Cooperative Spectrum Sensing for Cognitive Radio in Flat-Fading Environment

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Abstract

In cognitive radio system, the secondary users can use the frequency bands when the primary users are not present. Therefore, the secondary users need to sense the channel periodically. When the primary users are detected, the secondary users have to stop using that channel. This makes the probability of detection important to the cognitive radio system. However, detection is compromised when a secondary user experiences fading. The simulation results show that the detection probability of Rayleigh fading channel is 10dB worse than the additive white Gaussian noise channel. The cooperative schemes have been shown to improve the performance in MIMO system. In this paper, we will discover weather the cooperative scheme can improve the probability of detection. The results indicate that with only a few users in cooperation, the detection probability can be increased by 40% in fading channel at low SNR.

1 Introduction

The spectrum, which is used for radio communications, is natural resources [1]. In the United States, the Federal Communication Commission (FCC) governs the usage of the spectrum. Recently, with the increase in the adoption of new electric devices, the unlicensed spectrum becomes increasingly scarce. Some recent government reports show that large part of licensed bands are unused in the sense of time and space: some frequency bands are not occupied by the licensed users in a particular time or at a particular location [2]. These results direct us to a new area of communications, in which the unlicensed users (secondary users) may occupy the free band when the licensed users (primary users) do not use the spectrum. Such a system is called cognitive radio system. In cognitive radio system, one of the issues is how the secondary users detect weather the primary users are using the spectrum or not. Therefore, spectrum sensing becomes critical in cognitive radio system.

As discussed in [3], there have been many discussions and proposed solutions for spectrum sensing. However, most solutions are still focusing on the single secondary user detection, which means each secondary user works independently. As presented in [3], the challenges in spectrum sensing include the hardware requirement since spectrum sensing needs high sampling rate, high resolution Analog-to-Digital Converter (A/D Converter), and high-performance signal processors. These challenges become more explicit in the cognitive radio applications of sensor network and ad hoc network. In addition, the results in [4] indicate that performance of signal detector degrades in shadowing and fading channel. An alternative solution is cooperative scheme. In cooperative scheme, two or more secondary users sense the channel coordinately and share the information between each other. Several authors have recently proposed collaboration scheme for spectrum sensing [1], [5], [6]. Most of the proposed methods are discussed in a time-invariant channel. In reality, the channel is time-varying. In this paper, our goal is to provide a comprehensive study, supported with the simulation results, that addresses the following problems in spectrum sensing:

- Performance of spectrum sensing degraded by fading with single secondary user.
- Performance improvements offered by cooperative spectrum sensing.

This paper is organized as follows. In Section 2, we define the system model for the cognitive radio network that is used in analysis and simulations. Section 3 explores the detection performance degraded by fading. Section 4 presents how the cooperative schemes improve the detection performance. Section 5 provides a discussion about the selected schemes and presents some future works. Section 6 concludes this work.

2 System Model

In this paper, we firstly investigate the spectrum sensing in a cognitive radio network with base station only. Then we explore cooperative spectrum sensing in a centralized cognitive radio network consisting of a base station and a number of cognitive radio users, as shown in Fig. 1. In the base station only network, the base station (secondary user) senses the channel

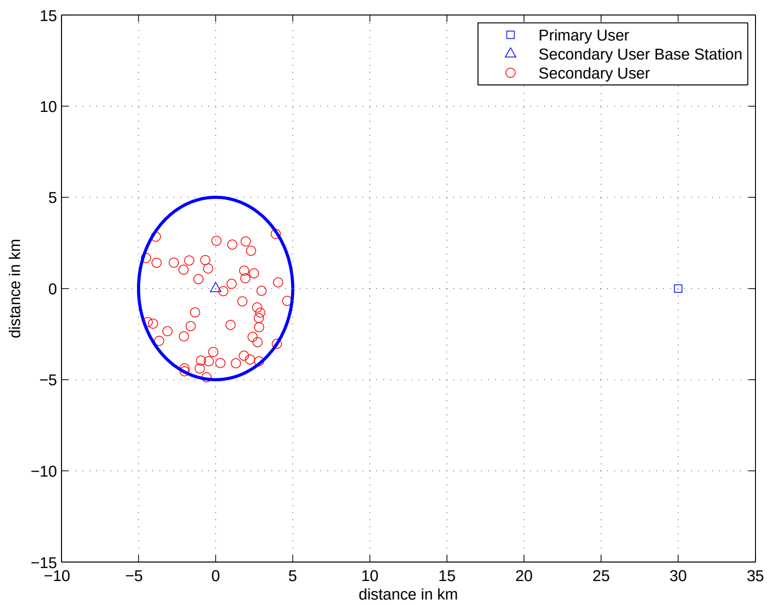

Figure 1: Topology of Cognitive Radio Network

periodically and makes the decision based on collected data. For the cooperative network, each secondary user senses the channel periodically and sends its sensing data or decision bit to the base station. Then the base station makes the decision on the presence or absence of the primary user. For simplicity, we assume that the channels between the base station and secondary users are free of error.

2.1 Local Channel Sensing Hypothesis

In a cognitive radio system, during sensing stage, the received samples have two hypothesis. Hypothesis $\mathcal{H}_0$ is that the primary user is inactive and $\mathcal{H}_1$ is that the primary user is active.

$$\mathcal{H}_0 : \qquad y_j[n] = u_j[n] \tag{1}$$

$$\mathcal{H}_1 : \qquad y_j[n] = h_j s_j[n] + u_j[n] \tag{2}$$

where h_j denotes the channel gain for user j, $s_j[n]$ denotes the primary user's signal and is assumed to be independently and identically distributed (iid) random process with mean zero and variance, σ_s^2, and $u_j[n]$ is the additive white Gaussian noise (AWGN) with mean zero and variance, σ_u^2. Here, we assume that $u_j[n]$ and $s_j[n]$ are independent.

In likelihood detection problem, we are interested in the probability of detection, P_d, and the probability of false alarm, P_f [7]. P_d and P_f are defined as the probability of detection under hypothesis $\mathcal{H}_1$ and $\mathcal{H}_0$ respectively. The higher P_d means the system has a better protection on the primary user. The lower P_f means the higher probability to sense the spectrum hold.

2.2 Local Signal Detector

The proposed signal detectors of spectrum sensing can be grouped into three categories: energy detection, matched filter detection, and cyclostationary detection [8]. Amongst them, energy detection has been widely used in research because it does not require the priori knowledge of the primary beacon [9]. Therefore, in this project, we use energy detector for local spectrum sensing.

In [10], the energy detector is proposed as

$$S_j = \sum_{n=1}^{N} |y_j[n]|^2 \tag{3}$$

where N denotes the number of samples. It also refers as the time-bandwidth product in [4], [10], and [11]. Here we assume $y_j[n]$ is pre-filtered by an ideal bandpass filter.

Since S_j is the sum of the squares of N Gaussian random variables under H_0, it can be easily shown that S/σ_u^2 is central chi-square distribution with N degrees of freedom. Similarly, under H_1, S/σ_u^2 is noncentral chi-square distribution with N degrees of freedom and non centrality parameter $2\gamma_j$, where γ_j denotes signal-to-noise ratio (SNR). Here, we define SNR as

$$\gamma_j = \frac{P_{pu}\beta}{d_j^\alpha \sigma_u^2} \tag{4}$$

where P_{pu} denotes the transmission power of primary user, d_j denotes the distance between the secondary user j and the primary user, α denotes the path loss exponent factor, and β is a scalar [12]. Now the decision statistic is

$$S_j \sim \begin{cases} \chi_N^2, & \mathcal{H}_0, \\ \chi_N^2(2\gamma_j) & \mathcal{H}_1. \end{cases} \tag{5}$$

Therefore, the probability density function (PDF) of S_j can be written as

$$f_{S_j}(s_j) = \begin{cases} \frac{1}{2^{\frac{N}{2}}\Gamma(\frac{N}{2})} \left(\frac{s_j}{\sigma_u^2}\right)^{\frac{N}{2}-1} \exp\left(-\frac{s_j}{2\sigma_u^2}\right), & \mathcal{H}_0, \\ \frac{1}{2}\left(\frac{s_j}{2\gamma_j \sigma_u^2}\right)^{\frac{N}{4}-\frac{1}{2}} \exp\left(-\frac{2\gamma + \frac{s_j}{\sigma_u^2}}{2}\right) \mathrm{I}_{\frac{N}{2}-1}\left(\sqrt{2\gamma_j \frac{s_j}{\sigma_u^2}}\right), & \mathcal{H}_1. \end{cases} \tag{6}$$

where $\Gamma(.)$ denotes the completed gamma function and I_v denotes the vth order modified Bessel function of the first kind [11].

3 Spectrum Sensing with Non-Cooperative Scheme

In this section, we are going to explore how the performances are degraded by fading channel. We assume only the base station in Fig. 1. In AWGN channel, for secondary user j, the probabilities of detection and false alarm can be represented as

$$P_d^j = \Pr(S_j \geq \lambda_j|\mathcal{H}_1) \tag{7}$$

$$P_f^j = \Pr(S_j \geq \lambda_j|\mathcal{H}_0) \tag{8}$$

where λ_j is the decision threshold. By applying (6), we get

$$P_f^j = \frac{\Gamma(N/2, \frac{\lambda_j}{2\sigma_u^2})}{\Gamma(N/2)}, \tag{9}$$

$$P_d^j = \mathrm{Q}_{\frac{N}{2}}\left(\sqrt{\frac{2\gamma_j}{\sigma_u^2}}, \sqrt{\frac{\lambda_j}{\sigma_u^2}}\right) \tag{10}$$

where $\Gamma(.,.)$ denotes the incomplete gamma function and $\mathrm{Q}_N(a,b)$ is the generalized Marcum Q-function with degree N.

Recalling (9), we see that P_f^j is independent with γ_j. Therefore, in the fading channel, P_f^j is as same as that in AWGN channel. In [4], the average detection probability $\bar{P}_d^j$ in Rayleigh fading is shown as

$$\begin{aligned} \bar{P}_{d,Ray}^j &= e^{-\frac{\lambda}{2\sigma_u^2}}\left(\sum_{n=0}^{N/2-2}\frac{1}{n!}\left(\frac{\lambda}{2\sigma_u^2}\right)^n\right) \\ &+ \left(\frac{\sigma_u^2+\bar{\gamma}_j}{\bar{\gamma}_j}\right)^{N/2-1}\left[e^{-\frac{\lambda_j}{2(\sigma_u^2+\bar{\gamma}_j)}} - e^{-\frac{\lambda_j}{2\gamma_u^2}}\sum_{n=0}^{N/2-2}\frac{1}{n!}\frac{\lambda_j\bar{\gamma}_j}{2\sigma_u^2(\sigma_u^2+\bar{\gamma}_j)}\right] \end{aligned} \tag{11}$$

where $\bar{\gamma}_j$ denotes the average SNR.

With the aid of [4] and [13], the average detection probability in Nakagami channel can be obtained as

$$\bar{P}_{d,Nak}^j = \xi\left[G_1 + \sum_{i=1}^{\frac{N}{2}-1}\frac{\Gamma(m)\left(\frac{b_2^2}{2}\right)^i e^{-\frac{b_2^2}{2}}}{2(i!)\left(\frac{v^2+b_1^2}{2}\right)^m}F_{1,1}\left(m; i; \frac{\lambda_j\bar{\gamma}_j}{\sigma_u^2(m\sigma^2+\bar{\gamma}_j)}\right)\right] \tag{12}$$

where m is the Nakagami fading parameter, $F_{1,1}(.;.;.)$ is the confluent hypergeometric function, $v^2 = \frac{m\sigma_u^2}{\bar{\gamma}_j}$, $b_1 = 1$, $b_2 = \sqrt{\lambda_j/\sigma_u^2}$, $\xi = (2/\Gamma(m))((m\sigma_u^2)/(2\bar{\gamma}_j))^m$, and

$$\begin{aligned} G_1 &= \left\{\sum_{k=0}^{N-2}\left(\frac{v^2}{v^2+b_1^2}\right)^k L_k\left(-\frac{b_2^2}{2}\frac{b_1^2}{v^2+b_1^2}\right) + (1+\frac{v^2}{b_1^2})(\frac{v^2}{v^2+b_1^2})^{N-1}L_{N-1}(-\frac{b_2^2}{2}\frac{b_1^2}{v^2+b_1^2})\right\} \\ &\times \frac{2^{N-1}(N-1)!}{v^{2N}}\frac{b_1^2}{v^2+b_1^2}\exp\left(-\frac{1}{2}b_2^2\frac{v^2}{v^2+b_1^2}\right) \end{aligned} \tag{13}$$

with $L_i(.)$ denotes the Laguerre polynomial of degree i. Details are shown in Appendix A.

3.1 Numerical Results

In this section, we will show the detector performance through its receiver operating characteristic (ROC) surces (P_d versus P_f) or complementary ROC curves ($P_m = 1 - P_d$ versus P_f) for different situations of interest. Fig. 2 illustrates the complementary ROC for AWGN channel, Rayleigh fading channel, and Nakagami fading channels with $N = 10$ and $\gamma = 10dB$. Here, we assume the noise variance, σ_u^2, is unity. In Fig. 2, the curves indicate that the performances of

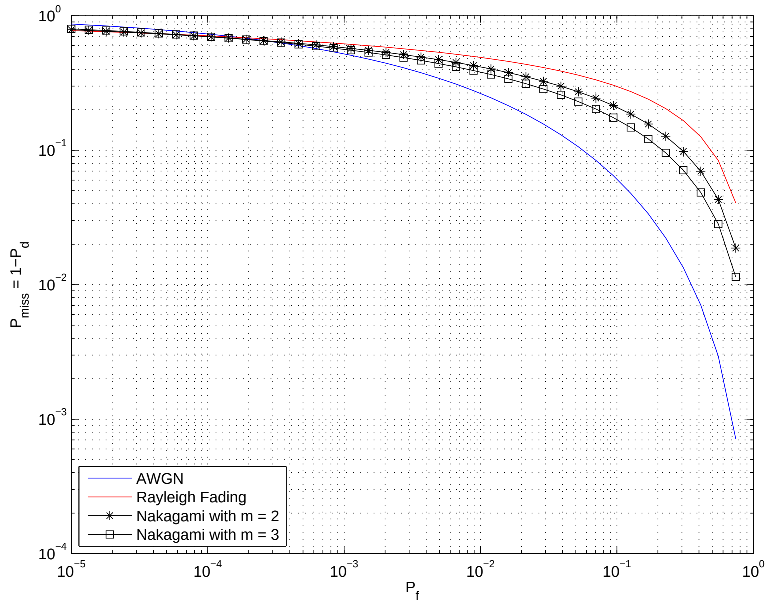

Figure 2: Complementary ROC curves for non-cooperative scheme with $N = 10$ and $\bar{\gamma} = 10dB$

the energy detector under different channels are almost the same when $P_f < 0.1\%$. After that point, the performance of the fading channel is degraded. For $P_d = 97\%$, P_f in Rayleigh fading channel is $10dB$ worse than that under AWGN channel.

Fig. 3 indicates how the performance changes under different SNRs. For AWGN channel, when γ increases from $10dB$ to $15dB$, the performance is improved by more than $40dB$. For the Rayleigh fading, the improvement is about $4dB$. These curves reflect that with the increase of SNR, the total performance can be improved, even in fading channel.

Fig. 4 asserts a fact that for the same signal energy, the fewer the samples, the better the performance, as is the case when signal energy increases for a given N. This fact is consistent with the dissuasion in [4].

4 Spectrum Sensing with Cooperative Scheme

The simulation results in previous section indicate that the performance of detection is strongly degraded by the fading channel. The cooperative communication has been widely discussed as an alternative solution for improving the system performance in fading environment [14]. Therefore, it is interesting to explore whether the cooperative schemes can improve the spectrum sensing performances in fading channels or not. In the rest of this paper, we are going to analyse the performances of the cooperative schemes given in [9] and [12]. In [12], the authors proposed a 1-bit feedback scheme, where each secondary user makes the decision locally and sends the

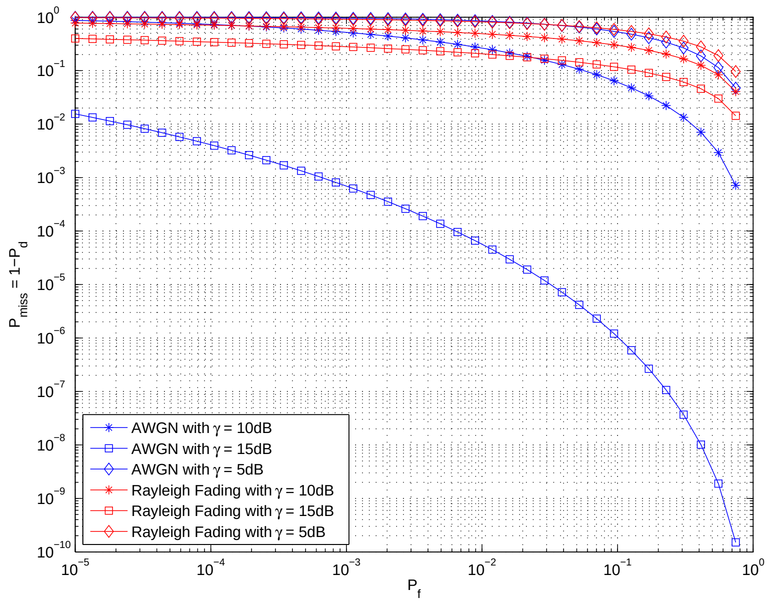

Figure 3: Complementary ROC curves for non-cooperative scheme under different γ with $N = 10$

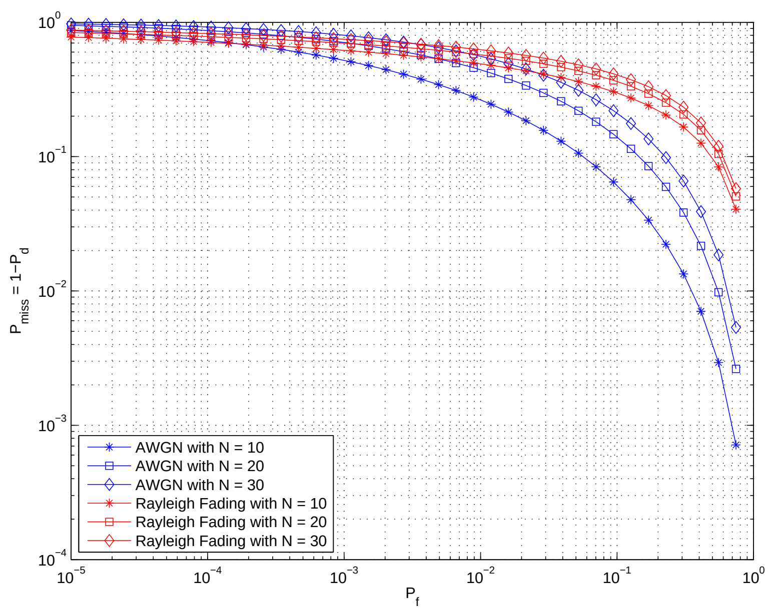

Figure 4: Complementary ROC curves for non-cooperative scheme under different N with $\gamma = 10dB$

decision bit back to the base station periodically. Then the base station makes the fusion decision based on logic OR operation or logic AND operation. Here, we define Q_d as the detection probability and Q_f as the false alarm probability of entire cognitive radio network. Hence, for logic OR operation,

$$Q_d = 1 - \Pi_{j=1}^{M}(1 - P_d^j), \tag{14}$$

$$Q_f = 1 - \Pi_{j=1}^{M}(1 - P_d^j), \tag{15}$$

where M is the number of cooperative user and P_d^j and P_f^j denote P_d and P_f of jth user. For AND operation,

$$Q_d = \Pi_{j=1}^{M} P_d^j, \tag{16}$$

$$Q_f = \Pi_{j=1}^{M} P_f^j, \tag{17}$$

.

In this analysis, we fix Q_f and explore how Q_d varies with the change of M. With fixed Q_f and M, in OR fusion, we have

$$P_f^j = 1 - \sqrt[M]{1 - Q_f}. \tag{18}$$

Yielding (18) into (9), we have

$$\lambda_j = 2\Gamma^{-1}(N, (1 - \sqrt[M]{1 - Q_f})\Gamma(N)). \tag{19}$$

Now we can use λ_j, combining with P_d^j in different channels and locations, to find the total probability of detection Q_d. Similar, we can find the detection threshold for AND fusion as

$$\lambda_j = 2\Gamma^{-1}(N, \sqrt[M]{Q_f}\Gamma(N)). \tag{20}$$

In [9], the authors presented a two-bit combination scheme. Compared with one-bit fusion, the two-bit scheme divides the energy region into four subregions and assigns different weights to each subregion. Therefore, now we need two bits to indicate the decision. We will declare the present of the primary user if any one of the observed energies, S, falls in region 3, or L ones fall in region 2, or L^2 ones fall in region 1. L is a parameter needed to be optimized and we will discuss the optimization process later. The protocol described above is equivalent to allocate the four subregions with different weights, $w_0 = 0$, $w_1 = 1$, $w_2 = L$, and $w_3 = L^2$, and the weighted summation is give by $S_c = \sum_{i=0}^{3} w_i S_i$, where S_i denotes the number of observed energies falling in region i. When $S_c > L^2$, we declare the present of the primary user. The scheme is shown in Fig. 5, where T_1, T_2, and T_3 are the new thresholds for the energy detector and they are corresponding to λ_1, λ_2, and λ_3 in [9].

For the two-bit combination scheme with M cooperative users, the Q_f is given as

$$(1 - Q_f)(1 + \rho)^M = \sum_{i=0}^{I} \binom{M}{j} \left\{ \sum_{j=0}^{J_i} \binom{i}{j} (1 - \beta_1)^{i-j} (\beta_1 - \beta_1\beta_2)^j \right\} \rho^j \tag{21}$$

where $I = L^2 - 1$, $J_i = \min\{\lfloor \frac{L^2-1-iw_1}{w_2-w_1} \rfloor, i\}$, $\beta_1 = P_{f2}/P_{f1}$, $\beta_2 = P_{f3}/P_{f2}$, and $\rho = \frac{P_{f1}}{1-P_{f1}}$. Here P_{fi} is the false alarm probability in subregion i and it can be computed by using (9).

For the detection probability, [9] obtains

$$\bar{Q}_D = 1 - \sum_{i=0}^{I} \binom{M}{i} (1 - \bar{P}_{D_1})^{M-i} \left\{ \sum_{j=0}^{J_i} \binom{i}{j} (\bar{P}_{D_1} - \bar{P}_{D_2})^{i-j} (\bar{P}_{D_2} - \bar{P}_{D_3})^j \right\}. \tag{22}$$

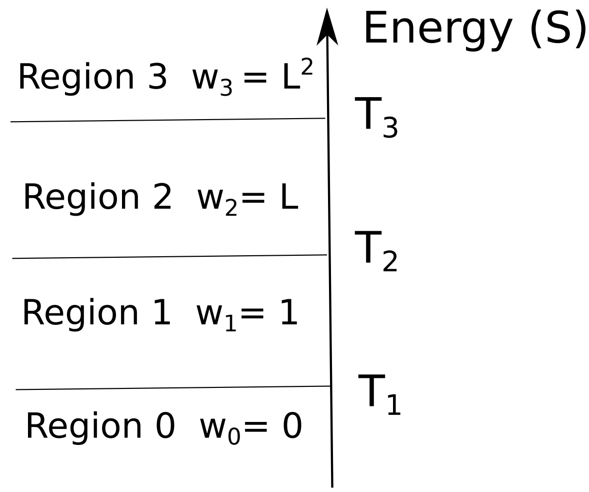

Figure 5: Principle of two-bit combination scheme

Here $\bar{P}_{D_i}$ is the detection probability in subregion i. It can be computed by applying the equations in previous section based on different fading models.

For a fixed Q_f, we firstly search the optimized parameter ρ over (21) numerically. Then we find P_{f1}, P_{f2}, and P_{f3} based on ρ, β_1, β_2. After that we can yield three thresholds based on AWGN model. Finally, we compute the average detection probability in each subregion and conclude the system detection probability.

4.1 Numerical Results

The Monte Carlo simulation results are presented to evaluate the performances improved by cooperative schemes over 50 iterations. The parameters used in the simulations of the cognitive radio system shown in Fig. 1 are as follows. The secondary users are randomly distributed within the $5km$ radius of the secondary users' BS. The BS is $30km$ away from the primary user. During the sensing time, 4 samples are used for energy detector. The path loss exponent factor α is 3.5. The channel noise variance is $\sigma_u^2 = 1$. For the two-bit combination scheme, we set $L = 2$, $\beta_1 = 0.1$, and $\beta_2 = 0.05$. In the following simulations, we fix the network false alarm probability to 5% and explore the performance changes under different situations of interest. The following $\bar{\gamma}$ refers the the average SNR received at the base station. We assume the base station knows the location or the SNR of each secondary user. Thus, we can compute the individual SNR. The threshold will be compute individually.

From Fig. 6, we observe that with the aid of the cooperative schemes, the Q_d is improved. For example, at $2dB$, the Q_d of two-bit combination scheme is about 40% higher than that of non-cooperative scheme. Among the three cooperative schemes, the best one is the two-bit combination scheme. The reasons are that we return more information to the base station and that the decision bits are combined with different weights at the base station. The second best is the OR fusion. The secondary user, who is far away from the primary user, has a low SNR. Therefore, this user experiences difficulty to detect the hold. The AND fusion requires that all the users need to detect the spectrum hold. Therefore, the performance of the AND fusion is the worst among these three schemes.

Fig. 7 illustrates Q_d in Rayleigh fading channel over different SNRs. Both the OR fusion and the two-bit combination schemes outperform the non-cooperative scheme since low SNR.

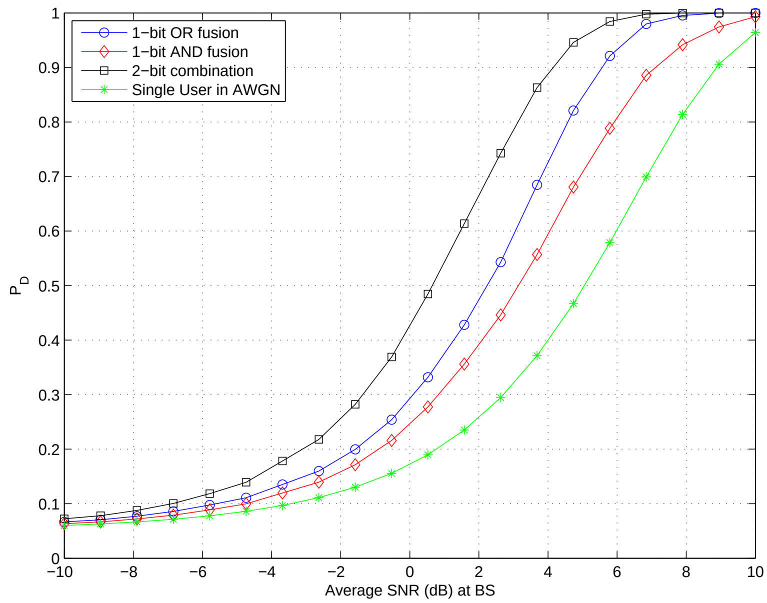

Figure 6: Detection probability curves under AWGN channels over different SNR with M = 6

At $2dB$, Q_d of the 2-bit scheme is about 20% higher than that of the non-cooperative scheme. The AND fusion is close to the non-cooperative scheme up to $2.5dB$ and then the latter one outperforms. Between $-4dB$ and $6dB$, the gap between the OR fusion and two-bit combination scheme is about $1dB$. The overall computational complexity of two-bit scheme is more higher than that of the 1-bit OR fusion since some parameters need to be optimized. Therefore, OR fusion is more suitable for the applications that have energy-constrain or computation-constrain.

Fig. 8 indicates Q_d in Nakagami fading channel. Similar to that in Rayleigh fading channel, the 2-bit scheme and the OR fusion have better performances. In addition, the gap between these two schemes are small.

Fig. 9 and Fig. 10 present how the probability of detection improved by a increase of number of cooperative users with $\bar{\gamma} = 10dB$. Fig. 9 indicates that with 10 users in cooperation and $Q_f = 0.1\%$, the cooperative scheme outperforms the non-cooperative scheme by $10dB$. Fig. 10 indicates that the cooperative scheme does not improve the performance. The AND fusion requires all the users to detect the primary user. If one user does not detect it, the overall decision is $\mathcal{H}_0$. The increase of the number of cooperative user cannot improve the individual SNR. Therefore, the overall performance does not increase.

5 Discussion and Future Work

The simulation results in the previous section motivate us to implement the cooperative schemes in spectrum sensing since with only a few cooperative users, e.g. 6, the overall performance is improved by a large percentage. Among these three schemes, two-bit combination scheme outperforms other two in all three channels. The reason, as discussed above, is that more information is used for decision and the feedback information is combined with weight at the base station. However, there are two major drawbacks for the two-bit scheme. The first one is that the computational complexity is too high. Each secondary user needs to search

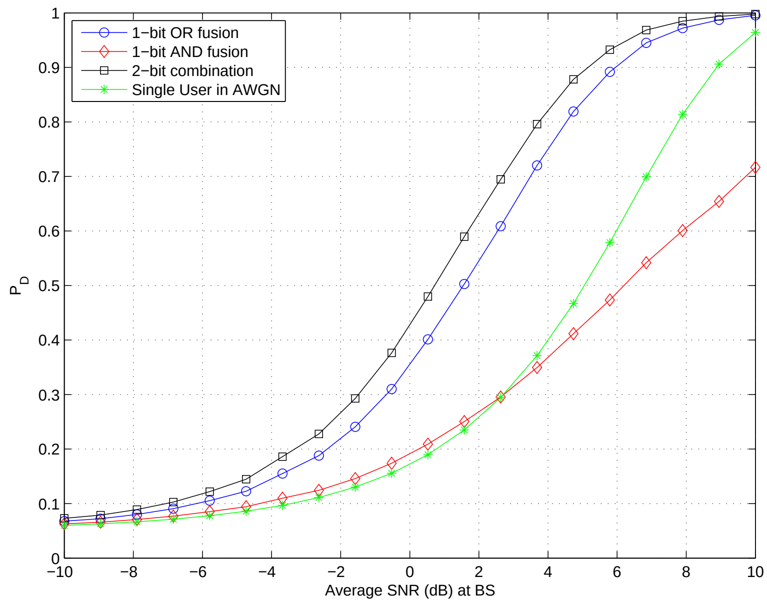

Figure 7: Detection probability curves under Rayleigh fading channels over different SNR with M = 6

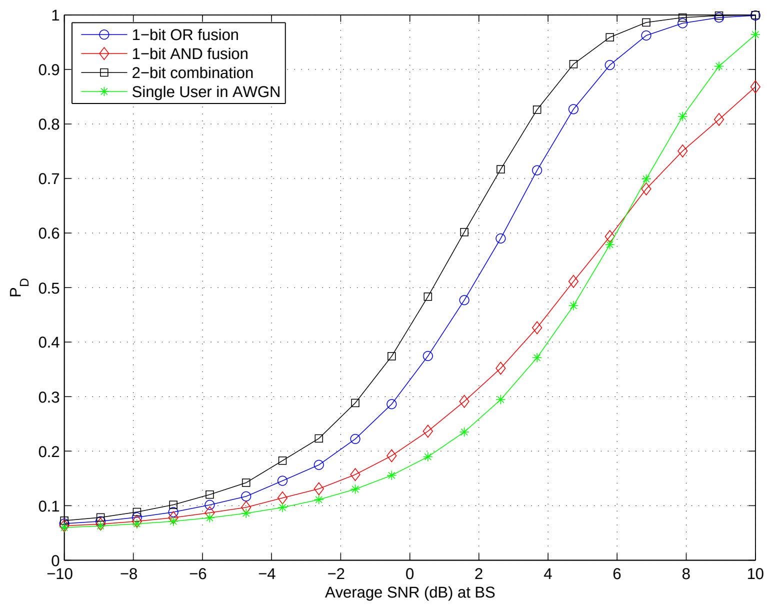

Figure 8: Detection probability curves under Nakagami fading channels over different SNR with M = 6

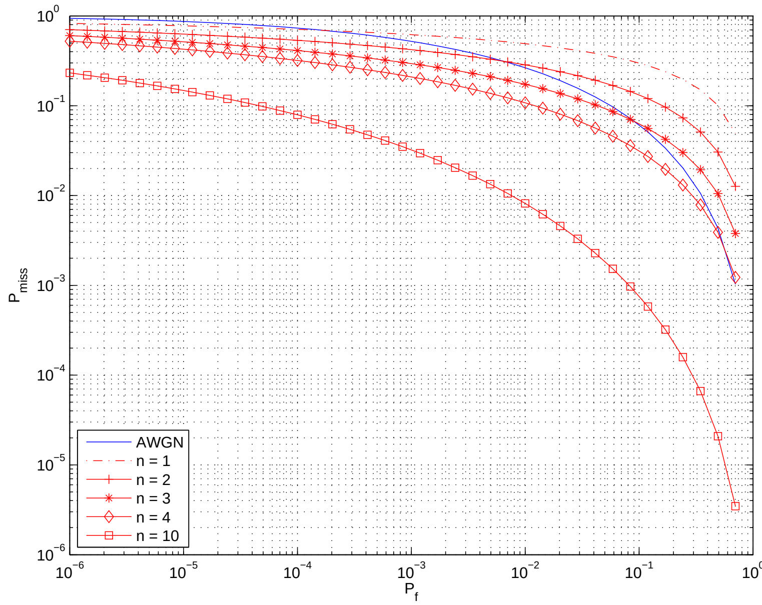

Figure 9: Complementary ROC curves with different cooperative users under OR funsion in Rayleigh fading

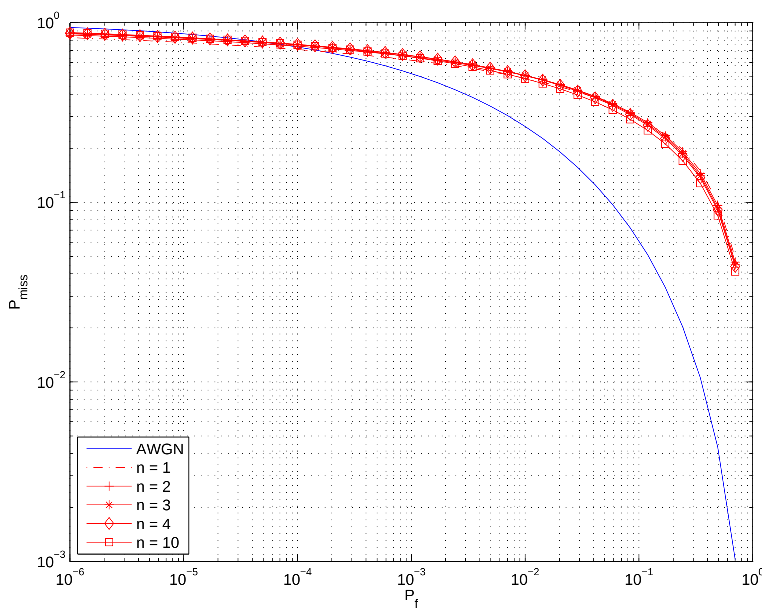

Figure 10: Complementary ROC curves with different cooperative users under AND funsion in Rayleigh fading

the threshold based on (21) numerically. In addition, the optimized parameter, L, needs to be generated before deploying and it may vary with the change of channel. The secondary drawback is that the overhead is higher than other two. The worst scheme is the one-bit AND fusion since it has a hard requirement on each user.

There are many possible areas and works for future research on the topic of cooperative scheme for spectrum sensing. First of all, all the works presented in this paper have a fixed Q_f. The reason that we did not explore the performance with fixed Q_d is that the computational complexity of P_d inversion in fading channels, e.g. (11) and (12), is high. To our best knowledge, there is no literature presenting such results in close form. However, this work is very important because in some applications, the detection probability is more important than the false alarm probability. One possible approach is using Gaussian Q function. The energy statistics in (5) can be approximated to Gaussian random variable by applying the Central Limited Theorem. Some approximations of Q function have been presented in [15] and [16]. These approximations eliminate the integration. Therefore, there may be possible to reduce the detection probability to an invertible form.

All the schemes discussed only send decision bits back to the base station. One alternative approach is sending the observed energies to the base station. Some related works include [9] and [17]. A common disadvantage is that they did not present the schemes in fading channel. In addition, all three schemes have a base station. In many applications, it is not possible to have a base station. Therefore, a decentralized scheme will also be interested for many people. [2] is a related work.

6 Conclusion

In this paper, we firstly showed that the fading channel can degrade the performance of the energy detector. The simulation results point that the probability of detection in Rayleigh fading is reduced by $10dB$. Then we investigated how the cooperative schemes improve the detection probability under different SNRs. The simulation results show that with only 6 users in cooperation, the detection probability is increased by 20% in fading channel. Also, we explore the improvement over number of cooperative user. The figures reflect that the detection probability is improved by $10dB$ with 10 users in cooperation at low SNR. In addition, we discuss some potential research topics and areas on the topic of cooperative spectrum sensing. We believe this paper would provide good understanding about the spectrum sensing in fading channel for the researchers who want to work on this area.

7 Acknowledgement

I would like to thank Prof. Andrea Goldsmith for her helps, feedbacks, comments and insights on this paper and the associated projects.

Appendix

A Evaluation of $\bar{P}_{d,Nak}$ in (12)

The probability density function of Nakagami fading is

$$f_{Nak}(\gamma) = \frac{1}{\Gamma(m)} \left(\frac{m}{\bar{\gamma}}\right)^m \gamma^{m-1} \exp\left(-\frac{m}{\bar{\gamma}}\gamma\right) \tag{23}$$

Therefore, averaging (10) over (23) while using the change of variable $x = \sqrt{2\gamma/sigma_u^2}$ yields

$$\bar{P}_{d,Nak} = \xi \int_0^\infty \gamma^u e^{-v^2\gamma^2/2} Q_M(b_1\gamma, b_2) d\gamma = \xi G_M \tag{24}$$

where $\xi = (2/\Gamma(m))((m\sigma_u^2)/(2\bar{\gamma}_j))^m$, $u = 2m-1$, $v^2 = m\sigma^2/\bar{\gamma}_j$, $M = N/2$, $b_1 = 1$, $b_2 = \sqrt{\lambda_j/\sigma_u^2}$ [4].

For $u > -1$, G_M can be recursively evaluated with the aid of (18) in [4]. Now we have

$$\begin{aligned} G_M &= G_{M-1} + D_{M-1}F_M \\ &= G_{M-2} + D_{M-2}F_{M-1} + D_{M-1}F_M \\ &= G_1 + \sum_{i=1}^{M-1} D_i F_{i+1} \end{aligned} \tag{25}$$

where

$$D_i = \frac{\Gamma(\frac{u+1}{2}) \left(\frac{b_2^2}{2}\right)^i e^{-b_2^2/2}}{2(i!) \left(\frac{v^2+b_1^2}{2}^{\frac{u+1}{2}}\right)} \tag{26}$$

$$F_i = F_{1,1}\left(\frac{u+1}{2}; i; \frac{b_1 b_2}{2(v^2+b_1^2)}\right). \tag{27}$$

Now, G_1 is

$$G_1 = \int_0^\infty x^u \exp(-v^2\gamma^2/2) Q(b_1\gamma, b_2) d\gamma \tag{28}$$

where $Q(.,.)$ is the first-order Marcum Q function. With the aid of (9) in [13], we obtain

$$\begin{aligned} G_1 &= \left\{ \sum_{k=0}^{N-2} \left(\frac{v^2}{v^2+b_1^2}\right)^k L_k\left(-\frac{b_2^2}{2}\frac{b_1^2}{v^2+b_1^2}\right) + (1+\frac{v^2}{b_1^2})(\frac{v^2}{v^2+b_1^2})^{N-1} L_{N-1}(-\frac{b_2^2}{2}\frac{b_1^2}{v^2+b_1^2}) \right\} \\ &\times \frac{2^{N-1}(N-1)!}{v^{2N}} \frac{b_1^2}{v^2+b_1^2} \exp\left(-\frac{1}{2}b_2^2 \frac{v^2}{v^2+b_1^2}\right) \end{aligned} \tag{29}$$

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