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Energy-Efficient Method for Cooperative Spectrum Sensing in Cognitive Radio Networks

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Abstract—**Energy detection is one of the popular spectrum sensing technique for cognitive radio. Better performance can be obtained by cooperative detection, but only when cognitive radios did not have different geographic locations and channel environment. To avoid this drawback, the paper presents an improved energy-based weighted cooperative spectrum sensing method which allows to achieve higher detection probability, to reduce the number of cognitive nodes involved in the detection procedure and to use efficiently the channel resources.**

Keywords—**cognitive radio, cooperative spectrum sensing, energy detection, optimization**

I. Introduction

Cognitive radio technology has been proposed as a possible solution to improve spectrum utilization via opportunistic spectrum sharing, due to the capacity to dynamically and autonomously adjust its operating parameters and so maximize throughput, mitigate interference and facilitate interoperability [1]. Cognitive radios (CR) are designed in order to provide highly reliable communication for all users of the network, wherever and whenever needed and to facilitate effective utilization of the radio spectrum, but the technique requires knowledge of noise and detected signal powers, namely energy detection. The signal power is difficult to estimate as it changes depending on ongoing transmission characteristics and the distance between the cognitive radio and primary user [2]. One of the great challenges of implementing spectrum sensing is the hidden terminal problem, which occurs when the cognitive radio is shadowed, while a primary user (PU) is operating in the vicinity. In order to deal with this problem, multiple cognitive users can cooperate to conduct spectrum sensing. It has been shown that spectrum sensing performance can be greatly improved with an increase of the number of cooperative partners [3]. Recent studies have shown that utilizing cooperation among secondary users in spectrum sensing can dramatically increase the probability of detecting a primary user. Moreover, solutions for the optimization of cooperative spectrum sensing with energy detection to minimize the total error rate were proposed, mainly by optimal spectrum sensing under data fusion [4], or weighted data fusion [5].

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II. Related work

Various methods for spectrum sensing proposed in literature; among them are energy detection [6], cyclostationary based sensing [7], waveform based sensing [8], multi taper method for spectrum sensing [9], matched filtering [10], radio identification based sensing [11]. Energy detection is the most common method of spectrum sensing because it is fast, but it has some limitations, as it cannot differentiate between signal and noise. Spectrum sensing is of two types: individual spectrum sensing and cooperative spectrum sensing. In individual spectrum sensing only one secondary user sense whether any spectrum hole is available or not but in cooperative spectrum sensing secondary users sense spectrum hole collectively in clusters and thus performance is better. On the other hand, regardless of the improvements in detection performance, cooperation among CR users may also increase overheads (sensing, reporting and synchronization delay) that limit system performance. Various methods showed cooperative spectrum sensing performs better than individual spectrum sensing for a particular SNR value. As expected, an increase in the number of CR users in a cluster increases the performance of cooperative spectrum sensing. The scheme based on voting rules [12] is one of the simplest suboptimal solution, which counts the number of sensor nodes that vote for the presence of the signal and compares it against a given threshold. In [13], a fusion rule known as the OR logic operation was used to combine decisions from several secondary users. In [14], two decision-combining approaches were studied: hard decision with the AND logic operation and soft decision using the likelihood ratio test.

III. Energy Detection Based Cooperative Spectrum Sensing

A. *Principles of energy detection*

Energy detector based approach, also known as radiometry, is the most common way of spectrum sensing because of its low computational complexity. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. If the selection of the threshold for detecting primary users is not a difficult operation, inability to differentiate interference from primary users and noise and poor performance under low signal-to-noise ratio (SNR) values are challenging tasks. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals. The decision on the occupancy of a band can be obtained by comparing the decision metric D against a fixed threshold λ. In the energy detection approach, the radio frequency energy in the channel or the received signal strength indicator (RSSI) is measured in a fixed bandwidth W over an observation time window T to determine whether the channel is occupied or not.

Let consider a cognitive radio network (CRN) composed of a primary user (PU), N cognitive radios (secondary users SU) CR_i (i=1,..,N) and a common receiver, as shown in Fig. 1. The common receiver functions as a base station (BS) which manages the cognitive radio network and all associated N cognitive radios. We assume that each CR performs local spectrum sensing independently, by deciding between the following two hypotheses:

$$H_0: y_i(t) = n_i(t), \text{ if PU is absent}$$

$$H_1: y_i(t) = h_i s(t) + n_i(t), \text{ if PU is present} \qquad (1)$$

where $y_i(t)$ is the observed signal at the i^{th} CR, $s(t)$ is the PU signal assumed to be with zero mean and variance σ_s^2, $n_i(t)$ is the additive white Gaussian noise (AWGN) with zero mean and variance σ_n^2, and h_i is the complex channel gain of the sensing channel between the PU and the i^{th} cognitive radio.

We assume that the sensing channel is time-invariant and that the status of the PU remains unchanged during the spectrum sensing process. The energy collected in the frequency domain which serves as a decision statistic is denoted by E_i. For each decision M samples of the received signal are considered, i.e. $E_i = \sum_{j=1}^{M} \left| y_i^j \right|^2$. As E_i is the sum squares of M Gaussian random variables, its distribution can be characterized, by a χ^2 distribution [15] as:

$$H_0: E_i \sim \chi_M{}^2 \sigma_i{}^2; \; H_1: E_i \sim \chi_M{}^2(\eta_i)\sigma_i{}^2, \; \eta_i = \frac{h_i * E_i}{\sigma_i^2} \qquad (2)$$

The instantaneous signal-to-noise ratio (SNR) of the received signal at the i^{th} cognitive radio is γ_i and $u = TW$ is the time-bandwidth product.

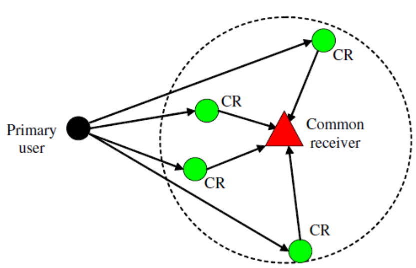

Figure 1. Basic structure of a CRN (after [16])

The goal of the local spectrum sensing is to reliably decide on the two hypotheses with high probability of detection, P_d and low probability of false alarm, P_f. The probability of missed detection over AWGN channels P_m is P_{md} =1-P_d. At a CR_i, $P_{d,i}$ and $P_{f,i}$ can be defined as the probabilities that the sensing SU algorithm detects a PU under H_0 and H_1, respectively.

$$P_{f,i} = \Pr\{E_i > \lambda_i \mid H_0\} = \frac{\Gamma(u, \lambda_i/2)}{\Gamma(u)}$$

$$P_{d,i} = \Pr\{E_i > \lambda_i \mid H_1\} = Q_u(\sqrt{2\gamma_i}, \sqrt{\lambda_i}) \qquad (3)$$

where λ_i denote the energy detection threshold, γ_i denote the instantaneous signal-to-noise ratio (SNR) at the i^{th} CR, respectively and $u=TW$ is the time-bandwidth product of the energy detector. $\Gamma(a)$ is the gamma function, while $\Gamma(a,x)$ is the incomplete gamma function given by $\Gamma(a,x) = \int_x^{\infty} t^{a-1} e^{-t} dt$ and $Q_u(a,b) = \frac{1}{a^{u-1}} \int_x^{\infty} t^u e^{-\frac{t^2+a^2}{2}} I_{u-1}(at) dt$ is the Marcum Q-function used as a cumulative distribution function for noncentral chi-squared distributions, $I_{u-1}(\cdot)$ being the modified Bessel function of first kind and order $u-1$ [16].

B. Cooperative Spectrum Sensing Schemes

In cooperative spectrum sensing (CSS), each cooperative partner makes a binary decision based on its local observation and then forwards one bit of the decision D_i (1 standing for the presence of the PU, 0 for the absence of the PU) to the common receiver through an error-free channel. The structure of centralized cooperative spectrum sensing in CR networks is shown in figure 2. The general process is as follows: first, every CR user executes local single-node detection independently and gets detection statistic y_i, second, the local dual-decision $D_i \in \{0,1\}$is obtained by comparing y_i with the detection threshold, and then, all CR users sent D_i to FC; the final decision is made according to AND, M rank and OR criteria [17]. At the common receiver, all 1-bit decisions are fused together according to logic rule

$$Z = \sum_{i=1}^{N} D_i \begin{cases} \geq n, H_1 \\ < n, H_0 \end{cases} \qquad (4)$$

where H_0 and H_1 denote the inferences drawn by the common receiver that the PU signal is not transmitted or transmitted.

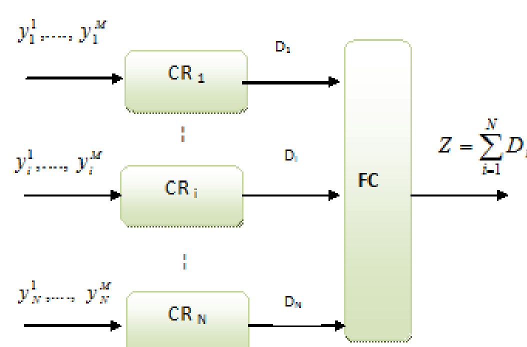

Figure 2. Centralized cooperative spectrum sensing

The threshold n is an integer, representing the "n-out-of-N" voting rule. It can be seen that the OR rule corresponds to the case of n=1 and the AND rule corresponds to the case of n=N.

If all CR users have the same geographic locations and channel environments, the same detection method is used for local single-node detection. If we assume that, compared with the distance from any CR to PU, the distance between any two CR is small, one can consider that the received signal at each CR experiences almost identical path loss. Therefore, in the case of an AWGN environment, we can assume that $\gamma_i = \gamma, \forall i = 1,...,N$ Furthermore, we assume that all CR use the same threshold, i.e. $\lambda_i = \lambda, \forall i = 1,...,N$. It results that $P_{f,i}$ is independent of i, and we denote it as P_f. In a similar manner, in the case of an AWGN channel, $P_{d,i}$ is independent of i, and we denote it as P_d. Therefore, the false alarm probability of cooperative spectrum sensing is given by

$$Q_f = \Pr\{H_1 \mid H_0\} = \sum_{l=k}^{N} \binom{N}{l} P_f^l (1-P_f)^{N-l} \tag{5}$$

The missed detection probability of cooperative spectrum sensing is given by:

$$Q_m = \Pr\{H_0 \mid H_1\} = 1 - \sum_{l=k}^{N} \binom{N}{l} P_d^l (1-P_d)^{N-l} \tag{6}$$

where P_f and P_d are detection probability and false alarm probability of single-node detection, respectively.

It results that, for the same false alarm needs, the detection probability of CSS is higher than single-node detection, or for the same detection needs, the false alarm probability of CSS is lower than single-node detection. In other words, in the ideal environment, whether from the point of the protection for PU or frequency utilization, cooperative sensing is much better than single-node detection. On the other hand, in many cases, every CR nodes are placed in different channel environment, in other words, so the detection performance of each user is not the same, and then traditional CSS may no longer be better than single-node detection and can not always meet the protection requirements for PU. A solution to avoid this drawback, due to the fact that even the same single node detection method is used, the detection probability of each node is not the same and consequently each CR user's detection results have different influence on the final decision is the cooperative spectrum sensing based on the weighting (CSSW) [18]. In CSSW different trust factors are given to the different CR users, therefore their local decision is weighted, and the weighted detection results are fused and the final decision is made in the data fusion center FC.

Provided that the weighting factor of the i^{th} CR user for the n^{th} sensing is $w_i(n)$, the initial

weighting factors of all CR are one, namely, $w_i(1) = 1$, and $w_i(n)$ updates once in every detection. Then the weighting factor of the i^{th} CR user for the $(n+1)^{th}$ sensing can be expressed as:

$$w_i(n+1) = w_i(n) P_{d,i} / w_{med} \tag{7}$$

where $w_{med} = \frac{1}{N}\sum_{i=1}^{N} w_i(n) P_{d,i}$ and $P_{d,i}$ is the detection probability of the i^{th} CR user for the n^{th} sensing Thus, for a particular sensing moment, the sum of all CR user's weighting factors is a constant N. All CR users in CSSW sent their local binary decision $D_i \in \{0,1\}$and the associated weighting factor $w_i(n)$ to FC for information fusion, and then detection statistics $Z(n)$ of the n^{th} CSS can be obtained by using $Z(n) = \sum_{i=1}^{N} w_i(n) D_i(n)$. According to this fusion rule, the final decision can be made to confirm whether PU is present or not.

C. *Improved CSSW Scheme*

There are some difficulties in applying traditional WCSS, especially when the number of CR nodes is too large, situation when the public control channel can be crowded and the decisional process in FC is delayed. In this paper an improved CSSW scheme based on credibility is proposed, which implies screening nodes firstly from CR networks before all local decisions and weighted factors are sent to FC, and then the final information fusion is making by CR nodes obtained from nodes screening stage. The detailed process of the improved cooperative spectrum sensing is as follows:

Step1: preliminary test.

In this step, all the CR nodes do local single-node energy-based detection independently; every CR node do energy detection M times, the j^{th} local decision result of the i^{th} CR node d_{ji} is equal to 0 or 1, which represent that the detection result is the absence or presence of the primary user, respectively, with j=1,..,M (samples), i=1,..,N (nodes). Then, the detection probability of the i^{th} CR node $P_{d,i}$ is given by $P_{d,i} = \sum_{j=1}^{M} d_{ji} / M$.

Step 2: nodes screening.

The principle of nodes screening is to obtain the largest global detection probability of CSS for a particular probability of false alarm. The largest detection probability is seen as a benchmark, and the detailed process of nodes screening is as follows: Firstly, select the two CR nodes which have the two largest detection probabilities for CSS and compare the global detection probability with the largest single-node detection probability; if the former is smaller, the single node who has the largest detection probability will be the node screened, otherwise, choose the three nodes which have the three largest detection probabilities to cooperative detection and repeat the comparing process above, until the CR nodes meeting the requirements are screened out. Let Q_{di} represent the global detection probability of the i nodes that have the i largest detection probabilities, that is, the nodes screening is not finish until both conditions Q_{di}>$Q_{d(i-1)}$ and Q_{di}>$Q_{d(i+1)}$ are satified. Then the i CR nodes are selected for cooperation detection in this sensing cycle.

Step 3: weighted information fusion.

$D_i(n)$ and $w_i(n)$ being the nth n^{th} decision result and weighting factor of the i^{th} CR node, respectively, the global test statistics at FC is given by $Z(n)=\sum_{i=1}^{N} w_i(n)D_i(n)$, and FC makes a final decision according to AND, *M* rank and OR rules.

Therefore, the improved cooperative spectrum sensing scheme only needs to send part of the local testing results and weighting factors of CR nodes to data fusion center, and thereby, reduces the number of CR nodes attending cooperative information fusion and therefore saves channel resources.

IV. Simulation results

All simulation was done on MATLAB, under AWGN channel model. We used receiver characteristics (ROC) analysis to study the performance of the energy detector. ROC has been widely used in the signal detection theory due to the fact that it is an ideal technique to quantify the tradeoff between the probability of detection (P_d) and the probability of false alarm (P_f). The simulation was carried out for the analysis of detection probability under different number of SNR from 0dB to 25dB, imposing P_f =0.01 as a threshold and time bandwidth factor u=100.

In order to evaluate the performance of the proposed CSSW scheme two main issues were addressed:
1) For a fixed number N of CR nodes , to determine the optimal voting rule, i.e., what is the optimal n, which we denote as n_o, that minimizes the total error rate Q_t=Q_f + Q_m. From (5) and (6) results:

$$Q_t=\sum_{l=k}^{N}\binom{N}{l}[1+P_f^l(1-P_f)^{N-l}-P_d^l(1-P_d)^{N-l}] \tag{8}$$

The value of n_o can be obtained by the annulment of the partial derivative Q_t with respect to n. Table 1 presents the values of n_o obtained for 3 values of SNR (0dB, 5dB and 10dB) and for 5 values of the decision threshold λ, for N=16 CR nodes.

TABLE I. OPTIMAL VOTING RULE RESULTS

λ	Signal to Noise Ratio		
	0dB	*5dB*	*10dB*
10	16	16	16
15	14	14	15
20	8	10	14
25	4	6	10
30	2	3	6
35	1	2	4
40	1	1	2

The following general remarks which apply to any detector can be formulated by examinating the results in Table 1:

- if P_f and P_m have the same order, the optimal choice of n is N/2.

- for large values of N and when the detection threshold λ is very large, $P_f \ll P_m$ and therefore the OR rule (n=1) is optimal

- for a very small value of λ, $P_f \gg P_m$ and the AND rule (n=N) is optimal.

2) Demonstration of the efficiency of the nodes screening stage of CSSW by using AND and OR rules at FC, by determining the value n_{so} which represent the least number of collaborating (screening) CRs that can achieve a target total error rate Q_t smaller than an imposed limit ε. The simulation was made for a network with N=50, at an SNR of 10 dB in an AWGN channel, for three values of the threshold (30, 40 and 50) and two values of the given target ε (0.01 and 0.001), applying a traditional CSS method and the proposed CSSW scheme. The results are shown in Table 2.

TABLE II. MINIMAL NUMBER OF SCREENING NODES

λ	Classic CSS		Proposed CSSW	
	ε≤0.01	ε≤0.001	ε≤0.01	ε≤0.001
30	8	14	8	12
40	14	22	12	18
50	30	50	24	40

It can be seen that the improved nodes screening method proposed in this paper more efficient, using up to 20% less nodes for cooperative detection, the advantage being more obvious as the target error limit is smaller and detection threshold is higher. For the same false alarm request, the detection probability of the improved CSSW based on nodes screening is higher than the traditional detection corresponding probability, and even better than the best single-node testing, whatever using AND rule or OR rule.

V. Conclusions

We have studied the performance of cooperative spectrum sensing with energy detection in cognitive radio networks. Taking into account that in the actual cognitive radio cooperative spectrum sensing, different cognitive radio users have different geographical location and channel conditions, and experience different fading environment, which could cause that local decisions have different influence to the final decision at the fusion center, we have proposed an improvement of a cooperative spectrum sensing method based on weighting, which filters out CR nodes being better SNR condition to participate in the final cooperative detection. Each CR node participating in cooperative detection has different confidence weighted factor based on the above screening nodes.

The simulation results show that the cooperative detection based on the node selection can achieve good detection performance, and the new trust degree detection algorithm, based on the node selection and weighted CR users, has better performance because requires fewer than the total number of cognitive radios in cooperative spectrum sensing while satisfying a given error bound and so saves channel resource and reduces the fusion complexity.

In this research, some parameters were assumed to be constants such as the SNR values of PU and total frame duration. Further research can be done by observing the effect of varying such parameters in the overall performance of CRs network. Another aspect not taken into account is the amount of bandwidth available in the secondary channel. We would look into methods that can help us decrease the amount of bandwidth utilization for cooperation.

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