \min_{\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]} Q\left(\frac{\gamma - \left(P + \sigma^2\right)}{\sqrt{2/N}(P + \sigma^2)}\right) = Q\left(\frac{\gamma - \left(P + \sigma_n^2/\rho\right)}{\sqrt{2/N}(P + \sigma_n^2/\rho)}\right), \quad (7)$$

$$P_{\mathrm{FA}} = \max_{\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]} Q\left(\frac{\gamma - \sigma^2}{\sqrt{2/N}\sigma^2}\right) = Q\left(\frac{\gamma - \rho\sigma_n^2}{\sqrt{2/N}\rho\sigma_n^2}\right). \quad (8)$$

By eliminating γ, we get the following expression involving P_D, P_{FA}, N, ρ, and SNR:

$$N = 2\left[\rho Q^{-1}(P_{\mathrm{FA}}) - \left(\frac{1}{\rho} + \mathrm{SNR}\right) Q^{-1}(P_D)\right]^2 \cdot \left[\mathrm{SNR} - \left(\rho - \frac{1}{\rho}\right)\right]^{-2}. \quad (9)$$

Comparing Eq. (9) with Eq. (6) and using the property of $Q^{-1}(\cdot)$ and $\rho \approx 1$, we find almost no contribution to the whole expression for a tiny change of ρ. However, the second half [i.e., SNR^{-2}or $[\mathrm{SNR} - (\rho - 1/\rho)]^{-2}$] must be discussed and compared. When $\rho \approx 1$, then $\mathrm{SNR}^{-2} \approx [SNR - (\rho - 1/\rho)]^{-2}$, and Eq. (9) gives approximately the same result as Eq. (6). When ρ is larger (e.g., $\rho = 1.05$), then $(\rho - 1/\rho) = 0.0976 \approx 0.1$. Given $\mathrm{SNR} = 0.1$, then $[\mathrm{SNR} - (\rho - 1/\rho)]^{-2} \approx 0$ and Eq., substituting into Eq. (9) gives $N \to \infty$. In other words, only an infinite detection duration can complete detection, which is impracticable. A tiny fluctuation of average noise power causes a significant drop in performance, especially with a lower SNR.

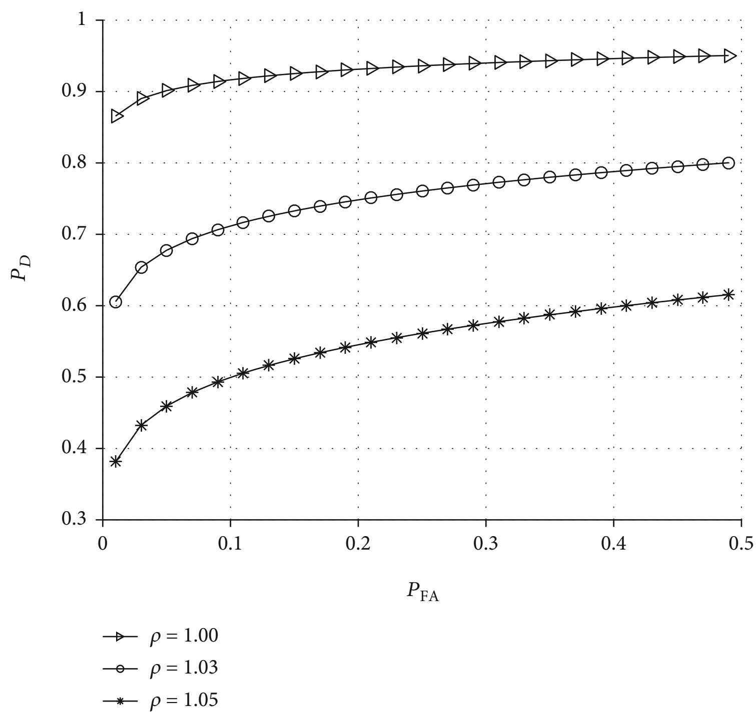

Figure 1: Plot of P_D vs.P_{FA} for $\rho = [1.00, 1.03, 1.05]$.

Figure 1 shows the numerical results from Eqs. (6) and (9). The parameters are SNR = 0.14 (i.e., snr = 10 lg (SNR) ≈ −8.5 dB), false alarm probability $P_{FA} \in (0, 0.5)$, detection duration $N = 500$, and noise uncertainty factor $\rho = 1.00$, 1.03, and 1.05.

The performance curve marked with triangles (▷) corresponds to constant average power of noise and does not consider noise uncertainty. The curves marked with open circles (○) and asterisks (∗) correspond to an average power fluctuation in noise of $\rho = 1.03$ and $\rho = 1.05$, respectively. In Figure 1, when $P_{FA} = 0.1$ and $\rho = 1.03$, then $P_D \approx 0.71$, so the sensing is completed within the detection duration $N = 500$. The detection performance drops significantly to $P_D \approx 0.5$ when $P_{FA} = 0.1$ and $\rho = 1.05$, even though the false alarm probability $P_{FA} = 0.5$. A detection probability $P_D \approx 0.61$ is unacceptable; in this case, the algorithm fails. According to this analysis, the energy detector is extremely sensitive to noise uncertainty, especially for low SNR.

4. Average Power Fluctuation in Noise and Sensing Sensitivity

Comparing Eq. (6) with Eq. (9) shows that when ρ approaches 1, the first half of the two equations only weakly affect the results. We thus focus on the relationship between the second half of each equation, SNR^{-2} and $[\mathrm{SNR} - (\rho - 1/\rho)]^{-2}$. When $\rho \approx 1$, $\mathrm{SNR}^{-2} \approx [\mathrm{SNR} - (\rho - 1/\rho)]^{-2}$, and Eqs. (6) and (9) are almost the same. When ρ is larger, (e.g., $\rho = 1.05$), $(\rho - 1/\rho) \approx 0.1$. In the low-SNR case (e.g., SNR = 0.1), $[\mathrm{SNR} - (\rho - 1/\rho)]^{-2} \approx 0$, and $N \to \infty$, which indicates an infinite detection duration. This is impossible to realize, especially in a low-SNR environment, which shows that in cognitive radio systems, the cognitive performance is strongly influenced by the average power fluctuation in noise and the SNR with average power fluctuations in noise is closely related to the detection duration.

We now discuss the relationship between average power fluctuations in noise, detection length, received SNR, and sensitivity. We define the detection sensitivity $\mathrm{SNR}_s = \rho - 1/\rho$ in Eq. (9); if the SNR for the cognitive radio signal received satisfies $\mathrm{SNR} = (\rho - 1/\rho) \approx 0$, it cannot complete the detection even if given infinite test duration. Therefore, $\mathrm{SNR} = \mathrm{SNR}_s$. Let $S = 10\lg(\rho - 1/\rho) = 10\lg(\mathrm{SNR}_s)$ with the SNR in dB, so the detection sensitivity is the SNR threshold SNR_s. If the SNR received by the cognitive user is less than SNR_s, then the spectrum sensing cannot be completed no matter how long the sensing time is.

We now discuss the expected detection performance for a detection probability $P_D = 0.9$ and a false alarm probability $P_{FA} = 0.1$. When $\rho = 1.000$, $10\lg(\rho) = 0$(dB), and $S \to -\infty$ dB. If $\rho = 1.002$, $10\lg(\rho) = 0.0087$dB and $S \approx -23.98$dB. If $\rho = 1.020$, $10\lg(\rho) = 0.086$dB and $S \approx -14.02$dB. When $\rho = 1.200$, $10\lg(\rho) = 0.7918$dB and $S \approx -4.36$dB. Figure 2 shows the detection sensitivity as a function of detection duration and for several values of average power fluctuation in noise. Figure 2 shows that when $\rho = 1.0$, the detection sensitivity of the spectrum is very high for the cognitive user provided the detection duration is sufficiently long. The cognitive user is able to detect low-power signals without subjecting authorized users to interference. When $\rho = 1.002$, the detection sensitivity for the cognitive user is −23.98 dB; in other words, when the cognitive user has a SNR below −23.98 dB, it may declare that this band contains no authorized users if the

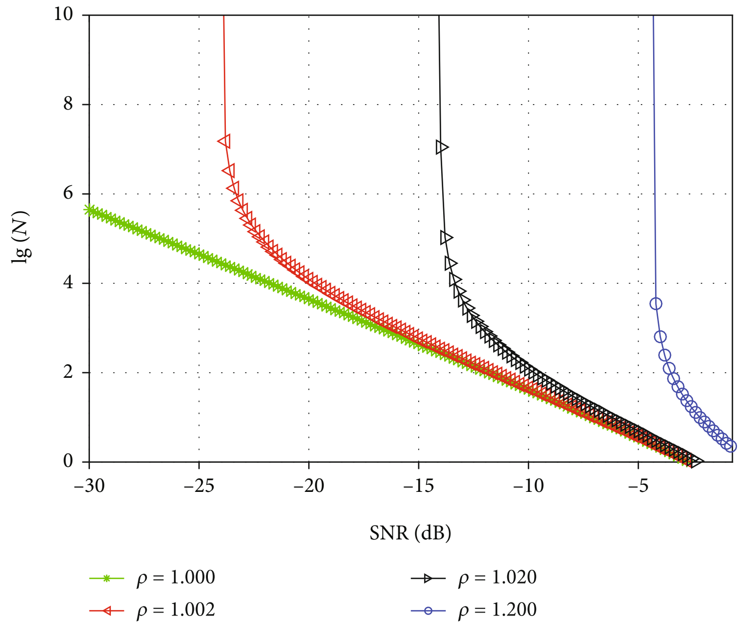

Figure 2: Plot of SNR(dB)vs.lg (N).

cognitive users occupying the spectrum at this time cause interference with the authorized users. When $\rho = 1.020$, the sensitivity is −14.02 dB; that is, when the SNR of the second user received is less than −14.02 dB, the cognitive user decides that this band can be dynamically accessed. If $\rho = 1.200$, the sensitivity of detection is −4.36 dB, that is, when the SNR of the second user received is less than −4.36 dB, the cognitive user considers that this band is idle. Thus, the detection sensitivity of the cognitive user declines as the average power fluctuation in the noise increases, especially in situations with low SNR. Given a big undulation such as $\rho = 1.200$, the spectral-sensing sensitivity is greater than −4.36 dB, which is fatal for cognitive radio. As noted in Refs. [9, 12], the sensitivity of cognitive radio detection may be up to −22 dB for the Advanced Television Systems Committee authorization system.

Average power fluctuation in noise reduces the sensing sensitivity, rapidly reduces the detection accuracy, and results in the cognitive user interfering with the authorized users. Motivated by this, we present a dynamic threshold algorithm based on energy detection to suppress the influence of noise fluctuation and improve the sensing sensitivity.

Let ρ represent the average power fluctuation in noise, and let the average power $\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]$. P_D and P_{FA} are then

$$P_D = \min_{\gamma' \in [\gamma/\rho', \rho'\gamma]} \min_{\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]} Q\left(\frac{\gamma' - (P+\sigma^2)}{\sqrt{2/N}(P+\sigma^2)}\right) = Q\left(\frac{\gamma/\rho' - (P+\sigma_n^2/\rho)}{\sqrt{2/N}(P+\sigma_n^2/\rho)}\right), \tag{10}$$

$$P_{FA} = \max_{\gamma' \in [\gamma/\rho', \rho'\gamma]} \max_{\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]} Q\left(\frac{\gamma' - \sigma^2}{\sqrt{2/N}\sigma^2}\right) = Q\left(\frac{\rho'\gamma - \rho\sigma_n^2}{\sqrt{2/N}\rho\sigma_n^2}\right). \tag{11}$$

Eliminating γ yields

$$N = \frac{2\left[\left(\rho/\rho'\right)Q^{-1}(P_{FA}) - \rho'(1/\rho + \text{SNR})Q^{-1}(P_D)\right]^2}{\left(\rho'\text{SNR} + \rho'/\rho - \rho/\rho'\right)^2}. \tag{12}$$

We next discuss the relationship between the dynamic threshold factor, the average power fluctuation in noise, and the received SNR. In Eq. (12), the denominator $(\rho'\text{SNR} + \rho'/\rho - \rho/\rho')^{-2}$ takes the form

$$\rho'\text{SNR} - \left(\frac{\rho}{\rho'} - \frac{\rho'}{\rho}\right) > 0, \tag{13}$$

so

$$\rho'^2 > \frac{\rho}{\text{SNR} + 1/\rho}, \tag{14}$$

$$\rho' > \sqrt{\frac{\rho}{\text{SNR} + 1/\rho}}. \tag{15}$$

We now compare Eq. (12) with Eq. (6) and focus on $[\rho'^2\text{SNR} + (\rho'^2 - 1)]^{-2}$ and SNR^{-2}. When $\rho' \approx 1$, then $\text{SNR}^{-2} \approx [\rho'^2\text{SNR} + (\rho'^2 - 1)]^{-2}$, so Eqs. (10) and (6) are almost identical. If ρ' is larger (e.g., $\rho' = 1.050$), then $(\rho'^2 - 1) = 0.1025 \approx 0.1$ in the case of low SNR and supposing $\text{SNR} = 0.1$, so $[\rho'^2\text{SNR} + (\rho'^2 - 1)]^{-2} \approx 22$ and $\text{SNR}^{-2} = 100$. If the detection probability equals the false alarm probability, the detection duration obtained from Eq. (12) is less than the result of Eq. (6) by almost an order of magnitude. Therefore, given equal detection performance, the scheme of the dynamic threshold clearly shortens the detection duration.

In other words, if the detection duration is the same, sensing with the dynamic threshold is significantly better than sensing with the traditional energy-sensing scheme.

We now discuss the relation between dynamic threshold factor, detection sensitivity, and received SNR. To facilitate the analysis, we assume a detection probability $P_D = 0.9$ and a false alarm probability $P_{FA} = 0.1$. In this section, the average noise power is constant at $\rho = 1.000$ [i.e., $10 \lg(\rho) = 0.0$dB] and we discuss how the dynamic threshold factor relates to the detection sensitivity S, the detection duration N, and $[\rho'^2 \mathrm{SNR} + (\rho'^2 - 1)]^{-2}$. Given SNR = 0.1, when the dynamic threshold factor $\rho' = 1.002$, 1.020, and 1.050, then $[\rho'^2 \mathrm{SNR} + (\rho'^2 - 1)]^{-2} \approx 92$, 48, and 22, respectively. This conclusion increases with the value of ρ', $[\rho'^2 \mathrm{SNR} + (\rho'^2 - 1)]^{-2}$ gradually decreases, and the detection duration N gradually shortens, but the detection sensitivity remains essentially the same. In theory, these cases can detect any low-power signal (see Figure 3).

Comparing Eq. (12) with Eq. (9), one gets $(\rho' \mathrm{SNR} + \rho'/\rho - \rho/\rho')^{-2} \approx \mathrm{SNR}$ and $(\rho' \mathrm{SNR} + \rho'/\rho - \rho/\rho')^{-2} \gg [\mathrm{SNR} - (\rho - 1/\rho)]^{-2}$ for low SNR. Therefore, with the dynamic threshold detection scheme, the same detection performance may be achieved with a significantly shorter detection duration.

We now assume $P_D = 0.9$ and $P_{FA} = 0.1$. As discussed in Section 3, the detection sensitivity S is about −14.02 dB when $\rho = 1.020$ and $\rho' = 1.000$. This section introduces the dynamic threshold algorithm based on energy detection. Let S_d be the detection sensitivity and keep $\rho = 1.020$ unchanged. We discuss how S_d is related to $\rho'/\rho - \rho/\rho'$ with different dynamic threshold factors. If $\rho' = 1.020$, then $S_d = 10 \lg(\rho'/\rho - \rho/\rho') \to -\infty$dB, and the degradation of the detection performance caused by the average power fluctuation in the noise can be eliminated. If $\rho' = 1.015$dB, then $S_d \approx -20.08$dB, so $S_d - S = -6.06$dB and the detection sensitivity increases by about 6.06 dB. If $\rho' = 1.010$, then $S_d \approx -17.05$dB and $S_d - S = -3.03$dB, and the sensing sensitivity increases by about 3.03 dB. If $\rho' = 1.000$, then $S_d \approx -14.02$dB, which is equivalent to the result with no dynamic threshold, so the detection sensitivity is unchanged, as shown in Figure 4.

5. Multinode Cooperative Sensing Scheme

References [14, 15] show that cooperation can improve communication quality, and collaborative spectrum sensing is also discussed in Refs. [7, 8], which show that multiuser collaboration benefits spectrum sensing.

We formulate a binary hypothesis testing problem for user j based on the following hypotheses:

$$\begin{aligned} \mathcal{H}_0 &: Y_j(n) = W_j(n), \quad & n = 1, 2, \cdots, N, \\ \mathcal{H}_1 &: Y_j(n) = X_j(n) + W_j(n), \quad & n = 1, 2, \cdots, N, \end{aligned} \tag{16}$$

where $X_j(n)$ and $W_j(n)$ are the transmitted signals at the primary nodes and the white noise samples, respectively, and they are independently and identically distributed with respect to each other. If the noise variance is known and there is no noise uncertainty, the central limit theorem gives the following approximations:

$$\begin{cases} D(Y_j)|\mathcal{H}_0 \sim \mathcal{N}\left(\sigma_n^2, \dfrac{2}{N}\sigma_n^4\right), \\ D(Y_j)|\mathcal{H}_1 \sim \mathcal{N}\left(P + \sigma_n^2, \dfrac{2}{N}(P + \sigma_n^2)^2\right), \end{cases} \tag{17}$$

where P is the signal power and σ_n^2 is the noise variance, supposing M cognitive radio users collaborate and each is independent of the others. Denoting the weighting factor by ω_j, the received signal can be expressed as the sum of the signals received by M users:

$$Y = \sum_{j=1}^{M} \omega_j Y_j. \tag{18}$$

Therefore, the sensing model of for multiuser cooperation can be expressed as follows:

$$\begin{cases} D(Y)|\mathcal{H}_0 \sim \mathcal{N}\left(\sum_{j=1}^{M} \omega_j \sigma_n^2, \dfrac{2}{N}\sum_{j=1}^{M} \omega_j^2 \sigma_n^4\right), \\ D(Y)|\mathcal{H}_1 \sim \mathcal{N}\left(\sum_{j=1}^{M} \omega_j (P_j + \sigma_n^2), \dfrac{2}{N}\sum_{j=1}^{M} \omega_j^2 (P_j + \sigma_n^2)^2\right). \end{cases} \tag{19}$$

In expression (19), $P_j = 1/N \sum_{n=1}^{N} X_j^2(n)$, $\omega_j = \mathrm{SNR}_j / \sqrt{\sum_{i=1}^{M} \mathrm{SNR}_i^2}$, and $\sum_{j=1}^{M} \omega_j^2 = 1$, so

$$P_D = \Pr\left(D(Y)|\mathcal{H}_1 > \gamma\right) = 1 - P_{MD} = Q\left(\frac{\gamma - \sum_{j=1}^{M} \omega_j (P_j + \sigma_n^2)}{\sqrt{2\sum_{j=1}^{M} \omega_j^2 (P_j + \sigma_n^2)^2 / N}}\right), \tag{20}$$

$$P_{FA} = \Pr\left(D(Y)|\mathcal{H}_0 > \gamma\right) = Q\left(\frac{\gamma - \sum_{j=1}^{M} \omega_j \sigma_n^2}{\sqrt{\sum_{j=1}^{M} \omega_j^2 \sigma_n^4 / N}}\right). \tag{21}$$

Eliminating γ gives the following expression involving P_D, P_{FA}, N, ω_j, M, and SNR_j:

$$N = 2\left[\sqrt{\sum_{j=1}^{M} \omega_j^2 Q^{-1}(P_{FA})} - \sqrt{\sum_{j=1}^{M} \omega_j^2 (1 + \mathrm{SNR}_j)^2 Q^{-1}(P_D)}\right]^2 \cdot \left(\sum_{j=1}^{M} \omega_j \mathrm{SNR}_j\right)^{-2}. \tag{22}$$

Now consider the case with uncertainty in the noise model. The variance of noise with uncertainty can be

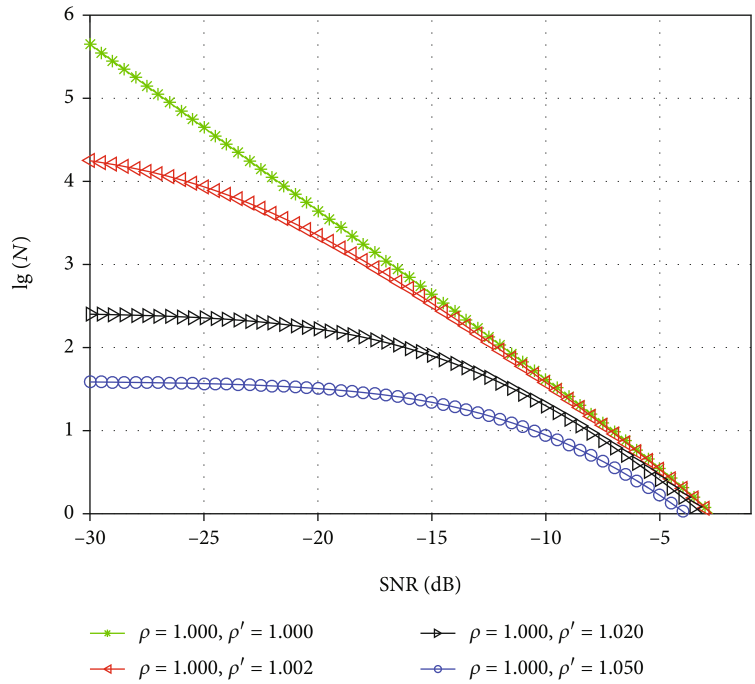

Figure 3: Plot of lg (N)vs.SNR(dB).

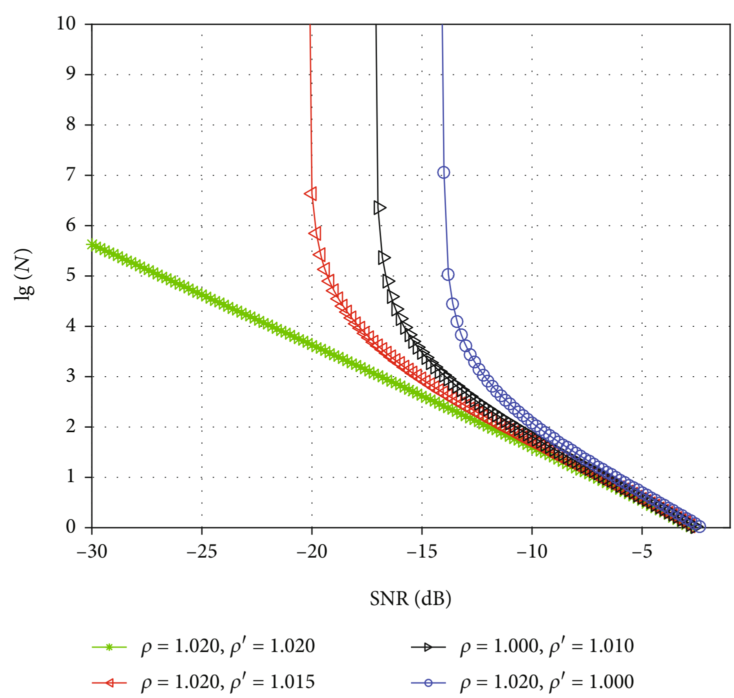

Figure 4: Plot of lg (N)vs.SNR(dB).

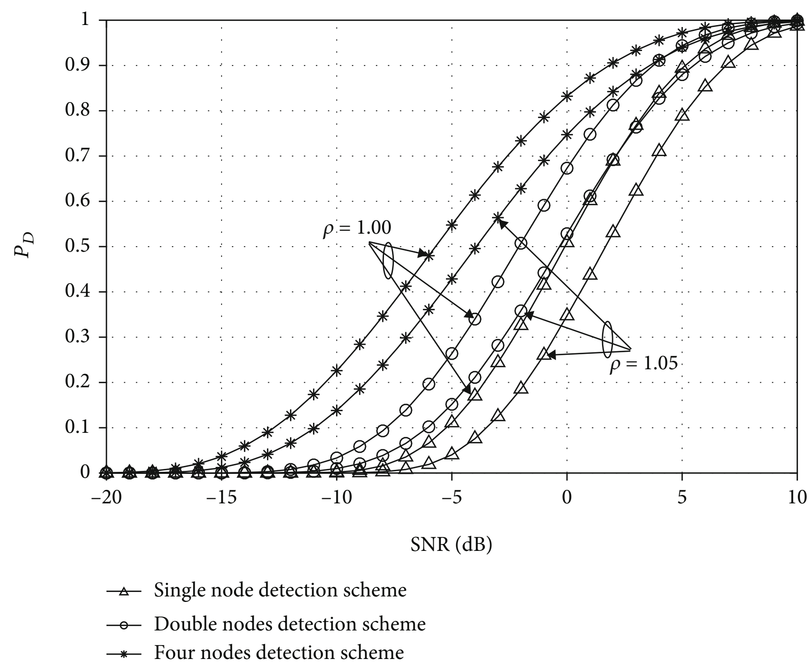

Figure 5: Plot of $P_D$vs.SNR for $N = 500$, $\rho = [1.00, 1.05]$.

included in a single interval $\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]$, where ρ is the noise uncertainty factor and the value of $\rho$is close to 1 (i.e., $\rho > 1$ and $\rho \approx 1$), so

$$P_D = \Pr\left(D(Y)|\mathscr{H}_1 > \gamma\right) = \min_{\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]} Q\left(\frac{\gamma - \sum_{j=1}^{M}\omega_j\left(P_j + \sigma^2\right)}{\sqrt{2\sum_{j=1}^{M}\omega_j^2\left(P_j + \sigma^2\right)^2/N}}\right) = Q\left(\frac{\gamma - \sum_{j=1}^{M}\omega_j\left(P_j + \sigma_n^2/\rho\right)}{\sqrt{2\sum_{j=1}^{M}\omega_j^2\left(P_j + \sigma_n^2/\rho\right)^2/N}}\right), \quad (23)$$

$$P_{\text{FA}} = \Pr\left(D(Y)|\mathscr{H}_0 > \gamma\right) = \max_{\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]} Q\left(\frac{\gamma - \sum_{j=1}^{M}\omega_j\sigma^2}{\sqrt{2\sum_{j=1}^{M}\omega_j^2\sigma^4/N}}\right) = Q\left(\frac{\gamma - \sum_{j=1}^{M}\omega_j\rho\sigma_n^2}{\sqrt{2\sum_{j=1}^{M}\omega_j^2\rho^2\sigma_n^4/N}}\right). \quad (24)$$

Eliminating γ gives the following expression involving P_D, P_{FA}, N, ω_j, M, and SNR_j:

$$N = 2\left[\rho\sqrt{\sum_{j=1}^{M}\omega_j^2}Q^{-1}\left(P_{\text{FA}}\right) - \sqrt{\sum_{j=1}^{M}\omega_j^2\left(\frac{1}{\rho} + \text{SNR}_j\right)^2}Q^{-1}\left(P_D\right)\right]^2 \cdot \left(\sum_{j=1}^{M}\omega_j\left[\text{SNR}_j - \left(\rho - \frac{1}{\rho}\right)\right]\right)^{-2}. \quad (25)$$

Figure 5 shows the results of a sensing simulation of a single node and multiple nodes. The parameters are SNR $\in (-20, 10)$ dB, false alarm probability $P_{\text{FA}} = 0.01$, detection duration $N = 500$, and average power uncertainty in noise $\rho = 1.00$ and $\rho = 1.05$, respectively.

Figure 5 shows the receiver operating characteristic (ROC) curves corresponding to constant average noise power and average power fluctuation in noise. The curves marked with triangles (△), open circles (∘), and asterisks (∗) are for single-node sensing, double-node sensing, and four-node sensing, respectively. Given equal average power fluctuation in noise, energy detection is significantly better with the multinode collaborative detection scheme than with the single-node detection scheme. The detection performance improves with the number of collaborative nodes. For a given detection performance, the multinode scheme detects a lower SNR than the single-node scheme. Figure 5 shows that the same scheme with SNR = 0 dB results in a decrease of 0.16 dB for single-node detection, 0.14 dB for double-node detection, and 0.09 dB for four-node detection. Therefore, the resistance to noise improves, and the performance degradation caused by the average power uncertainty in the noise may be eliminated by increasing the number of cooperative nodes. Multinode collaborative schemes can thus improve the sensing performance in cognitive radio sensing systems.

6. Conclusions

Traditional energy-detection schemes are sensitive to the average power uncertainty in the noise. In this paper, we investigate how energy-detection performance and detection sensitivity are related to detection duration and average power fluctuation in noise for short-duration signal sensing.

Detection performance and detection sensitivity drop rapidly with increasing average power fluctuation in noise and is worse for the situation with a low signal-to-noise ratio. We therefore propose a new energy-detection algorithm based on cooperation between nodes. Noise creates a larger uncertainty for a short-duration detection, and the deterioration in detection performance caused by uncertainty due to average noise power can be eliminated by increasing the number of cooperating nodes to a certain level. Simulations show that the proposed scheme improves resistance to average power fluctuation in noise and allows for good detection performance provided sufficient cooperative nodes are used. In other words, the proposed scheme makes the detection robust against noise and improves the capacity of spectrum sensing.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request and with permission from the funders.

Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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References

[1] X. Li, M. Zhao, M. Zeng et al., "Hardware impaired ambient backscatter NOMA systems: reliability and security," *IEEE Transactions Communications*, p. 1, 2021.

[2] X. Li, M. Zhao, Y. Liu, L. Li, Z. Ding, and A. Nallanathan, "Secrecy analysis of ambient backscatter NOMA systems under I/Q imbalance," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 10, pp. 12286–12290, 2020.

[3] I. F. Akyildiz, W. Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey," *Computer Networks*, vol. 50, no. 13, pp. 2127–2159, 2006.

[4] I. F. Akyildiz, W. Y. Lee, M. C. Vuran, and S. Mohanty, "A survey on spectrum management in cognitive radio networks," *IEEE Communications Magazine*, vol. 46, no. 4, pp. 40–48, 2008.

[5] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in *Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, 2004*, pp. 772–776, Pacific Grove, USA, 2004.

[6] D. Cabric, A. Tkachenko, and R. W. Brodersen, "Experimental study of spectrum sensing based on energy detection and netwotk cooperation," in *ACM International Workshop on Technology and Policy for Accessing Spectrum*, Boston, USA, 2006.

[7] A. Ghasemi and E. S. Sousa, "Collaborative spectrum sensing for opportunistic access in fading environments," in *IEEE International Symposium on Dynamic Spectrum Access Networks*, pp. 131–136, Baltimore, USA, 2005.

[8] S. M. Mishra, A. Sahai, and R. W. Broderson, "Cooperative sensing among cognitive radios," in *2006 IEEE international conference on communications*, Istanbul, Turkey, 2006.

[9] S. M. Kay, *Fundamentals of Statistical Signal Processing: Detection Theory*, vol. 2, Prentice-Hall, Englewood Cliffs, 1998.

[10] J. Li, Y. He, P. Ma, X. Zhang, and Q. Wu, "Direction of arrival estimation using sparse nested arrays with coprime displacement," *IEEE Sensors Journal*, 2021.

[11] R. Tandra and A. Sahai, "SNR walls for signal detection," *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, no. 1, pp. 4–17, 2008.

[12] R. Tandra, *Fundamental Limits on Detection in Low SNR*, Master's thesis, University of California, Berkeley, 2003.

[13] C. Cordeiro, M. Ghosh, D. Cavalcanti, and K. Challapali, "Spectrum sensing for dynamic spectrum access of TV bands (invited paper)," in *2007 2nd International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, pp. 225–233, Orlando, FL, USA, 2007.

[14] A. Nosratinia, T. E. Hunter, and A. Hedayat, "Cooperative communication in wireless networks," *IEEE Communications Magazine*, vol. 42, no. 10, pp. 74–80, 2004.

[15] J. Ma and Y. G. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," *IEEE Global Telecommunications Conference IEEE*, 2007.

[16] H. Wang, L. W. Xu, Z. Q. Yan, and T. A. Gulliver, "Low-complexity MIMO-FBMC sparse channel parameter estimation for industrial big data communications," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, pp. 3422–3430, 2021.

[17] J. Li, P. Ma, X. Zhang, and G. Zhao, "Improved DFT algorithm for 2D DOA estimation based on 1D nested array motion," *IEEE Communications Letters*, vol. 24, no. 9, pp. 1953–1956, 2020.

[18] X. P. Wang, M. X. Wang, and L. T. Wang, "Joint 2D-DOD and 2D-DOA estimation for coprime EMVS-MIMO radar," *Circuits, Systems, and Signal Processing*, 2021.