An Efficient Weighted-Collaborative Sensing Scheme in Cognitive Radio

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ABSTRACT

Cognitive Radio is an advanced enabling technology for efficient utilization of under-utilized spectrum since it is able to sense the temporally available spectrum and adapt its parameters to fully utilize the frequency band. Recent investigation suggests that spectrum sensing is compromised when a cognitive radio user suffers from the environment with fading or shadowing. In order to combat the effect, collaborative sensing is considered to be a promising way, which combines the sensing result of each user to achieve good performance. However, the conventional collaborative sensing is not efficient when users suffer different fading environments. In this paper, we propose a weighted-collaborative scheme that considers using the weights of each collaborative CR user, which can achieve better sensing performance under both fast and slow fading environments. The analysis of the simulation resultsproves that the weighted-collaborative scheme improves sensing performance obviously and outperforms the conventional method.

Key Words : Cognitive Radio, Collaborative Sensing, Spectrum Sensing, Weighted Collaborative Sensing

Ⅰ. INTRODUCTION

Recently, the traditional approaches for spectrum management have been reconsidered to the actual use of spectrum. The FCC's (Federal Communications Commission) Spectrum Policy Task Force has reported plentiful temporal and geographic variations in the usage of allocated spectrum [1]. The FCC frequency chart (see Figure 1) indicates the multiple allocations over all of the frequency bands, where there is a drastic competition for use of spectra, especially in the frequency below 3 GHz. One way of increasing spectrum utilization called Opportunistic Spectrum Sharing is to reuse the spectrum when their hosts (Primary users) are absent. With this concept, secondary users are allowed to access the frequency bands without agreement from the primary users.

Cognitive Radio (CR) is considered as a potential solution to improve spectrum utilization via opportunistic spectrum sharing. It is an intelligent wireless communication system that is aware of its surrounding environment and uses the method of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimulate by making corresponding changes of its parameters in time [2]. The fundamental requirement is to keep non-interfering co-existence to the primary users.

There are three fundamental tasks for Cognitive Radio: spectrum sensing, dynamic spectrum allocation and transmit-power control [2].

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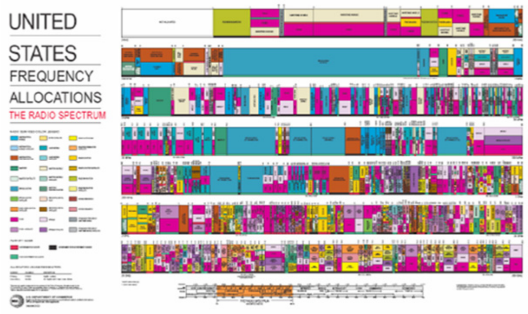

Fig. 1 FCC frequency chart

Among them, spectrum sensing has been identified as the key technique to ensure that cognitive radios would not interfere to primary users, by reliably detecting primary user signals with the help of some novel algorithms such as enhanced energy detection[3], cyclostationary feature detection[4,5]. In order to confront fading environment, collaborative sensing among secondary users has recently be proposed in [6,7,8], where they investigate the collaborative spectrum sensing techniques to overcome multipath fading and shadowing, which have attracted a lot of attentions from the research community. With cooperation between some numbers of CR users, the collaborative sensing method may improve sensing performance significantly compared to the individual sensing.

However, most of the collaborative methods in recent study assume that all the collaborative participants experience independent and identically distributed (i.i.d.) fading with the same average SNR. Furthermore, the performance of proposed methods under different average SNR is not discussed yet. In this paper, we quantify the performance of collaborative sensing in fading environments with the same average SNR, as well as the collaborative users with different average SNR. Moreover, we propose a weighted - collaborative scheme to make a more accurate sensing decision than conventional one.

The remainder of this paper is organized as follows: Section II reviews the local spectrum sensing, while conventional collaborative sensing is outlined in section III. The weighted -collaborative sensing scheme is introduced in section IV. Some simulation results are analyzed in section V. Finally, we conclude this paper in section VI.

Ⅱ. LOCAL SPECTRUM SENSING

Generally, local spectrum sensing is carried out by using classic energy detection as shown in fig. 2. It can be easily implemented by squaring the received signal and integrating over the time interval, and then comparing the output of energy detector with the threshold that depends on the noise floor. If the estimated energy of the received signal is larger than the preset threshold, the existence of primary user would be declared. Because of low computational complexity, energy detector has been considered as the most common way for individual spectrum sensing in secondary users.

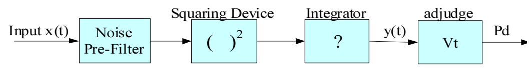

Fig. 2 Block diagram of the classic energy detection

The classical energy detection is under the test of the following two hypotheses:

$$H_0 : y(t) = n(t) \tag{1}$$
$$H_1 : y(t) = h(t) * x(t) + n(t) \tag{2}$$

where y(t) is the signal received by secondary user, x(t) is the transmitted signal by primary user and n(t) indicates the additive white Gaussian noise, h(t) is the amplitude gain of the channel. Under H_0, the received signal y(t) is noise alone while under H_1, y(t) consists of PU signal and noise.

In order to evaluate the performance of sensing schemes, we generallytest the statistics to achieve two kinds of probabilities, probability of detection and false alarm, which can be defined as:

$$P_d = P_r(Y > \lambda | H_1) \tag{3}$$
$$P_{fa} = P_r(Y > \lambda | H_0) \tag{4}$$

where λ is the preset threshold level.

Ⅲ. Collaborative Sensing in Cognitive Radio

In order to improve the reliability of spectrum sensing, collaborative sensing is proposed in [7] that different secondary users are allowed to collaborate by sharing their sensing information under the assumption that all the users suffer the i.i.d. fading with the same average SNR.

Here, we first quantify and analyze the performance of the conventional collaborative sensing scheme, which apply the OR-rule as the collaborative decision criterion [9]. Then, according to this criterion, the probabilities of detection and false-alarm for the collaborative scheme denoted by Q_d and Q_{fa} can be written as follows:

$$Q_d = 1-(1-P_d)^N \tag{5}$$

$$Q_{fa} = 1-(1-P_{fa})^N \tag{6}$$

where N denotes the number of the collaborative users, P_d and P_{fa} are the individual probabilities of detection and false-alarm.

Fig.3 shows the ROC (receiver operating characteristics) for different numbers of collaborative users under AWGN, the average SNR of each user is 5dB. As the number of collaborative user increases, the sensing performance of the collaborative scheme is much better than the individual sensing. For example, when P_{fa} is equal to 0.1, the P_d of individual sensing is less than 0.65, while the collaborative sensing with 10 users can achieve as large as 0.9.

In conventional collaborative scheme, all the users are assumed to experience the i.i.d. fading with the same average SNR. However, in practical, the collaborative users are likely to suffer different fading due to their variable environments. Consequently, the average SNR must be different from user to user. In order to evaluate the performance under this case, we assume that each collaborative user has different average SNR denoted by $\overline{r_i}$, which is randomly selected from 1dB to 5dB. Fig.4 and Fig.5 show the performance of conventional collaborative method in which each user experiences the different environments under AWGN and Rayleigh fading respectively, where the N=1 case denotes the best local sensing result. The related parameters are defined in table 1.

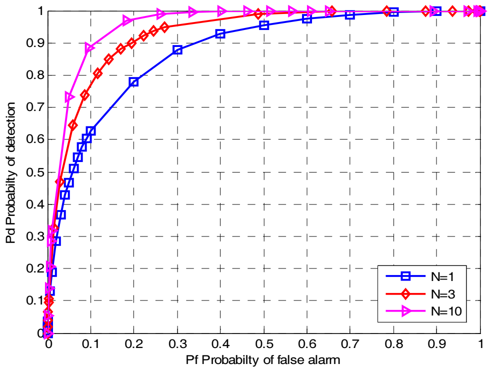

Fig. 3 ROC curves of collaborative sensing under AWGN

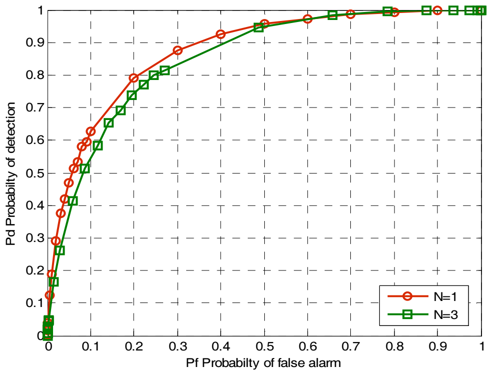

Fig. 4 ROC curves of collaborative sensing vs. best local sensing under AWGN

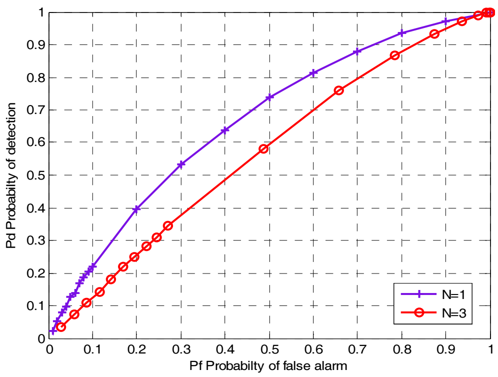

Fig. 5 ROC curves of collaborative sensing vs. best local sensing under Rayleigh fading

Table 1. The related parameters in simulation

Parameter	Value
Modulation Type	BPSK
Average SNR	1~5dB
Bandwidth	1000Hz
Maximum Doppler freq	160Hz

As shown in the figure, in the AWGN environment, the collaborative decision is inferior to the local decision all along. For the case under Rayleigh fading environment, the collaborative user with bad channel condition may degrade the performance of the total collaborative sensing, which leads to worse collaborative result than the individual one under good condition. Therefore, the conventional collaborative sensing is not always useful but only increases the complexity.

Ⅳ. The Weighted-Collaborative Sensing Method

In conventional collaborative sensing method, it is inefficient to arrange the same role for each collaborative user when they suffered different fading environments. The collaborative users should be given different roles to indicate their contributions to the final decision. In this paper, we propose a weighted-collaborative sensing scheme that assigns the dynamic weight factors to different collaborative users based on their contributions to enhance the performance of the collaborative sensing effectively.

We suppose two kinds of environments. One is the slow fading environment under which collaborative users are stationary or move slowly and the result of each sensing process is assumed to be constant or changed a little; the other is the fast fading environment under which collaborative users' locations change greatly during a short period and the sensing results change greatly for each sensing process. When the change of users' detection probability is within a pre-defined level compared to the previous sensing process we consider they are under slow fading environment, otherwise they are considered under the fast fading environment. In this paper we set this level to 5%. Accordingly, the way to update weight factors is different based on the kind of the environment. In the proposed sensing scheme, each collaborative user is active and operates availably during the whole process.

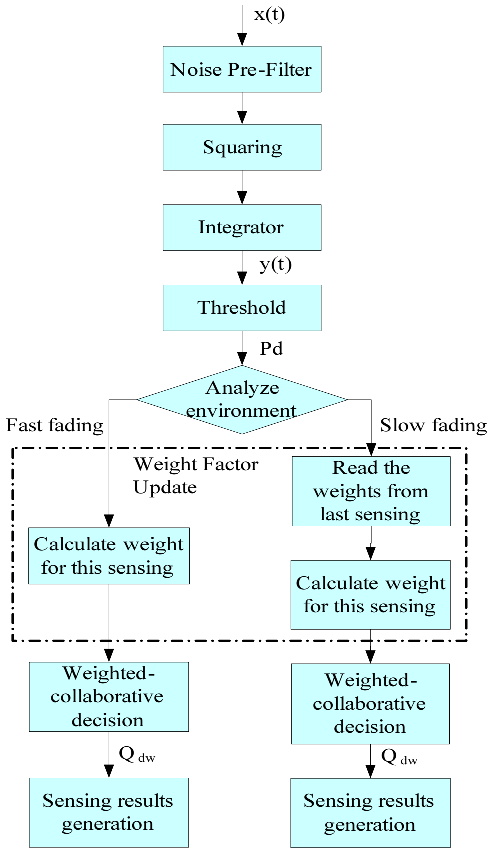

Fig. 6 The weighted-collaborative sensing scheme

Due to the different locations and environments, the average SNR for each user is different. The decision process will be divided into two steps: weight factor update and sensing results generation. Fig.6 shows the block diagram of the proposed weighted-collaborative scheme.

We do not give the weight factor to probability of false alarm, because it is considered for the case of no signal transmission and independent of SNR, it can not be affected by the channel environment.

4.1 Weight Factor Update

The weight factor is defined as $W_i(n)$, where i denotes the ith user, n denotes the nth sensing. Assign a weight factor $W_i(n)$, to the ith user, after each sensing process, each user updates its weight factor, according to (7) and (10).

4.1.1 Slow Fading Environment

As analyzed above, under the slow fading environment, each sensing process of collaborative users can be assumed to be stationary. Therefore, we can update the weight for each collaborative user based on their contribution in the last sensing, which can be derived as follows:

$$W_i(n+1) = W_i(n) P_{d\ i}(n) / \overline{W(n) P_d(n)} \tag{7}$$

where

$$\overline{W(n) P_d(n)} = \frac{1}{N} \sum_{i=1}^{N} W_i(n) P_{d\ i}(n) \tag{8}$$

$P_{d\ i}(n)$ is the detection probability of the ith user in the nth sensing. Initially, we assign the same weight factor $W_i(0)=1$ to each user. After the n sensing, the weight factor for each user is updated and would be used in the decision of the (n+1)th sensing. Therefore, we can dynamically change the weight of each collaborative user based on their last contribution, while satisfying $\sum_{i=1}^{N} W_i = N$ for every sensing.

4.1.2 Fast Fading Environment

Different from the slow fading environment, it is improper to get weight factor from the previous sensing result under fast fading environment. In this case, we decide the weight factor for each user only by the current sensing result, as follows:

$$W_i(n) = P_{d\ i}(n) / \overline{P_d(n)} \tag{9}$$

$$where \qquad \overline{P_d(n)} = \frac{1}{N} \sum_{i=1}^{N} P_{d\ i}(n) \tag{10}$$

We directly calculate the weight factor of each user based on the current sensing decision. If the user demonstrates more contribution in the final decision result of the current sensing, then it would be assigned largerweight value. In this case, $\sum_{i=1}^{N} W_i = N$ is also satisfied in every sensing.

As a result, the weight factor of the user who has more contribution to the final decision will be increased gradually. In other words, if a user experiences deep fading with lower SNR, its weight factor will be decreased to reduce its contribution to the final collaborative decision.

4.2. Sensing Results Generation

Based on the calculated weight value for each collaborative user from the above analysis, in this step, each collaborative user carries the assigned weight factors to contribute to the final decision. Therefore, the whole probabilities of detection for the weighted-collaborative scheme denoted by Q_{dw} can be expressed as:

$$Q_{dw} = 1 - \prod_{i=1}^{N} W_i (1 - P_{d\ i}) \tag{11}$$

With contrast to equation (5), (11) considers the dynamically controlled weight factor for each $P_{d\ i}$ to evaluate each contribution to the final decision, which is studied to enhance the sensing performance and achieve better performance.

V. Simulation Results

In order to analyze the performance of the proposed scheme, we are interested in illustrating the ROC curves for different conditions of interest. The referred collaborative method is the conventional scheme in our simulation. All our simulations are based on the energy detection. We focus on the impact of the user number N, as well as the number of sensing process n to evaluate the performance of the proposed scheme. Furthermore, we consider the set of users under different fading environments, a part of them are with good channel conditions and others are with bad channel conditions.

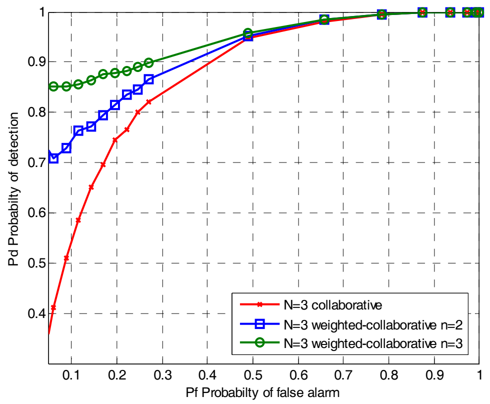

Fig. 7 ROC curves of collaborative sensing vs. weighted-collaborative sensing under AWGN with slow fading environment

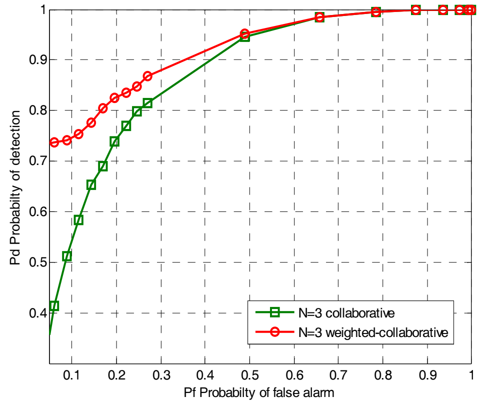

Fig. 10 ROC curves of collaborative sensing vs. weighted-collaborative sensing under AWGN with fast fading environment

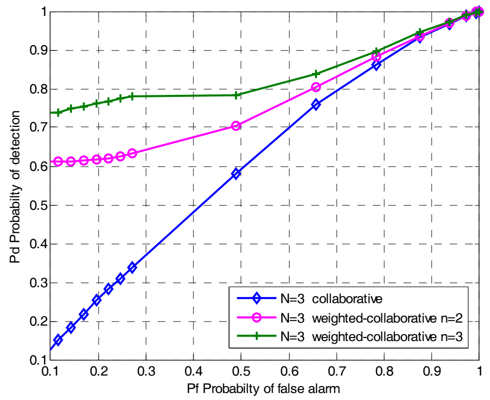

Fig. 8 ROC curves of collaborative sensing vs. weighted-collaborative sensing under Rayleigh fading with slow fading environment

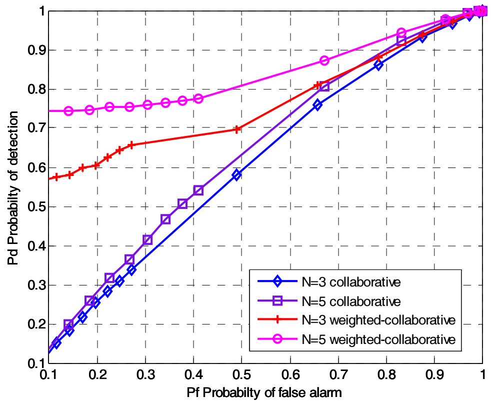

Fig. 11 ROC curves of collaborative sensing vs. weighted-collaborative sensing under Rayleigh fading with fast fading environment

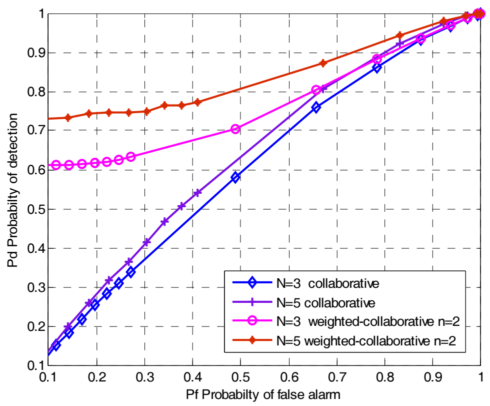

Fig. 9 ROC curves of collaborative sensing vs. weighted-collaborative sensing under Rayleigh fading with slow fading environment

The simulation results from Fig.7 to Fig.9 are based on the slow fading environment. As shown in Fig.7, when the collaborative users have different average SNRs, after the second sensing, our proposed method achieves a significant improvement.

As n increases gradually, the performance becomes better. The potential unfairness in the conventional method is ameliorated by varying weight factors of collaborative users depend on their contributions. Especially, the improvement with low P_{fa} is notable. In Rayleigh fading environment as illustrated in Fig.8, even with low P_{fa} we can obtain very high Pd. For example, when P_{fa} = 0.2, the P_d increase to 0.61 with n=2, and as large as 0.78 for n=3. Moreover, Fig.9 shows how N impacts the performance of the proposed weighted-collaborative scheme under Rayleigh fading. As expected, the better performance of weighted sensing is achieved when different users have different average SNRs. With increasing N, the performance of the weighted-collaborative scheme will be better. When the number of collaborative user increases to 5, the P_d approaches to 0.75 with P_{fa} =0.2 and n=2, the collaborative sensing scheme shows robustness under the fading environment. The simulation results in Fig.10 and Fig.11 are based on the fast fading environment. When the collaborative users have different average SNR, even under fast fading environment, the performance of proposed weighted method is much better than the conventional collaborative one. Furthermore, Fig.11 shows the impacts of collaborative user number N. With the increasing of N, the weighted-collaborative method can achieve better performance. The proposed weighted-collaborative sensing well overcomes the impact of fading environment by giving different roles to different users based on their contributions to the final decision.

Ⅵ. CONCLUSIONS

In this paper, we propose a weighted-collaborative sensing scheme that can enhance the performance of spectrum sensing when different users suffer different channel environments. We address the problem of traditional collaborative structure and improve it with the proposed method. Our analysis and simulation results show that the proposed spectrum sensing scheme can achieve better performance under different fading environments. Further work will be continued to evaluate the more related parameters includes optimum individual threshold, the spatial distribution of users and other more important propagation characteristics

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