Spectrum Sensing and Power Efficiency Trade-off in Cognitive Radio Networks over Fading Channels

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Abstract: - Multiple secondary users can cooperate to increase the reliability of spectrum sensing in cognitive radio networks. However, the total transmission power grows approximately linearly with the number of cooperative secondary users. This paper proposes a new approach to optimize the trade-off between sensing reliability and power efficiency in cooperative cognitive radio networks over fading channels. We assume K cooperative secondary users each collect N samples during the sensing time. The proposed approach is based on dividing the spectrum sensing into two phases. In the first phase, we use only n of N samples, ($n \leq N$) to check the channels state, then k of K cooperative secondary users, ($k \leq K$) which are in deeply faded channels are discarded. We call this n a check point of the sensing time. The spectrum sensing with relatively less-faded channels are continued during the second phase. Therefore, there is a check point at which the sensing time can be optimized in order to maximize the probability of detection and the power efficiency. Several experiments are carried out to test the performance of the proposed approach in terms of detection probability and power efficiency. The obtained results show that the proposed approach enhances the detection probability as well as it shortened the optimal sensing time. Moreover, it improves the overall power efficiency.

Key-Words: - cognitive radio, cooperative spectrum sensing, power efficiency.

1 Introduction

One of the major challenges in design of wireless networks is the use of the frequency spectrum. Recent measurements by Federal Communications Commission (FCC) show that 70% of the allocated spectrum is in fact not utilized [1]. Spectrum utilization can be improved significantly by allowing a secondary user (SU) to utilize a licensed band when the primary user (PU) is absent. Cognitive radio (CR) has been proposed as a promising technique for future wireless communication systems [2]–[4]. CR is able to fill in spectrum holes and serve its users (secondary users) without causing harmful interference to the licensed user (PU). To do so, the CR must continuously sense the spectrum it is using in order to detect the reappearance of the PU. Once the PU is found to be active, the SU is required to vacate the channel. Therefore, spectrum sensing is of significant importance in CR networks. Moreover, periodic sensing is essential where the SU has to be aware of the channel status at all times. This is achieved by using a frame structure as in [5]–[6]. In this structure, each frame consists of a sensing period and a transmission period. At the end of each sensing period, the SU transmission starts when the licensed channel is idle. Otherwise, the SU will wait until the next frame to sense the licensed channel again.

There are two important parameters associated with spectrum sensing: probability of detection and probability of false alarm. From the primary user's perspective, the higher the detection probability, the better protection it will have from the SU. However, from the secondary user's perspective, the lower the false alarm probability, the more secondary transmission opportunities it will have. Therefore, a better sensing quality can be obtained by using a longer sensing period or, large number of samples.

Cooperative communications refer to the class of techniques, where the benefits of multiple-input-multiple-output (MIMO) techniques are gained via sharing information between multiple cooperating terminals in a wireless networks. Wireless relay networks that employ cooperative diversity have sometimes been referred to as virtual MIMO systems [7]–[8]. Multiple secondary users can cooperate to increase the reliability of spectrum sensing. The key challenge of spectrum sensing is the detection of weak signals in noise channels with a large probability of detection. Cognitive radio sensing performance can be improved using secondary users cooperation where users share their spectrum sensing measurements. Having multiple cooperating users increases diversity by providing multiple measurements of the signal and thus guarantees a better performance at low signal-to-noise ratio (SNR). It also provides a possible solution to the hidden-terminal problem that arises due to shadowing or severe multipath fading environments [9]–[10].

From the above discussion it is clear that, increasing the number of cooperative secondary users will increase the number of collected samples during the sensing time and this will improve the reliability of spectrum sensing in terms of detection probability. On the other hand, the more the collected samples during the sensing time, the more the power would be consumed. Thus, there exists a trade-off between power consumption (power efficiency) and detection probability; we can get higher detection probability but we need to consume more power instead. The authors in [11]–[12], considered the trade-off between the sensing quality and the achievable throughput. The spectrum sensing duration and the achievable throughput trade-off in a cooperative cognitive radio network over Nakagami fading conditions was introduced in [13]. However, none of these papers have examined the trade-off between detection probability and power efficiency in cooperative cognitive radio networks. Therefore, it is of great interest to consider this trade-off in this paper.

In this paper, we first study the trade-off between sensing quality in terms of detection probability and power efficiency. Then we propose a new approach to optimize the trade-off between detection probability and power efficiency in cooperative cognitive radios over fading wireless channels. The basic idea of the proposed approach can be explained as follows; assume K cooperative secondary users each collect N samples during the sensing time. The proposed approach is based on dividing the spectrum sensing into two phases. In the first phase, we use only n of N samples, ($n \leq N$) to check the channels state, then k of K secondary users, ($k \leq K$) which are in deeply faded channels are discarded. We call this n a check point of the sensing time. The spectrum sensing with relatively less-faded channels are continued during the second phase. Therefore, there is a check point at which the sensing time can be optimized in order to maximize the probability of detection and the power efficiency.

The remainder of this paper is organized as follows; Section 2 presents the general system model for spectrum sensing. The relation between probability of detection and probability of false alarm is also established in this section. In Section 3, presents the energy detection over Rayleigh fading channels. Spectrum sensing based on decision fusion is explained in Section 4. In Section 5 we explain the sensing-power efficiency trade-off. The proposed approach used to optimize this trade-off is also presented in this section. Simulation results and discussion are given in Section 6. Finally, conclusions are drawn in Section 7.

2 General System Model for Cooperative Spectrum Sensing

In this section, the general model for spectrum sensing is presented. Then we introduce the energy detection scheme and analyze the relationship between the probability of detection and the probability of false alarm.

2.1 Cooperative Spectrum Sensing

The critical challenging issue in spectrum sensing is the hidden terminal problem, which occurs when the SU is shadowed or in severe multipath fading. To address this problem, multiple secondary users can cooperate in spectrum sensing [9]–[10]. Therefore, cooperative spectrum sensing can greatly improve the detection probability in Rayleigh fading channels [14]. In general, cooperative spectrum sensing can be performed as shown in Fig. 1. Each SU performs its own local spectrum sensing measurements independently and then makes a binary decision on whether the PU is present or not. Then all of the secondary users forward their decisions to a common receiver, R_c. The common receiver fuses the SU decisions and makes a final decision to infer the absence or the presence of the PU.

In this paper we consider a cognitive radio network with K cooperative secondary users as shown in Fig. 1. Spectrum sensing is performed periodically every N samples, which is the total number of samples for each SU. The spectrum sensing problem at the i-th SU is modeled as a binary hypothesis test to determine the absence or the presence of the PU. Let H_0 denote the absence of the PU and H_1 designate the presence of the PU. Spectrum sensing is to decide between the following two hypotheses

$$\begin{aligned} &H_0 : y_i(n) = w_i(n), \quad \text{for } i = 1,\dots,K, \text{ and } n = 1,\dots,N \\ &H_1 : y_i(n) = h_i(n)s(n) + w_i(n) \end{aligned} \tag{1}$$

where $y_i(n)$ is the received signal at the i-th SU, $s(n)$ represents the primary user's signal samples which are independently and identically distributed (i.i.d.) with zero mean and variance E[$|s(n)|^2$] = σ^2_s, $w_i(n)$ is the additive white Gaussian noise, and $h_i(n)$ is the complex channel gain of the sensing channel between the PU and the i-th SU. When the channel is non-fading, $h_i(n)$ is constant during the sensing process. On the other hand, when the channel is fading, $h_i(n)$ includes multipath and fading effects. It is assumed that noise samples are i.i.d. with zero mean and variance E[$|w_i(n)|^2$] = σ^2_w. Denote $\gamma = \sigma^2_s / \sigma^2_w$ as the received signal-to-noise ratio (SNR) of the PU measured at the secondary receiver of interest, under the hypothesis H_1.

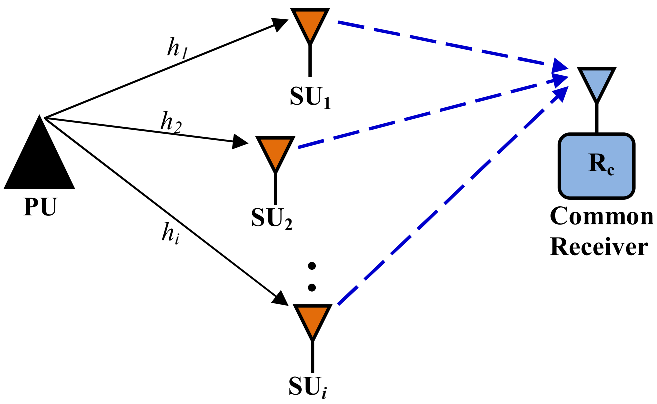

Figure 1: Cooperative spectrum sensing.

Generally, two probabilities are of interest for indicating the performance of a sensing algorithm; probability of detection, P_d, which defines the probability of the sensing algorithm correctly detecting the presence of primary signal under hypothesis H_1; and probability of false alarm, P_f, which defines the probability of the sensing algorithm falsely declaring the presence of primary signal under hypothesis H_0. Obviously, for a good detection algorithm, the probability of detection should be as high as possible while the probability of false alarm should be as low as possible.

2.2 Energy Detection over Non-Fading Channels

The spectrum sensing algorithm considered in this paper is the energy detection algorithm [15] because of its relatively low computational complexity, ease of implementation and the fact that it does not require any prior information about the primary user's signal. Once the signal y_i has been collected, the i-th SU computes its energy, the test statistic for the energy detector is given as [12], [14]:

$$T(y_i) = \frac{1}{N}\sum_{n=1}^{N}\left|y_i(n)\right|^2 \qquad (2)$$

Under hypothesis H_0, the test static $T(y_i)$ is a random variable whose probability density function (PDF) $p_0(x)$ is a Chi-square distribution with $2N$ degrees of freedom for complex valued case [12]. The energy detection is performed by measuring the energy of the received signal $y_i(n)$ in a fixed bandwidth W over an observation or sensing time window T_s. If ε_i is the i-th SU detection threshold, the probability of false alarm, P_{fi}, is given by

$$P_{fi}(\varepsilon_i, T_s) = \text{Prob}(T(y_i) > \varepsilon_i | H_0) = \int_{\varepsilon}^{\infty} p_0(x)dx \qquad (3)$$

where P_{fi} denotes the false alarm probability of the i-th SU in its local spectrum sensing. Under hypothesis H_1, let $p_1(x)$ represent the PDF of the test static $T(y_i)$. For a chosen threshold ε_i, the probability of detection, P_{di} is given by

$$P_{di}(\varepsilon_i, T_s) = \text{Prob}(T(y_i) > \varepsilon_i | H_1) = \int_{\varepsilon}^{\infty} p_1(x)dx \qquad (4)$$

where P_{di} denotes the detection probability of the i-th SU in its local spectrum sensing. From the central limit theorem, we can approximate the probabilities of detection and false alarm as follows [12]; for a large N, $T(y_i)$ can be approximated as a Gaussian random variable with mean,

$$\begin{aligned} H_0 &: \ \mu_0 = \sigma_w^2 \\ H_1 &: \ \mu_1 = (\gamma+1)\sigma_w^2 \end{aligned} \qquad (5)$$

and variance

$$\begin{aligned} H_0 &: \ \sigma_0^2 = \frac{1}{N}\left[E|w(n)|^4 - \sigma_w^4\right] \\ H_1 &: \ \sigma_1^2 = \frac{1}{N}\left[E|s(n)|^4 + E|w(n)|^4 - \left(\sigma_s^2 - \sigma_w^2\right)^2\right] \end{aligned} \qquad (6)$$

If we consider circularly symmetric complex Gaussian (CSCG) noise case and for the primary signal $s(n)$, we consider the complex phase shift keying (PSK) modulated signal; the probabilities of false alarm and detection can be approximated, respectively as follows:

$$P_{fi}(\varepsilon_i, T_s) = Q\left(\sqrt{N}\left(\frac{\varepsilon_i}{\sigma_w^2} - 1\right)\right) \qquad (7)$$

$$P_{di}(\varepsilon_i, T_s) = Q\left(\sqrt{\frac{N}{2\gamma+1}}\left(\frac{\varepsilon_i}{\sigma_w^2} - \gamma - 1\right)\right) \qquad (8)$$

where $Q(.)$ is the complementary distribution function of the standard Gaussian, and given as

$$Q(x)=\frac{1}{\sqrt{2\pi}}\int_{x}^{\infty}\exp\left(-\frac{t^2}{2}\right)dt \qquad (9)$$

It is clear that, P_{fi} in Eq.(7) is independent of SNR since under H_0 there is no primary signal present. It is clear also from Eq.(8) that, for a large number of samples, N it is more likely to detect a signal with higher probability of detection.

If the decision is H_0 when there is a primary user present, it is called missed detection and its probability is called missed detection probability, P_{mi} which can be written as

$$P_{mi}(\varepsilon_i,T_s)=1-P_{di}(\varepsilon_i,T_s) \qquad (10)$$

Equation (8) can be rewritten in terms of detection threshold as

$$\left(\sqrt{\frac{N}{2\gamma+1}}\left(\frac{\varepsilon_i}{\sigma_w^2}-\gamma-1\right)\right)=Q^{-1}\left(\overline{P}_{di}\right) \qquad (11)$$

where $\overline{P}_{di}$ is the i-th SU target probability of detection. Using Eq. (7) this threshold is related to the probability of false alarm as follows:

$$\left(\sqrt{N}\left(\frac{\varepsilon_i}{\sigma_w^2}-1\right)\right)=Q^{-1}\left(P_{fi}\right) \qquad (12)$$

For a target probability of detection, $\overline{P}_{di}$, the probability of false alarm is related to the target detection probability as follows:

$$P_{fi}=Q\left(Q^{-1}\left(\overline{P}_{di}\right)\sqrt{2\gamma+1}+\sqrt{N}\gamma\right) \qquad (13)$$

Note N is the maximum integer not greater than $T_s\times f_{sa}$, where f_{sa} is the received signal sampling frequency. In a similar way, the probability of detection for a target probability of false alarm is given by

$$P_{di}=Q\left(\frac{1}{\sqrt{2\gamma+1}}\left(Q^{-1}\left(\overline{P}_f\right)-\sqrt{N}\gamma\right)\right) \qquad (14)$$

3 Energy Detection over Rayleigh Fading Channels

In this section, we derive the average detection probability over Rayleigh fading channels [14]. Note that the probability of false alarm, however, remains the same under any fading channel since it is considered for the case of no signal transmission and as such is independent of SNR. When the channel is varying due to fading effects, the previously given equations for probability of detection represents the probability of detection conditioned on the instantaneous SNR. Therefore, by averaging the conditional probability of detection over the SNR fading distribution, we can find the expressions in closed form of detection probability in fading channels.

$$P_{di,fading}=\int_{\gamma}Q\left(\sqrt{2B\gamma},\sqrt{\varepsilon_i}\right)f_{\gamma}(x)dx \qquad (15)$$

where B is the time-bandwidth product and $f_{\gamma}(x)$ is the probability of distribution function of SNR under fading. Under Rayleigh fading, the signal amplitude follows a Rayleigh distribution. In this case, the SNR follows an exponential PDF,

$$f(\gamma)=\frac{1}{\overline{\gamma}}\exp\left(-\frac{\gamma}{\overline{\gamma}}\right) \qquad (16)$$

where $\overline{\gamma}$ is the average SNR. Therefore, in Rayleigh fading, a closed-form formula for detection probability over Rayleigh fading channels may be obtained as follows,

$$P_{di,Ray.fading}=\exp\left(-\frac{\varepsilon_i}{2\left(1+B\overline{\gamma}\right)}\right)\left(1+\frac{1}{B\overline{\gamma}}\right)^{B-1}\times\left[1-\frac{\Gamma\left(B-1,\frac{\varepsilon_i B\overline{\gamma}}{2\left(1+B\overline{\gamma}\right)}\right)}{\Gamma\left(B-1\right)}\right]+\frac{\Gamma\left(B-1,\frac{\varepsilon_i}{2}\right)}{\Gamma\left(B-1\right)} \qquad (17)$$

where $\Gamma(.)$ is the gamma function.

4 Spectrum Sensing Based on Decision Fusion

In cooperative spectrum sensing, all secondary users identify the availability of the PU independently. Each SU makes a binary decision based on its local spectrum sensing and then forwards one bit of the decision to the common receiver as in Fig. 1. Let d_i represent the local spectrum sensing result of the i-th SU. The value of d_i for i = 1,…, K, can be given as follows

$$d_i=\begin{cases}0 & \text{The SU infers the absence of the PU}\\ 1 & \text{The SU infers the presence of the PU}\end{cases} \qquad (18)$$

Once the decision is made by each SU, there are different rules available for making the final decision on the presence of the PU [17]. At the common receiver, all 1-bit decisions are fused together according to the following logic rule:

$$R_c = \sum_{i=1}^{K} d_i \begin{cases} < k \Rightarrow H_0 \\ \geq k \Rightarrow H_1 \end{cases} \quad (19)$$

Equation (19) demonstrates that the common receiver infers the presence of PU signal, i.e., H_1, when there exists at least k out of K secondary users inferring H_1. Otherwise, the common receiver decides the absence of PU signal, i.e., H_0.

A. Logic-OR Rule

The common receiver infers the presence of the PU signal when there exists at least one SU that has the local decision H_1. Therefore, the OR rule corresponds to the case of $k = 1$, i.e., $R_c \geq 1$. Otherwise, there is no PU signal. Assuming that all decisions are independent, the probability of detection and probability of false alarm of cooperative spectrum sensing based on the OR rule is given, respectively as,

$$P_d = 1 - \prod_{i=1}^{K} \left(1 - P_{di}\right) \quad (20)$$

$$P_f = 1 - \prod_{i=1}^{K} \left(1 - P_{fi}\right) \quad (21)$$

B. Logic-AND Rule

The common receiver infers the presence of the PU signal if all decisions say that there is a primary user. It can be seen that the AND rule corresponds to the case of $k = K$. The probability of detection and probability of false alarm of cooperative spectrum sensing based on the OR rule is given, respectively as,

$$P_d = \prod_{i=1}^{K} P_{di} \quad (22)$$

$$P_f = \prod_{i=1}^{K} P_{fi} \quad (23)$$

C. Majority Rule

This decision rule is based on majority of the individual decisions of SU. If half or more of the decisions say that there is a PU signal, the final decision declares that there is a primary user. The probability of detection and probability of false alarm can be obtained as in [12]. It can be seen that the OR rule is very conservative for the secondary users to access the licensed band of the PU. As such, the chance of causing interference to the PU is minimized as will be shown in results and discussion section.

5 Sensing-Power Efficiency Trade-off and the Proposed Approach

In this section, we study the fundamental trade-off between sensing quality in terms of probability of detection and power efficiency then we discuss how the sensing time can be optimized in order to maximize the probability of detection and the power efficiency.

5.1 Problem Formulation

For a cognitive radio network with K cooperative secondary users each collects N samples during the sensing time. The received $K \times N$ data matrix D is represented as

$$D = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,N} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ y_{K,1} & y_{K,2} & \cdots & y_{K,N} \end{bmatrix} \quad (24)$$

As mentioned before, to improve the probability of detection we have to increase the number of samples we collect for the sensing process, this can be achieved by increasing the number of cooperative secondary users. The probability of detection versus the number of samples under a non-fading channel is illustrated in Fig. 2 for $K = 2$, $N_{max} = 400$, SNR = -10 dB, and $P_f = 0.1$. It is clear that, the detection probability keeps increasing as more numbers of samples are utilized.

Generally, the large the number of cooperative secondary users, the more the samples we collect for the sensing process, the higher detection probability but the more power would be consumed during the spectrum sensing process. Thus, there exists a trade-off between power consumption and probability of detection on spectrum sensing; one gets higher probability of detection but has to consume more energy instead.

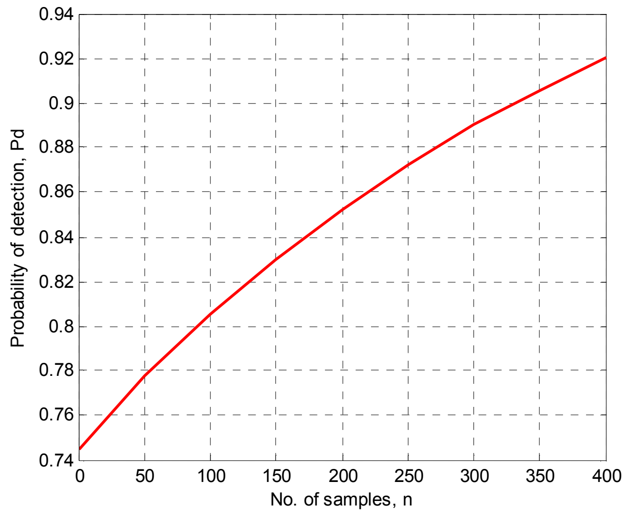

Figure 2: The probability of detection versus the number of samples under a non-fading channel.

5.2 The Proposed Approach

The proposed approach is based on dividing the spectrum sensing into two phases. In the first phase, we use only n of N samples, $n \leq N$ to check the channels state, we call this n a check point of the sensing time. Then k of K cooperative secondary users, $k \leq K$ which are in a deeply faded channel are discarded. Thus, after the check point, there are only $K - k$ secondary users employed for $N - n$ samples. Eq. (25) shows the received data matrix under this new approach. It is clear from Eq. (25) that, after sensing n samples of K cooperative secondary users, the proposed approach selects k of cooperative secondary users, which are considered to be more faded than others, to discard. Therefore, discarding the cooperative secondary users with faded channel increases the overall power efficiency as explained next.

Let $N \times P$ is the required power for each secondary user. Therefore, the power required for the sensing process using K cooperative secondary users will be $K \times N \times P$.

To explain how the proposed approach improve the overall power efficiency, consider first the case of discarding one SU ($k = 1$), after n samples of sensing; this saves $(N - n) \times P$ in power. Now, if k cooperative secondary users are chosen to be discarded after n samples of sensing, we can save $k \times (N - n) \times P$ in power compared to that $K \times N \times P$ for all N samples from K cooperative secondary users. Power efficiency is proportional to the energy saved during the sensing process by discarding the deeply faded secondary users. That is, power efficiency should be an indicator of how much energy could be saved compared to the sensing of whole samples of all K cooperative secondary users. Therefore, we may represent the power efficiency η_p as follows.

$$\eta_p(n,k) = \frac{k \times (N - n)}{K \times N} \tag{26}$$

Figure 3 shows the power efficiency η_p versus the number of samples, using $K = 8$ and $N_{max} = 200$ for different values of k. It is clear from this figure that, the power efficiency decreases as more numbers of samples are utilized. On the other hand, the power efficiency improved when discarding more secondary users, changing k from 1 to 6. Also for a given number of k, the power efficiency is improved when less number of samples n is employed before the check point. However, the probability of detection increases when more number of samples is employed. This trade-off can be optimized by finding the optimum sensing time for the proposed CR network.

5.3 The Optimum Sensing Time

What we want now is to derive a target function to determine the optimal sensing time that jointly maximizes the probability of detection and minimizes the power consumption under given parameters. As there is a trade-off between the probability of detection and power efficiency, the target function can be defined as

$$T_F(n,k) = (1 - \beta) \times P_d + \beta \times \eta_p(n,k) \tag{27}$$

where $0 \leq \beta \leq 1$.

$$D = \left[\begin{array}{ccc|cccc} y_{1,1} & \cdots & y_{1,n} & y_{1,n+1} & \cdots & y_{1,N-1} & y_{1,N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{K-2,1} & \cdots & y_{K-2,n} & - & \cdots & - & - \\ y_{K-1,1} & \cdots & y_{K-1,n} & y_{K-1,n+1} & \cdots & y_{K-1,N-1} & y_{K-1,N} \\ y_{K,1} & \cdots & y_{K,n} & - & \cdots & - & - \end{array}\right] \tag{25}$$

Deep-fading

Discarded cooperative SU

Deep-fading

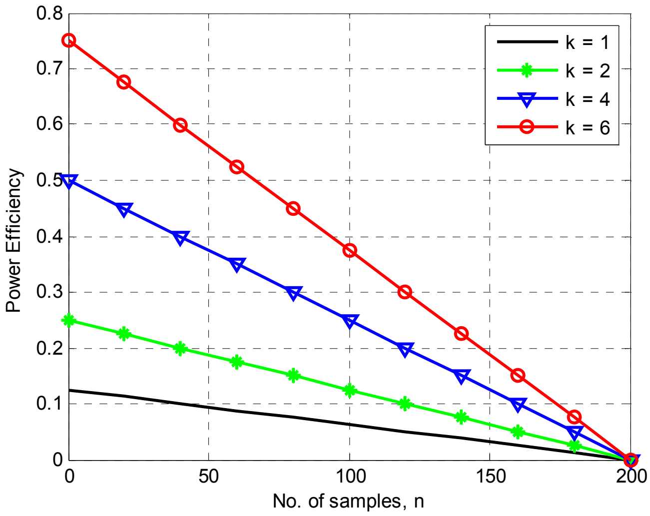

Figure 3: The power efficiency, η_p versus the number of samples.

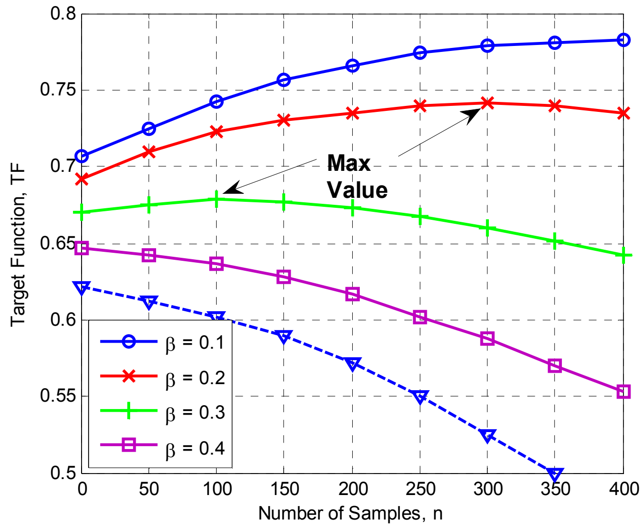

Figure 4: The target function over non-fading channels for different values of β.

As explained above, P_d is proportional to the number of sensing samples N, while η_p decreases as more number of samples are employed; thus, the constant β controls the overall level of this target function as well as it controls this target function to have a maximum point. There are two extreme cases as follows;

1. $\beta \to 0$; The detection probability is regarded as the more important factor. Therefore, more number of samples are favorable to maximize the target function.
2. $\beta \to 1$; Power efficiency is regarded as more important than the detection probability.

Therefore, there may exist some range for β at which the optimal sensing time could be found. It would be varied by other parameters, such as probability of false alarm, the size of the data matrix, and so on.

Figure 4 presents the target function over non-fading channels for different values of β using $K = 2$, $N = 400$, and $P_f = 0.1$. From this figure it is clear that, the target function does not have a maximum point for $\beta \leq 0.1$ and $\beta \geq 0.4$. It is clear also that, the optimum check point which maximizes the target function tends to have lower for large values of β. For example, at β = 0.2 the optimal sensing time occurs at n = 300 samples, while at β = 0.3 the optimal sensing time occurs at n = 100 samples. However, from Eq. (27), increasing the value β will reduce the detection probability. Note that, the range of β to make the target function have a maximum point is altered if we change the above mentioned parameters.

6 Simulation Results and Discussion

Figure 5 shows the complementary receiver operating characteristic (ROC) curves (probability of missed detection versus probability of false alarm) of the AWGN and Rayleigh fading channels, Eq. (17). The average SNR value □γ = 5 dB and B = 5. It is clear that, the detection performance showed significant degradation under Rayleigh fading scenario. Therefore, under Rayleigh fading conditions, it becomes even more important to continue with less-faded channels (discarding the deeply faded channels) to maintain a certain level of performance.

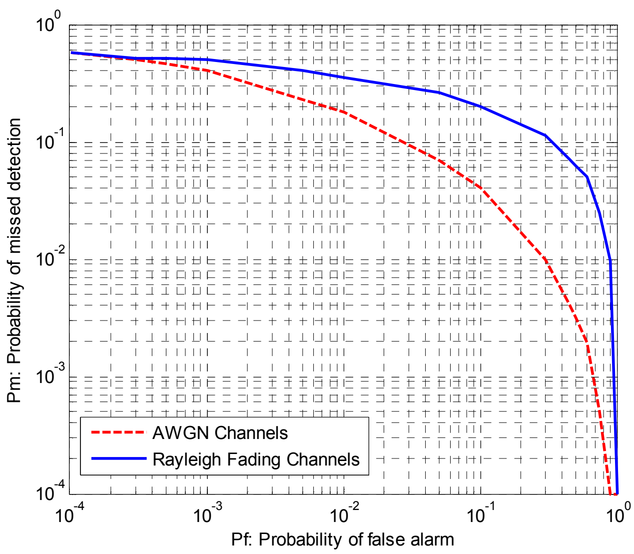

Figure 5: P_m versus P_f over AWGN and Rayleigh fading channels.

Figure 6 shows the ROC curves of cooperative spectrum sensing for different numbers of secondary users over Rayleigh fading channels with average SNR value, □γ = 5 dB and P_f = 0.1. It is clear that the probability of missed detection is greatly reduced when the number of cooperative secondary users increase for a given probability of false alarm.

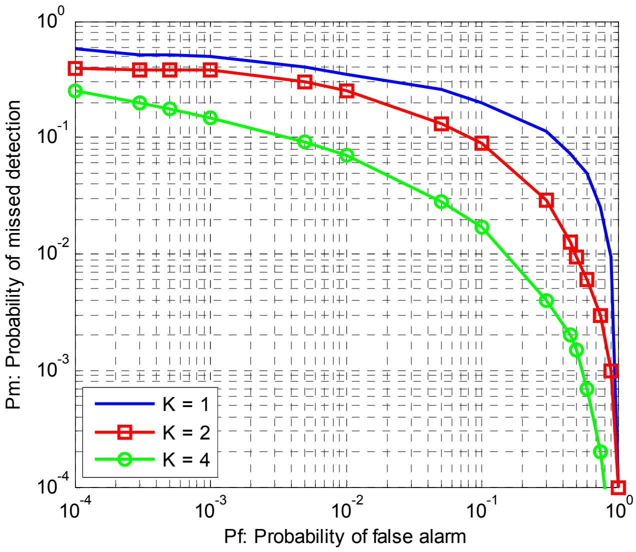

Figure 6: P_m versus P_f over Rayleigh fading channel and different number of SU.

Figure 7 shows the cooperative spectrum sensing performance with different fusion rules. It can be seen that the OR rule is the best among the fusion rules. In [16], it was also found that for many cases of practical interest, the OR rule gives better performance than other rules. The following results are obtained using the OR rule.

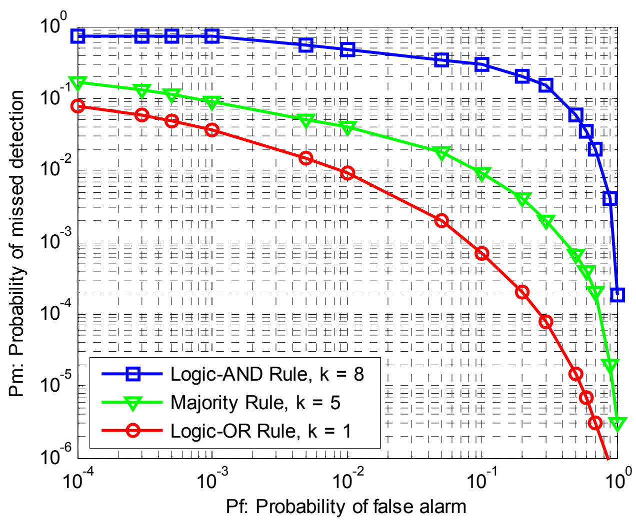

Figure 7: P_m versus P_f over Rayleigh fading channel and different fusion rules with □γ = 10 dB and K = 8.

In the following results, we assume that there are two secondary users, K = 2 and each collects 400 samples during the sensing time over Rayleigh fading channel, $0.1 < \beta \leq 0.3$, and P_f = 0.1. A fundamental parameter determining the quality of detection is the average SNR, which mainly depends on the primary user's transmitted power as well as its distance to the secondary users. Since our goal is to achieve optimum sensing time over the proposed approach, let us assume the following scenario, where the averages SNR of two secondary users have big differences. This scenario shows an environment in which one SU is experiencing rather severe fading, while the other is in a better condition. The average SNR values of the first and second secondary users are 5 dB and -15 dB, respectively.

Two different schemes are used to discard the secondary users. In the first scheme, the secondary users are randomly discarded from the CR network. While the second scheme select the secondary users with the highest signal strength to keep tracking the activity of the PU and discarding the users with the lowest signal strength. The second scheme requires additional feedback information to report the signal strength.

Figure 8 shows the target function over Rayleigh fading channels using the first scheme, the secondary users are randomly discarded at different values of β.

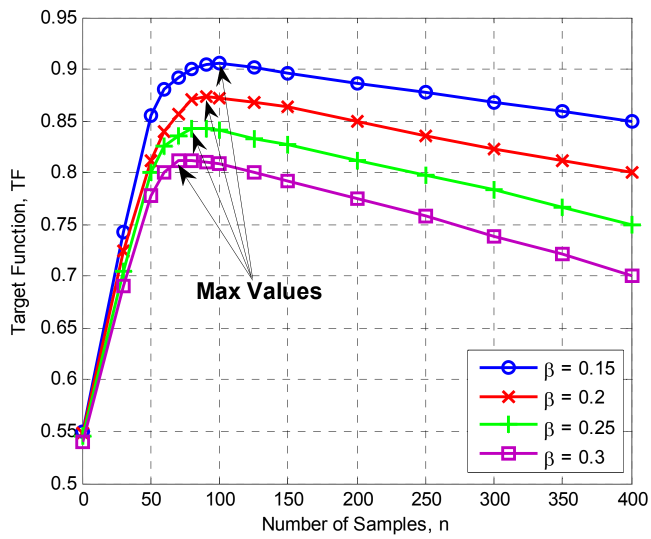

Figure 8: The target function over Rayleigh fading channels when the SU is randomly discarded.

Figure 9 shows the above results when we consider the second scheme, the secondary users are discarded according to their signal strength. It is noticeable that the overall level and maximum points of target functions are higher than those of Fig. 8. The target function for this scheme reaches its maximum point much earlier than the first scheme shown in Fig. 8.

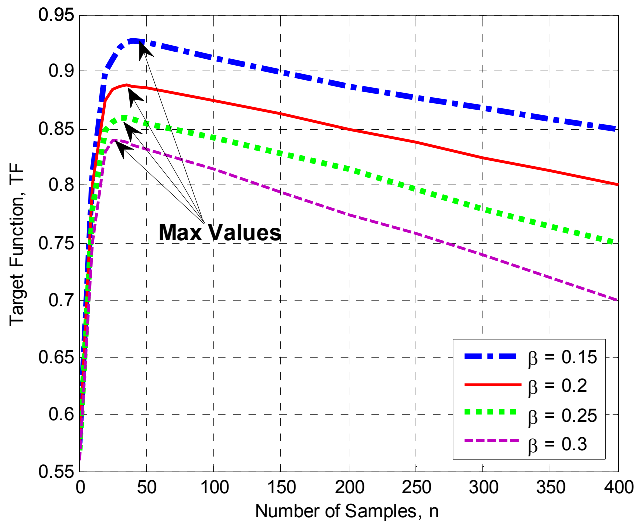

Figure 9: The target function over Rayleigh fading channels when the SU is discarded according to the signal strength.

Figure 10 presents a comparison in terms of detection probability using first and second schemes. It is clear that the detection probability of the second scheme has much higher value than of the first scheme, where it saturates approximately to 1 at $n \approx 40$ samples compared to $n \approx 100$ samples when we used the first scheme.

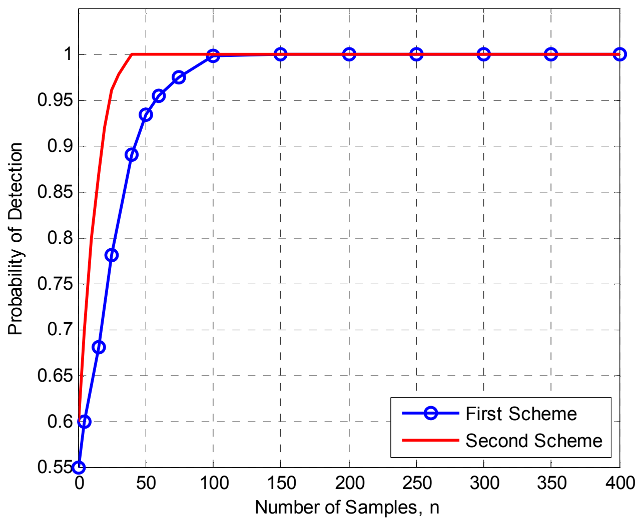

Figure 10: Detection probability comparison using first and second schemes.

β	First Scheme (Randomly discard the SU)		Second Scheme (Discarding SU according to signal strength)	
	Max. T_F	Opt. n	Max. T_F	Opt. n
0.15	0.906	100	0.927	40
0.2	0.873	93	0.889	35
0.25	0.842	82	0.860	32
0.3	0.812	70	0.840	28

Table 1: comparisons of the target function for the two schemes over Rayleigh fading channels.

Table 1 shows the detailed comparisons of the target function for the two schemes. We can observe that, the second scheme in which the secondary users are discarded according to their signal strength, achieves the best performance. Not only the target function reaches its maximum point earlier but also it achieves higher performance. Therefore, by using the proposed approach with the second scheme, the overall power efficiency is improved while maintaining good detection probability.

7 Conclusions

In this paper we proposed a new approach to optimize the trade-off between sensing quality and power efficiency in cooperative cognitive radio networks over Rayleigh fading channels. The proposed approach is based on discarding the secondary users which are in deeply faded channels. Two different schemes were proposed to discard the secondary users. In the first scheme, the secondary users are randomly discarded. While the second scheme selecting the secondary users with the highest signal strength to keep tracking the activity of the PU and discarding the users with the lowest signal strength. The obtained results show that using the proposed approach with the second scheme enhances the detection probability as well as it shortened the optimal sensing time. Moreover, it improves the overall power efficiency.

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