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A Collaborative Sensor Selection Algorithm for Cooperative Sensing in Cognitive Radio

Zhifeng He[1+], Yong Zhang[1], Yinglei Teng[1], Mei Song[1] and Xiaojun Wang[2]

[1]School of Electronic Engineering, Beijing University of Posts and Telecommunications
Beijing, China
[2]School of Electronic Engineering, Dublin City University
Dublin, Ireland

Abstract. Cooperative spectrum sensing has been shown to be able to greatly improve the sensing performance in cognitive radio (CR) networks. To achieve a higher cooperative detection probability to the licensed channels in order to reduce the interference to the Primary Users (PUs), we should choose the Secondly Users(SUs) which can monitor the PUs reliably as cooperative sensing members. In this paper, the scenario where multiple SUs form multiple collaborative groups to cooperatively sense multiple PUs is considered, and we proposed a Dynamic Sensing Channels Allocation scheme in which SUs are allowed to sense the PUs to which they have higher detection probability. Simulation results show that compared with other scheme, the cooperative detection performance of our proposed scheme is promoted.

Keywords: cognitive radio, cooperative sensing, re-grouping

1. Introduction

Cooperative spectrum sensing has been demonstrated to be able to effectively alleviate the problem of corrupted detection by exploiting the spatial diversity to enhance the sensing reliability, which is accomplished by a network of spatially distributed SUs, which experience different channel conditions from the target, exchanging their respective sensing information or reporting to BS(Base Station) of the CR network[1], [2].

It is known that a higher SNR(Signal to Noise Ratio) of the PU signal at the SU receiver means a higher probability of detection to the PU signal, and the higher the detection probability of the collaborative SUs have, the higher the detection probability of cooperative sensing will be[3]. In[4], it is assumed that BS knows the location of PUs and SUs, and thus knows which SUs have higher SNR and it chooses these SUs to cooperatively sense the PUs to promote the cooperative detection probability. However, in many systems, the location of the PUs and SUs may not be known in a prior to the controller of the system, so it may be impossible to select the best SUs which have higher SNR to cooperatively sense the PUs according to their location.

In [5], a scheme is proposed to reduce energy consumption of the SUs by considering the “confidence” of the SUs to decide whether to allow the SUs to participate in cooperative sensing. However, the cooperative detection performance is degraded for the fact that some SUs which have better channel conditions may be prevented from collaboratively sensing in the scheme; what’s more, the scheme doesn’t take into account the problem of how to improve the overall cooperative detection probability to multiple PUs.

+ Corresponding author.
E-mail address: gdqyhzf@126.com.

The solution considered in this paper is to dynamically choose the SUs that can monitor PUs unfailingly to be the collaborative sensing members to enhance the cooperative detection probability in the absence of location information of PUs and SUs. In our scheme, multiple SUs form multiple groups, SUs of the same group cooperatively sense the same PU, and SUs of different groups sense different PUs. BS estimates the detection probability of the SUs based on the information recorded in the past history, and decides how to re-group the SUs into new groups according to their respective detection performance, in order to promote the overall cooperative detection probability to all PUs. Through this method, we don't need any priori knowledge about the location of the PUs and SUs or the SNR.

The remainder of this paper is organized as follows. Section II describes the basic idea of our proposed scheme. The system model is presented in Section III. Section IV briefly introduces the principle of energy detection and cooperative spectrum sensing. The detailed procedure of our proposed scheme is described in Section V. The performance of our proposed scheme is analyzed in Section VI. Finally Section VII concludes the paper.

2. The Basic Idea of Our Proposed Scheme

For the fact that the cooperative detection probability of BS using the OR fusion rule is higher than the detection probability of any collaborative SU[8], during multiple times of cooperative sensing (denoted as L), the number of times that BS correctly detecting the presence of PU signal will be higher than that of any collaborative SU. So it is reasonable for us to reckon that on the condition that cooperative false alarm probability of BS is very low(which means it is a rare case that BS mistakenly declares the PU signal is present on the condition that PU signal is actually absent), if the number of times that a certain SU reports the presence of PU signal is close to the number of times that BS declares the presence of PU signal, it is likely that the detection probability of the SU approximates to the cooperative detection probability of BS. Otherwise, if the number of times that a certain SU reports the presence of PU signal is much less than the number of times that BS declares the presence of PU signal, it is likely that the SU can not reliably detect the presence of PU signal.

Based on reasons listed above, by comparing the number of times that a SU reports the presence of PU signal with the number of times that BS declares the presence of PU signal in multiple times of cooperative sensing, BS could estimate whether or not the SU can detect PU signal reliably.

After comparison, to promote the cooperative detection probability to a certain PU(denoted as PUa), if BS estimates that the detection probability to PUa of a certain SU(denoted as SUa)is satisfying, it should keep SUa continue to sense PUa in the rest of time. And if BS decides that SUa can not reliably detect the PU signal, it should replace SUa with another SU to sense PUa, for the expectation that another SU may have a higher probability of detecting PUa, thus enhancing the cooperative detection probability to PUa; and then allocate SUa to sense other PUs until SUa find another PU that it can sense more reliably. For instance, if at a certain time SUa sense PUb, and BS estimates that SUa can monitor PUb more reliably, then BS keeps SUa continue to sense PUb for the rest of time. In this way, it is highly possible that the cooperative detection probability to most PUs be promoted for the reason that BS chooses the SUs who can reliably monitor these PUs to sense them. Note that L should be large enough to assure that the information BS collected in the past L times of cooperative sensing is of statistically significance.

3. System Model

We assume that there are one BS, M SUs and N PUs in the network, M=K*N, and there are N orthogonal frequency channels each of which is licensed to one PU, and a dedicated control channel for BS and SUs to exchange control messages. The M SUs are grouped into N groups to sense the N non-overlapping channels(PUs), and each of the N cooperative groups senses a different channel(PU). The N channels are denoted as $CH_1, CH_2, ..., CH_N$, and the N groups are denoted as $G_1, G_2, ..., G_N$, Where

$G_i \cap G_j = \varnothing,\ i \neq j, i, j = 1,2,...,N$. The K SUs of group G_i is denoted as $SU_i^j, j = 1,2,...,K$, where $i = 1,2,...,N$. The K SUs of group G_i sense channel CH_i, $i = 1,2,...,N$.

4. Energy Detection And Cooperative Sensing

In our model, we assume that PU signal experiences path loss in the air and is corrupted by the additive white Gaussian noise (AWGN) when received by the SUs. SU_i^j collects T measurements in the process of sensing PU_i and formulates the following binary hypothesis problem:

$$\begin{cases} H_0 : x_i^j(y) = v_i^j(y) \\ H_1 : x_i^j(y) = h_i^j s_i(y) + v_i^j(y), y = 1,2,....,Y \end{cases} \tag{1}$$

Where H_0 denotes the absence of PU_i's signal while H_1 denotes the presence of PU_i's signal. $v_i^j(y)$ denotes the AWGN which is a Gaussian i.i.d(independent and identically distributed) process at each of the SUs with mean zero and variance $E\left(\left|v_i^j(y)\right|^2\right) = \sigma_v^2$. $s_i(y)$ denotes the signal transmitted from PU_i and is assumed to be an i.i.d. process with zero mean and variance $E\left(\left|s_i(y)\right|^2\right) = \sigma_s^2$. h_i^j denotes the channel gain between PU_i and SU_i^j. Moreover, Y corresponds to the number of time samples.

We assume that PU signal is BPSK modulated and denote

$$\gamma_i^j = \frac{E\left(\left|h_i^j s_i(y)\right|^2\right)}{\sigma_v^2} = \frac{E\left(\left|h_i^j\right|\right)\sigma_s^2}{\sigma_v^2} \tag{2}$$

Then SU_i^j estimates whether PU_i' signal is present or not according to the following criterion

$$U_i^j = \sum_{y=1}^{Y} \left|x_i^j(y)\right|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \lambda_i \tag{3}$$

Where λ_i is the threshold for energy detector on PU_i.

It has been shown in [6] that when Y is large enough(practically when Y⩾10 [7]), the false alarm probability and detection probability of SU_i^j to PU_i can be expressed as [8]

$$P_{f_i}^j = P\left(H_1 \middle| H_0\right) = Q\left(\frac{\lambda_i - Y\sigma_v^2}{\sqrt{2Y}\sigma_v^2}\right) \tag{4}$$

$$P_{d_i}^j = P\left(H_1 \middle| H_1\right) = Q\left(\frac{\lambda_i - \left(Y + \gamma_i^j\right)\sigma_v^2}{\sqrt{2\left(Y + 2\gamma_i^j\right)}\sigma_v^2}\right) \tag{5}$$

Where λ_i is the threshold for the energy detector on PU_i, $Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^{+\infty} e^{-\frac{t^2}{2}}\mathrm{d}t$ is the tail probability of a zero-mean unit-variance Gaussian random variable. Because the AWGN is i.i.d at the $SU_i^j, j=1,2,...,K$, we have $P_{f_i}^j = P_{f_i}^l = P_f, j \neq l, j,l=1,2,...,K$.

After making a decision about the presence of PU_i's signal, $SU_i^j, j=1,2,...,K$ send their respective decisions to the BS, who makes a final decision about the presence of PU_i's signal. In this paper we consider the OR fusion rule, where BS declears the presence of PU signal if any of the collaborative SUs reports the presence of the PU signal. The cooperative false alarm probability and cooperative detection probability of the final decision is given by:

$$P_{F_i} = 1-\prod_{j=1}^{K}\left(1-P_{f_i}^j\right) \tag{6}$$

$$P_{D_i} = 1-\prod_{j=1}^{K}\left(1-P_{d_i}^j\right) \tag{7}$$

Because the K SUs have the same false alarm probability, for a targeted $\overline{P_{F_i}}$ of the final decision, the targeted $P_{f_i}^j$ at each of the K SUs is given by

$$\overline{P_{f_i}^j} = 1-\sqrt[K]{\left(1-\overline{P_{F_i}}\right)} \tag{8}$$

Thus the energy detection threshold for each of the K SUs is given by

$$\lambda_i = \left(Q^{-1}\left(\overline{P_{f_i}^j}\right)\frac{1}{\sqrt{T}}+1\right)\sigma^2 \tag{9}$$

5. The Detailed Procedures of Our Proposed Scheme

In this section we detailedly describe our proposed Dynamic Sensing Channels Allocation (DSCA) scheme in which BS randomly groups SUs into multiple collaborative groups in the initial stage and re-groups the SUs into new collaborative groups in the re-grouping time-slot of every re-grouping period, and each re-grouping period contains L cooperative sensing periods. The control messages are exchanged through a dedicated control channel.

5.1. The flow chart of our proposed scheme

In the initial stage, since BS has no information about the capability of detecting PU signal of the M SUs, BS randomly divides the M SUs into N groups to make them collaboratively monitor the N PUs, and broadcasts the grouping result to inform them which PU to monitor. Different groups should sense a different PU.

After receiving the grouping result, the N groups of SUs cooperatively sense the N PUs accoding to the grouping result and send their sensing results to BS respectively. BS records their sensing results, makes fusion results to decide the state of the N PUs, and records the fusion results as well. After that BS broadcasts the fusion results to the N groups, which is followed by the N groups continue to cooperatively sense the N PUs. We call the time between two times of cooperative sensing as a cooperative sensing period. SUs and BS go through L cooperative sensing periods before they step into the re-grouping time-slot.

After L cooperative sensing periods the re-grouping time-slot arrives. During the slot, BS estimates the detection capability of the SUs and decides how to re-group them into N new collaborative groups according to the information recorded during the past L cooperative sensing periods, and then broadcasts the fusion results of the L-th cooperative sensing period and the re-grouping result to the SUs.

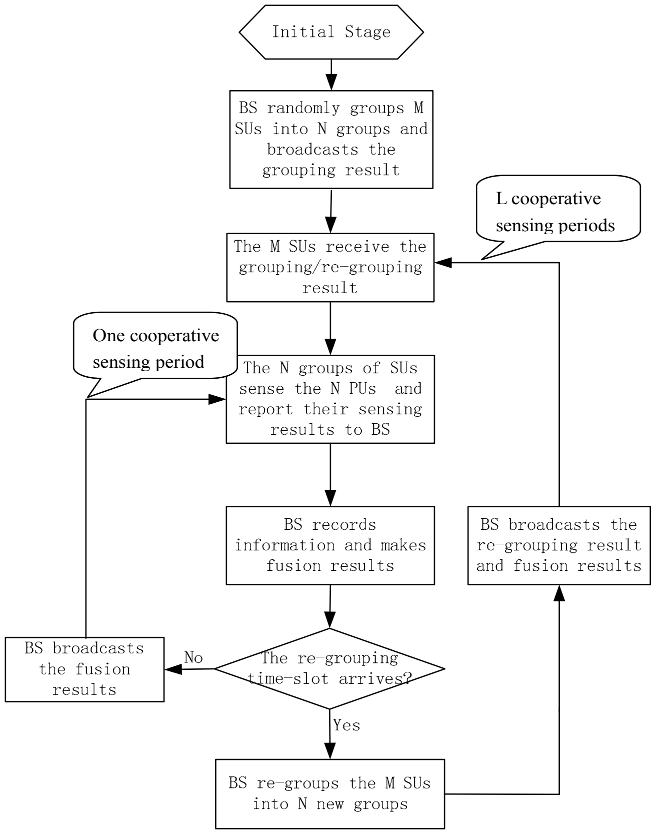

Fig.1. Flow chart of DSCA scheme

To estimate the detection probability of a certain SU to a certain PU, BS compares the number of times the SU reported the presence of the PU signal with the number of times that BS declared the presence of the PU signal in the past L times of cooperative sensing. If the comparison is larger than a given threshold, it is very likely that the SU have a higher detection probability to the PU signal, so BS maintain the SU as one of the cooperative sensing members for the PU for the next L times of cooperative sensing. Otherwise, it is possible that the SU cannot reliably detect the PU signal, so BS remove the SU from the group it stayed in the past L cooperative sensing periods and allocates it to another group to makes it sense another PU for the next L cooperative sensing periods, for the expectation that it can sense another PU more reliably. The concrete procedures is presented in the pesudo-code of our algorithm.

On receiving the re-grouping results the SUs get ready to sense the PUs according to the grouping result, and thus BS and SUs enter into the next re-grouping period. BS and SUs may have to go through many re-grouping periods to achieve a satisfying cooperative detection probability to most of the PUs.

5.2. The pesudo-code of our algorithm

Here we assume that our algorithm goes through X re-grouping periods.

1.The initial stage:

BS randomly groups the M SUs into N groups $G_1, G_2, ..., G_N$, and broadcasts the randomly grouping results to the M SUs.

2.The re-grouping periods:

for x=1 to x=X do

for m=1 to m=L do

for i=1 to i=N do

2-1.SUs of G_i cooperatively sense PU_i, and send their respective local sensing results $S_i^j, j=1,2,...,K$ to the BS, where S_i^j is the local sensing result of SU_i^j.

2-2. BS records information and makes fusion results:

2-2-1.BS records the local sensing results of $SU_i^j, j=1,2,...,K$: $NUM_i^j = NUM_i^j + S_i^j$, where NUM_i^j denotes the number of times SU_i^j reports the presence of PU_i in the L cooperative sensing periods of a re-grouping period, and BS resets NUM_i^j=0 at the initial stage or at the beginning of each re-grouping period.

2-2-2.BS makes a final decision about the presence of PU_i by the OR rule according to the local sensing results $S_i^j, j=1,2,...,K$

$$FU_i = \begin{cases} 1, & \sum_j^K S_i^j > 0 \\ 0, & \sum_j^K S_i^j = 0 \end{cases}$$

2-2-3.BS records the fusion result about the presence of PU_i : $NUM_i = NUM_i + FU_i$, where NUM_i denotes the number of times BS declares the presence of PU_i in the L cooperative sensing periods of a re-grouping period, and BS resets NUM_i =0 at the initial stage or at the beginning of each re-grouping period.

end-for

if m<L then

2-3.BS broadcasts the fusion results

else if m=L then

2-4.BS re-groups the M SUs into N new groups:

2-4-1.BS finds out the SUs whose detection

probability cannot meet BS's requirement:

Create $Idle\_SU\_list=\varnothing$

for i=1 to i=N do

for j=1 to j=K do

$Credit_i^j = NUM_i^j / NUM_i$

if $Credit_i^j \geq Credit$ then

Keep SU_i^j staying in G_i

else if $Credit_i^j < Credit$ then

Remove SU_i^j from G_i

Add SU_i^j into $Idle\_SU\_list$

end-if

end-for

end-for

Note that after the above procedures:

$Idle\_SU\_list = \{SU_i^j, i = 1,2,...,N, j = 1,2,...,K \mid Credit_i^j < Credit\}$

2-4-2. BS re-groups the M SUs:

Transpose $Idle\_SU\_list$

for i=1 to i=N do

Check the number of SUs of G_i, i.e., $\|G_i\|$

if $\|G_i\| < K$ then

Choose element(s) from $Idle\_SU\_list$ in sequence and allocate the element(s) to G_i until $\|G_i\| = K$

else if $\|G_i\| = K$ then

Continue;

end-if

end-for

2-5:BS broadcasts fusion results and re-grouping result of $G_1, G_2, ..., G_N$ to all the SUs

end-for

6. End-For Performance Analysis of DSCA Scheme

The performance of DSCA scheme is evaluated using simulation results by calculating the cooperative detection probability(PD) and the cooperative false alarm probability(PF) to different PUs.

6.1. Simulation parameters of DSCA scheme

Table 1: Simulation parameters of DSCA scheme

The number of SUs	45
The number of PUs	9
The number of re-grouping periods	100
The number of cooperative sensing periods contained in per re-grouping period, i.e., L	500
SNR at the each of the SUs	-10~-20dB
Credit	0.2
Cooperative false alarm probability to each of the PUs	0.05

For each PU, the PU's signal to noise ratio at each SU is a random number whose value is between -20~-10 dB, and is randomly generated in each simulation. Note that here the SNR is not used for re-grouping but for calculating PD to the PUs using equation (7).

6.2. Simulation results analysis

In simulation, we choose the randomly grouping scheme(RGS) as the referenced scheme, in which BS randomly groups the SUs into multiple collaborative groups in the initial stage and it will not re-group the SUs in the following time, which means that the PU each SU senses is constant during the whole process of simulation.

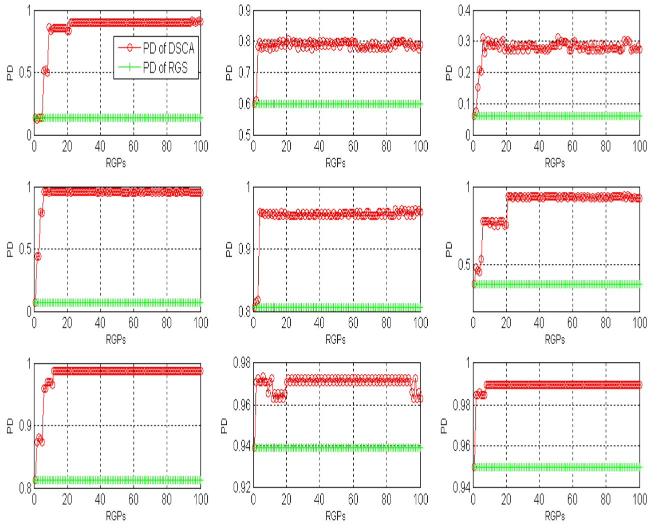

Fig.2. P_D to each of the total 9 PUs according to the number of re-grouping periods(denoted as RGPs in this figure).

Figure (2) shows how PD to each of the total 9 PUs is promoted in our proposed DSCA scheme as time progressing. In the initial stage, for the fact that BS randomly allocates the SUs to cooperatively sense the PUs, the PD is comparatively lower; as the increase of re-grouping periods, PD to most of the 9 PUs is enhanced significantly.

This is because in each time of re-grouping, BS keeps the SUs which can sense PU more reliably to keep on sensing the PU in the following time, and allocates the other SUs which have lower detection probability to sense other PUs, until the SUs find the PUs that they can sense more reliably, just as what we have illustrated in the previous section.

On the other hand, the PD of RGS is maintained as a constant value during the whole process of simulation, and is comparatively lower than that of our DSCA scheme.

6.3. Performance of DSCA under different $Credit$

In this simulation $Credit$ increases from 0 to 1, L=500, and the other simulation parameters are the same as that of the previous simulation. Here the Average PD in the figure is the average PD to the total 9 PUs.

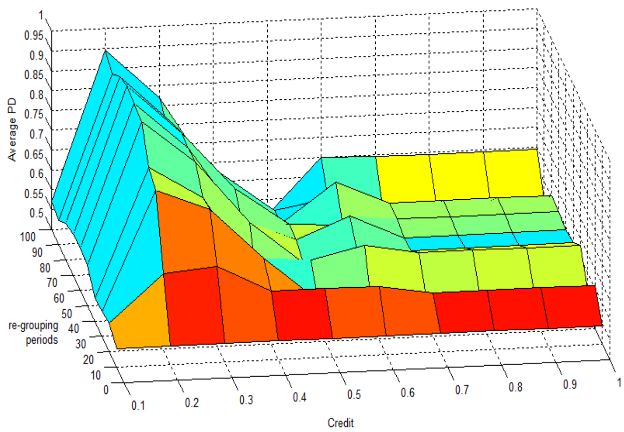

Fig.3. Average P_D to the total 9 PUs of DSCA according to value of $Credit$ and the number of re-grouping periods.

As can be seen from figure(3), when $Credit$ lies between 0.2~0.5, as time passage, the Average PD increases; particularly, when $Credit$=0.2, the Average PD increases rapidly and the extent of promotion is greater. when $Credit$=0.1, which means that each SU meets BS's requirement of detection probability, BS will not re-group the SUs and DSCA scheme equals to the RGS, thus the Average PD remains basically time-invariant and is comparatively lower. When $Credit$ lies between 0.6~1, which results in that the detection probability of most SUs can't meet BS's requirement, so BS re-groups most SUs in each re-grouping period, thus the curve of Average PD fluctuates dramatically; in addition, since a high $Credit$ indicates that SUs with comparatively higher detection probability can't meet BS's requirement as well and thus do not sense the quondam PU for the later time, the Average PD is comparatively lower.

7. Conclusion

In this paper, we propose a Dynamic Sensing Channels Allocation scheme to solve the problem of collaborative sensor selection in cooperative sensing, in order to promote the cooperative detection probability to the PUs in the absence of a priori knowledge about the SNR. BS estimates the detection performance of SUs by comparing the sensing results of the SUs and the fusion results of BS recorded during past multiple times of cooperative sensing, and then decides how to assign sensing tasks to the SUs according their estimated detection performance. Simulation results show that the performance of our proposed scheme is much favorable than that of the randomly grouping scheme.

8. Acknowledgment

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