Contribution based Cooperative Spectrum Sensing against Malfunction Nodes in Cognitive Radio Networks

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***Abstract*—In cognitive radio networks, secondary users can cooperate based on their own sensing observations so as to detect the primary user more accurately. However, since of location disadvantage, multipath fading or shadowing, sensing contribution of some secondary users may be untrustworthy, which are termed malfunction nodes in this paper. To mitigate this problem we propose a contribution based cooperative spectrum sensing scheme for cognitive radio networks. By assigning different sensing time to each secondary user based on their historic contribution to the global decision, the new scheme can exploit the merit of spatial advantage and save more energy for them when they are in a severe fading or shadowing environment. Numerical results show that the sensing performance is improved significantly as opposed to conventional spectrum sensing.**

I. Introduction

Within the current spectrum regulatory framework all frequency bands are exclusively licensed to specific users and no violation from unlicensed users is allowed. The increasing demands for the radio resource and the scarcity of vacant spectrum bands have pushed the regulatory agencies to be more aggressive in providing new way to use the spectrum. Recent measurements by Spectrum Policy Task Force within FCC indicate low utilization in spectrum, especially in the 3-6GHz bands [1]. One approach of improving spectrum utilization is to enable these unlicensed users to get access to frequency bands already allocated to primary or licensed users when the bands are unoccupied. Cognitive radio, as an agile radio technology, is viewed as a promising technology to improve spectrum utilization via negotiated or opportunistic spectrum sharing without interference to primary user [2]. Since cognitive radios are considered low priority users of spectrum allocated to primary users, a fundamental requirement is to avoid or minimize interference to an acceptable level to a potential primary user in its vicinity. The key challenge to meet this requirement is reliable detection of the presence of the primary signals.

There are already several spectrum sensing techniques proposed and theoretically analyzed in the literature, including non-coherent energy detection applicable to any signal type and coherent pilot detection that optimally detects known primary signal [3]. Although coherent detection outperforms non-coherent detection at the cost of perfect synchronization circuitry and a priori knowledge of the primary signal structure [4], energy detector [5] [6] is widely used for signal detection due to its simplicity and good performance. It is the optimal detector when the detector only knows the power of the received signal, which is often encountered in the cognitive radio scenarios. Spectrum sensing is a tough task because of fading, shadowing, the time-varying natures of wireless channels, and local interference. Cooperative spectrum sensing schemes [7] [8] [9] [10] have been proposed to exploit the spatial diversity. Having multiple cooperative users increases diversity by providing multiple measurements of the signal and thus guarantees better sensing performance.

In this paper, we study the malfunction sensing problem in the context of cooperative spectrum sensing for cognitive radio networks. Malfunction sensing can be caused by severe fading or shadowing. Either case could potentially cause interference to primary user and result in under-utilization of unoccupied licensed spectrum bands. To combat malfunction sensing we proposed contribution based cooperative spectrum sensing (CCSS) by assigning different sensing time to each cognitive radio user. The new scheme can exploit the merit of spatial advantage and save more energy for them when they are in a severe fading or shadowing environment.

The rest of this paper is organized as follows. In section II, we formulate the problem of primary signal detection in cognitive radio networks. In section III, the contribution based cooperative spectrum sensing scheme is proposed. Simulation results are presented and discussed in section IV. Finally, conclusions are given in section V.

II. Problem Formulation

Prior to access the licensed spectrum band, the secondary users should employ sensing technique to detect whether the primary signal is present or not. Energy detection is an optimal approach for detecting any unknown zero-mean constellation signal [4]. And also for implementation simplicity, we restrict our analysis to energy detection in the cooperative spectrum sensing for cognitive radio networks.

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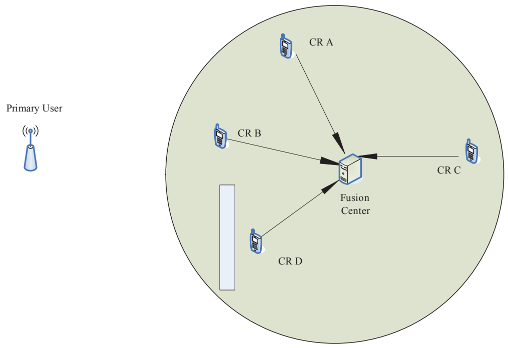


Fig. 1. Structure of cooperative spectrum sensing.

A. Energy Detection

For energy detection, the received signal at secondary user i is given by

$$y_{ij} = \begin{cases} n_{ij}, & H_0, \\ \sqrt{E_s} s_{ij} + n_{ij}, & H_1, \end{cases} \quad (1)$$

where n_{ij} and $\sqrt{E_s} s_{ij}$ represent the received noise and primary signal at the j-th sample of the i-th secondary user, respectively; H_0 and H_1 stand for the hypotheses corresponding to the primary signal absence and presence, respectively.

The energy of the received signal is measured at each secondary user. The test statistic for energy detection at secondary user i is given by

$$Y_i = \sum_{j=1}^{2u} |y_{ij}|^2, \quad (2)$$

where $u = TW$ is the time-bandwidth product.

The test statistic Y_i follows a central chi-square distribution with $2u$ degree of freedom under H_0 and a noncentral chi-square distribution with $2u$ degree of freedom and a noncentrality parameter $2\gamma_i$ under H_1, respectively [5]:

$$Y_i \sim \begin{cases} \chi^2_{2u}, & H_0, \\ \chi^2_{2u}(2\gamma_i), & H_1. \end{cases} \quad (3)$$

Let λ denote the local decision threshold for each secondary user, then the local detection probability P_d and false alarm probability P_f, can be obtained from [6] as

$$P_d = Pr(Y_i > \lambda | H_1) = Q_u(\sqrt{2\gamma_i}, \sqrt{\lambda}) \quad (4)$$

and

$$P_f = Pr(Y_i > \lambda | H_0) = \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)}, \quad (5)$$

where $Q_u(a, b)$ denotes the generalized Marcum Q-function; $\Gamma(\cdot)$ and $\Gamma(\cdot, \cdot)$ denote the gamma function and upper incomplete gamma function, respectively.

B. Cooperative Spectrum Sensing

It is a challenging task for single secondary user to carry out robust and reliable spectrum sensing. Because of fading, shadowing and local interference, the sensing performance by single secondary user will be deteriorated severely. To overcome these problems, the schemes of cooperative spectrum sensing are proposed to guarantee a better performance. As shown in Fig. 1, we consider a cognitive radio network which consists of M secondary users and one fusion center. Each secondary user can execute spectrum sensing via its observation and send its spectrum sensing data to a fusion center. The sensing data may be one-bit-decision or original sensing information, which named hard decision and soft decision, respectively.

Let $\boldsymbol{Y} = (Y_1, Y_2, \ldots, Y_M)$, then the corresponding likelihood ratio between hypothesis H_1 and H_0 is presented as

$$L(\boldsymbol{Y}) = \prod_{i=1}^{M} \frac{Pr(Y_i|H_1)}{Pr(Y_i|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \hat{\lambda}, \quad (6)$$

where $\hat{\lambda}$ is the threshold determined by the given false alarm probability or detection probability. Without loss of generality, we concentrate on maximizing the detection probability for a given false alarm probability in this paper.

III. Contribution based Cooperative Spectrum Sensing

In this section, we analyze the malfunction sensing problem in the context of cooperative spectrum sensing for cognitive radio networks and propose a new scheme to deal with this problem. In soft combination of cooperative spectrum sensing, original sensing information is transmitted to the fusion center without any local processing and the global decision is made at fusion center by combing them appropriately.

A. Malfunction Node

Just as Fig. 1 shows, node D may encounter severe fading or shadowing because of the location disadvantage regarding the received signal strength from primary user. Thus the local sensing information from node D when the primary signal is present, may be untrustworthy and contribute little to the global decision at fusion center compared to other nodes in good locations, like node A and B. For node D, its performance of spectrum sensing is not only unreliable, but also cost more energy consumption. This phenomenon is called malfunction sensing in context of cognitive radio networks in this paper. Node A is called malfunction node. In this paper, we will try to find a good solution to mitigate this problem.

In case of energy constraint mobile user, unnecessary energy waste is intolerable. In order to solve the problem of malfunction, one possible method is to shut down these secondary users which contribute litter to global decision at fusion center. Another issue we should consider is the contribution of each secondary user may vary from time to time. Node D, for example, may move to another location after some time, and it may contribute quite well to the global decision. To make a better tradeoff between these two issues we propose a contribution based cooperative spectrum sensing scheme (CCSS) for cognitive radio networks.

Algorithm 1 Contribution based Cooperative Spectrum Sensing

1: Initialize local spectrum sensing time. Each CR user is assigned a reasonable constant sensing time at the beginning;
$$\tau_1 = \tau_2 = \ldots = T_1. \quad (7)$$
The sensing time is selected in a set $\boldsymbol{T}$, which has k levels components.
$$\boldsymbol{T} = \{T_1, T_2, \ldots, T_k\}, \quad (8)$$
where we assume that $T_1 > T_2 > \ldots > T_k$.
2: Perform local sensing and send its sensing information to the fusion center;
3: Make global decision P_d at the fusion center;
4: **if** $P_d = 1$ **then**
5: Calculate contribution feedback D_i;
$$D_i = \begin{cases} 1, & \text{if } \; Y_i \geq \lambda, \\ -1, & \text{if } \; Y_i < \lambda. \end{cases} \quad (9)$$
6: Compute sensing time for each secondary user based on its previous contribution feedback D_i and maintain local spectrum sensing time;
7: **end if**
8: Check the sensing counts C and
9: **if** $C > C_{max}$ **then**
10: go to step 1
11: **else**
12: go to step 2
13: **end if**

B. Principle of CCSS

Without loss of generality, we assume that $T_1 > T_2 > \ldots > T_k$. Also the sensing time should not be too long or too short for individual secondary user. Let $T_1 = T_{\text{max}}$ and $T_k = T_{\text{min}}$ denote maximum and minimum value of sensing time, respectively. These two values should be predefined properly. The criteria to configure these values are as follows. Firstly, the T_{max} should be set large enough to satisfy the requirement of detection performance. Secondly, T_{min} should not be set too small. If T_{min} is too small, the malfunction nodes will lose the opportunity to perform positive contribution, which results that they are always treated as malfunction nodes. Finally, T_{max} and T_{min} should not set too large, which lead to more energy consumption.

In the sensing time maintenance step, each secondary user's sensing time is computed based on its historic contribution feedback. The contribution feedback value can be configured according to the following approach in this paper. The initial contribution feedback value is set to zero; based on (9) whenever its local spectrum sensing report is consistent with the global sensing decision, the value of the contribution feedback is set to 1, otherwise it is set to -1. The sensing time will be maintained based on the feedback when the primary signal is present. When $D_i = 1$, T_j is set to T_{j-1}. When $D_i = -1$, T_j is set to T_{j+1}. Also we should make sure that the sensing time is not great than T_{max} and not less than T_{min}. Obviously, given that the probability of the global decision being true is great than $\frac{1}{2}$, a sensing terminal with a more accurate local sensing report has a higher expected contribution value than a secondary user with a less accurate report. The sensing time is proportional to the previous contribution feedback within a predefined domain. When a secondary user always performs malfunction sensing, it will have a negative contribution, which results in sensing time decreasing. Thus to reduce the effect of malfunction is achieved. Also the unnecessary energy consumption of these malfunction nodes is mitigated.

The fusion center checks the overall sensing counts C after every global decision. Let C_{max} stands for the maximum counts in one sensing round. Then if $C < C_{\text{max}}$, go step 2. Otherwise go step 1 to launch a new round of spectrum sensing.

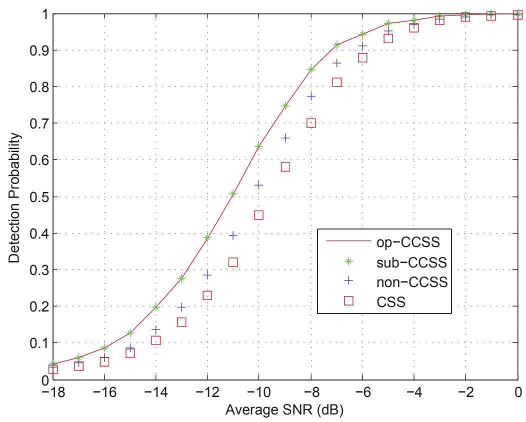
C. Analysis of CCSS

The primary goal of CCSS is to lower the amount of spectrum sensing time based on the fact that the malfunction nodes contribute litter to the global decision.

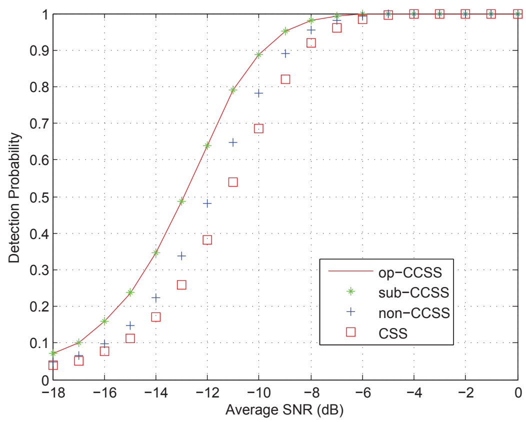
Suppose that the received signal at the secondary user is sampled at sample frequency f. The number of samples N is the maximum integer not great than τf , and we assume $N = \tau f$ for notation simplicity. The received signal at a secondary user can also be represented as (1). And the test statistic for energy detection is denoted by
$$Y_i = \sum_{j=1}^{\tau_i f} |y_{ij}|^2. \quad (10)$$

Similar to conventional cooperative spectrum sensing, the likelihood ratio of CCSS between two hypotheses is expressed as
$$L(\boldsymbol{Y}) = \prod_{i=1}^{M} \frac{Pr(Y_i|H_1)}{Pr(Y_i|H_0)}, \quad (11)$$
where M is the number of the cooperative secondary users.

Throughout this paper, we assume that the noise at each sample is Gaussian with zero mean and unit variance. Also we assume that s_{ij} 's are independently and identically distributed Gaussian random variables with zero means and unit variance for different i's and j's in (1). The conditional distribution under hypothesis follows a central chi-square distribution with $\tau_i f$ degrees of freedom. After a linear transformation, the conditional distribution under hypothesis H_1 also follows a central chi-square:
$$Pr(Y_i|H_1) = \frac{1}{1+\gamma_i} \frac{1}{2^{\frac{\tau_i f}{2}} \Gamma(\frac{\tau_i f}{2})} \left(\frac{Y_i}{1+\gamma_i}\right)^{\frac{\tau_i f}{2}-1} e^{-\frac{1}{2}\frac{Y_i}{1+\gamma_i}}, \quad (12)$$
$$Pr(Y_i|H_0) = \frac{1}{2^{\frac{\tau_i f}{2}} \Gamma(\frac{\tau_i f}{2})} Y_i^{\frac{\tau_i f}{2}-1} e^{-\frac{1}{2}Y_i}. \quad (13)$$



(a) $M = 5$



(b) $M = 10$

Fig. 2. Detection probability curves of CCSS under i.i.d Rayleigh channel.

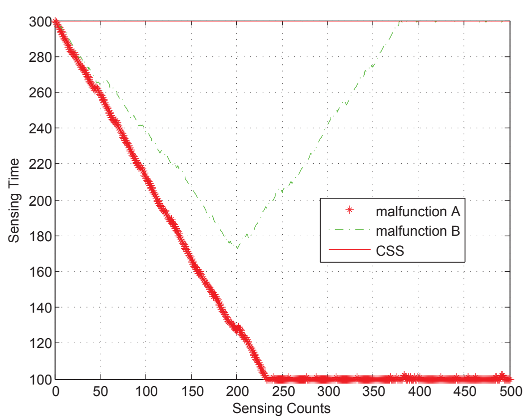


Fig. 3. Sensing counts vs. sensing time.

Thus the likelihood ratio in (11) can be represented as

$$L(\boldsymbol{Y}) = \prod_{i=1}^{M} \frac{Pr(Y_i|H_1)}{Pr(Y_i|H_0)} = \prod_{i=1}^{M} \left(\frac{1}{1+\gamma_i}\right)^{\frac{\tau_i f}{2}} e^{\frac{1}{2}\sum_{i=1}^{M}\frac{\gamma_i}{1+\gamma_i}Y_i}. \tag{14}$$

For a soft combination scheme with weight w_i , the weighted summation of the observation can be expressed as

$$Y = \sum_{i=1}^{M} w_i Y_i. \tag{15}$$

When $w_i = \gamma_i$, for a given probability of false alarm P_f, the threshold η is particularly give by

$$\eta = \sum\nolimits_{i=1}^{M} \tau_i f \gamma_i + \sqrt{\sum\nolimits_{i=1}^{M} 2\tau_i f {\gamma_i}^2 Q^{-1}(P_f)}, \tag{16}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{t^2}{2}} dt$ and $Q^{-1}(\cdot)$ is the inverse of Q function.

Substituting (16) into (4), the detection probability P_d can be approximately obtained as

$$P_d = Q\left(\frac{\sqrt{\sum_{i=1}^{M} 2\tau_i f {\gamma_i}^2} Q^{-1}(P_f) - \sum_{i=1}^{M} \tau_i f(\gamma_i)^2}{\sqrt{\sum_{i=1}^{M} 2\tau_i f {\gamma_i}^2 (1+2\gamma_i)}}\right). \tag{17}$$

IV. Simulation Results

In this section we present some simulation results to demonstrate the performance of the contribution based cooperative spectrum sensing in cognitive radio networks.

To obtain global decision at fusion center we consider three schemes to combine the information from secondary users based on CCSS: op-CCSS, sub-CSS and non-CCSS. The differences among these three schemes are the weights defined in (15) corresponding to each CR user. The weights for op-RCSS, sub-CCSS and Non-CCSS are $w_{op} = \gamma_i/(1+\gamma_i)$, $w_s ub = \gamma_i$ and $w_{non} = 1$, respectively.

Fig. 2 shows the detection probability curves of different soft combination schemes under i.i.d Rayleigh fading channels when the given probability of false alarm is 0.01. The number of cooperative users M is 5 in Fig. 2(a) and 10 in Fig. 2(b). Here we assume $f = 1$ for computation simplicity. The initial sensing time is 200 in Fig. 2(a) and 300 in Fig. 2(b). The maximum and minimum sensing time is predefined as $T_1 = T_{\max} = 200$, $T_k = T_{\min} = 100$ in Fig. 2(a) and $T_1 = T_{\max} = 300$, $T_k = T_{\min} = 200$ in Fig. 2(b), respectively. The maximum sensing count $C_{\max}$ is 100. Corresponding curves of the conventional cooperative spectrum sensing (CSS) are also plotted for comparison. The threshold for these schemes are derived numerically to meet the given false alarm probability exactly, which is set to 0.01.

From Fig. 2 we observe that op-CCSS does exhibit the best detection performance. The sub-CCSS and non-CCSS exhibit much better performance than the conventional cooperative spectrum sensing with the some total sensing time.

Fig. 3 shows the sensing counts versus sensing time. Let $C_{\max} = 500$, $T_{\max} = 300$, and $T_k = T_{\min} = 100$, respectively. Sensing time is fixed for conventional cooperative spectrum sensing scheme. Fig. 3 indicates two types of malfunction nodes how to reduce their energy consumption. Type I (malfunction A in Fig. 3): the malfunction node always performs malfunction sensing, and the sensing time gradually decreases to $T_{\min}$. The negative contribution to the fusion center thus can be decreased to the minimum. Saving energy for these malfunction nodes also achieved. Type II (malfunction B in Fig. 3): the sensing time gradually decreases when it performs malfunction sensing same to Type I. When the malfunction node moves to a good location, the sensing time will gradually increase to $T_{\max}$. In this case, when a node does not belong to the malfunction node, more sensing time will be assigned to this node gradually.

V. Conclusion

Cognitive radio is a promising technology that can potentially improve the spectrum utilization. In this paper, we discussed the malfunction nodes problem in context of cognitive radio networks. Then a contribution based cooperative spectrum sensing scheme was proposed. Our proposed scheme can exploit the merit of spatial advantage and save more energy. Simulation results demonstrated the proposed CCSS outperforms conventional cooperative spectrum sensing.

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