A Reliable Collaborative Spectrum Sensing Scheme Based on the ROCQ Reputation Model for Cognitive Radio Networks

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***Abstract*—Linear combination-based collaborative spectrum sensing, in which a coefficient is used to weight each cognitive radio (CR) user's sensing result in the linear fusion process at the central controller, is an effective mechanism to solve the fading and hidden terminal problem in cognitive radio networks (CRNs). For a reliable scheme, it is important to distinguish whether the CR user is reliable or not. In this paper, we proposed a collaborative spectrum sensing scheme based on the ROCQ reputation management model for CRNs. In the proposed scheme, each CR user has a reputation degree used to calculate its coefficient in the linear fusion process, and the reputation degree is initialized and adjusted by the central controller according to each CR user's sensing result, sensing correctness and report consistency. Simulation results show that our proposed scheme alleviates the corrupted sensing problem resulting from the destructive channel conditions between the primary transmitter and CR users. Moreover, compared to the optimal linear fusion scheme, the detection performance of our proposed scheme is approximately same while it requires no instantaneous SNRs. And the convergence of the reputation degree adjusting method also performs well.**

Keywords- Cognitive radio networks; Collaborative spectrum sensing; ROCQ model; Reputation

I. INTRODUCTION

With the rapid growth of different wireless services, radio frequency, as a non-renewable resource, is becoming scarcity. Cognitive radio (CR), a key technology to alleviate the frequency scarce, has been paid much attention to in recent years [1]. Spectrum sensing, which reliably detects weak primary radio signals in possibly-unknown-types, is an important technology enabling CR [2].

Energy detection-based spectrum sensing mechanism is most commonly adopted because of its low computational and implementation complexities, as well as it does not need any knowledge of the primary user's signal [3-4]. Since the detection performance of single user spectrum sensing is limited by fading and hidden terminal problems, collaborative spectrum sensing scheme is proposed to obtain the spatial diversity in CR networks (CRNs) [5], that is, several CR users collaborate to jointly detect the presence of the primary user to improve the detecting accuracy.

Collaborative spectrum sensing scheme in CRNs can be divided into two types, the hard decision fusion scheme and the soft data fusion scheme. It has been demonstrated in [6] that the soft data fusion scheme exhibits significant improvement over the hard decision fusion scheme. Hence, we focus on the energy detection-based collaborative spectrum sensing scheme with the soft data fusion in this paper.

The optimum spectrum sensing scheme based on energy detection is difficult to numerically evaluate since the probability distribution of the global test statistic involves many integrals. In this paper, we only consider collaborative spectrum sensing scheme based on the linear fusion rule. In recent years, several linear combination-based collaborative spectrum sensing schemes have been proposed [7-10]. In [7], Ma and Zhao proposed an optimal linear combination scheme that maximizes the detection probability for a given false alarm probability based on the Neyman-Pearson criterion. In [8] and [9], other linear collaborative spectrum sensing schemes were proposed by Quan and Shen to find the optimal weighted coefficients of the linear fusion rule. However, these optimal schemes are difficult to implement because they heavily rely on the accurate estimation of the average SNR. To solve this problem, we proposed a reputation-based linear collaborative spectrum sensing scheme without involving instantaneous SNRs in [10]. However, the reputation management model of the proposed scheme is simple, and the convergence of the proposed reputation adjusting method in [10] does not perform very well.

In this paper, introducing the ROCQ reputation management model proposed in [11] into collaborative spectrum sensing in CRNs, we propose a novel reputation-based collaborative spectrum sensing scheme with linear fusion rule. In the proposed scheme, each CR user has a reputation degree used to calculate the weighted coefficient of the corresponding sensing result in the linear combination process at the central controller. The reputation degree is estimated by the ROCQ reputation management model according to sensing report, sensing correctness and report consistency. This scheme can alleviate the harmful influence caused by the sensing result of CR user in the fading environment because the result has low sensing correctness and report consistency, and therefore low reputation degree of the CR user.

II. PROBLEM STATMENT

We consider our work in the IEEE 802.22 network with a radius of 33~100km service coverage and highly disparate CR users. The collaborative spectrum sensing is performed in a CR network with K CR users and a central controller as shown in Fig. 1.

Each CR user sends its sensing result to the central controller via the common control channel, and the central controller combines the sensing results from CR users with a linear weighted fusion rule to make the final decision, that is, the primary user is present or absent. It is assume that the primary signal received by CR users is independent because of

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the location diversity, and the sensing channel between the primary user and CR users corrupts the primary signal.

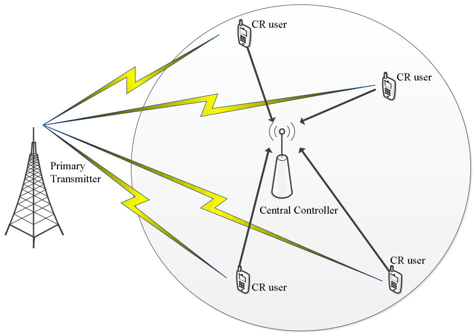


Fig. 1 Collaborative spectrum sensing model

Each CR user samples N times to perform energy detection in every sensing interval, the sensing result at the jth CR user is

$$Y_j = \begin{cases} \sum_{i=1}^{N} [n_j(i)]^2 & H_0 \\ \sum_{i=1}^{N} [h_j s(i) + n_j(i)]^2 & H_1 \end{cases}, j=1, 2, \ldots, K, \quad (1)$$

where $s(i)$ denotes the ith sample of the primary user's signal, and $n_j(i)$ is the ith sample of the sensing noise at the jth CR user. To simplify the sensing model, we assume that $n_j(i)$ is additive white Gaussian noise (AWGN) with zero-mean and variance σ_j^2, and $s(i)$ and $n_j(i)$ are independent each other. H_1 and H_0 represent the hypotheses of the presence of primary user and the absence of primary user, respectively.

From (1), it can be inferred that Y_j follows a central χ^2 distribution with N degrees of freedom if H_0 is true; otherwise, it follows a non-central χ^2 distribution with N degrees of freedom and a non-centrality parameter λ_j if H_1 is true.

When N is large enough (e.g. $N \geq 15$), according to the *Central Limit Theorem*, Y_j is asymptotically normally distributed with mean and variance as

$$Y_j \sim \begin{cases} \mathcal{N}\left(N\sigma_j^2,\ 2N\sigma_j^4\right) & H_0 \\ \mathcal{N}\left((N+\lambda_j)\sigma_j^2,\ 2(N+2\lambda_j)\sigma_j^4\right) & H_1 \end{cases}, j=1, 2, \ldots, K, \quad (2)$$

where $\lambda_j = N\mu_j$, μ_j represents the average SNR of the received signal, and $\mu_j = h_j^2 \sum_{i=1}^{N} s^2(i) / N\sigma_j^2$.

In collaborative spectrum sensing, each CR user sends its sensing result to a central controller via the common control channel. Although the sensing result may be corrupted by the noise in the common control channel, it can be avoided with an efficient error correction coding, and then we neglect the impact of the noise in the transmission channel between the CR user and the central controller. Hence, the received sensing result from the jth CR user is

$$Z_j = Y_j,\ j=1, 2, \ldots, K. \quad (3)$$

The central controller collects all sensing results from collaborative CR users and combines them with the linear weighted fusion rule. That is,

$$Z_c = \sum_{j=1}^{K} w_j Z_j,\ j=1, 2, \ldots, K, \quad (4)$$

where w_j is the weighted coefficient of received sensing result from the jth CR user, $j=1, 2, \ldots, K$, and $\sum_{j=1}^{K} w_j = 1$.

Since $\{Z_j | j=1, 2, \ldots, K\}$ are normally distributed random variables, Z_c is also a random variable in normal distribution with

$$Z_c \sim \begin{cases} \mathcal{N}\left(N\sum_{j=1}^{K} w_j\sigma_j^2,\ 2N\sum_{j=1}^{K} w_j^2\sigma_j^4\right) & H_0 \\ \mathcal{N}\left(\sum_{j=1}^{K} w_j(N+\lambda_j)\sigma_j^2,\ 2\sum_{j=1}^{K} w_j^2(N+2\lambda_j)\sigma_j^4\right) & H_1 \end{cases}. \quad (5)$$

The objective of collaborative spectrum sensing is to make a decision between H_0 and H_1. That is, the central controller compares Z_c to the decision threshold γ_c, and makes the decision as follows

$$Z_c \underset{H_0}{\overset{H_1}{\gtrless}} \gamma_c. \quad (6)$$

From (4) and (6), it is observed that the detection performance of the linear combination-based collaborative spectrum sensing scheme depends on two aspects, the detection rule to determine γ_c and the set of coefficients $\{w_j | j=1, 2, \ldots, K\}$ to weight the received sensing results from CR users.

In this paper, our primitive objective is to design a reliable linear weighted fusion rule at the central controller to solve the fading and hidden terminal problem so as to improve the detection performance of the collaborative spectrum sensing scheme. Moreover, to improve the convergence performance of the reputation adjusting method presented in [10], our purpose is to find another practical method for calculating the weighted coefficients of the reputation-based linear fusion rule with a tolerable computational complexity.

III. A Reliable Collaborative Spectrum Sensing Scheme Based On The ROCQ Reputation Model

A. *Reputation-based collaborative spectrum sensing*

As we know, the missed detection probability measures the interference of CR user on the primary user, and the false alarm probability determines the upper bound of the spectrum utilization. Assuming the spectrum is used by CR users only when the primary user is absent. Hence, we consider the Neyman-Pearson formulation in this paper. Given the upper bound on the spectrum utilization, i.e. the required false alarm probability, the detection problem is formulated as to maximize the detection probability.

According to (4)-(6), the false alarm probability and the detection probability of the linear combination-based collaborative spectrum sensing scheme can be calculated as

$$Q_f = Q\left(\frac{\gamma_c - E(Z_c | H_0)}{\sqrt{Var(Z_c | H_0)}}\right) = Q\left(\frac{\gamma_c - N\sum_{j=1}^{K} w_j\sigma_j^2}{\sqrt{2N\sum_{j=1}^{K} w_j^2\sigma_j^4}}\right). \quad (7)$$

$$Q_{\mathrm{d}} = Q\left(\frac{\gamma_{\mathrm{c}} - E(Z_{\mathrm{c}} \mid H_1)}{\sqrt{Var(Z_{\mathrm{c}} \mid H_1)}}\right) = Q\left(\frac{\gamma_{\mathrm{c}} - \sum_{j=1}^{K} w_j (N+\lambda_j)\sigma_j^2}{\sqrt{2\sum_{j=1}^{K} w_j^2 (N+2\lambda_j)\sigma_j^4}}\right). \quad (8)$$

Hence, if the required false alarm probability, $Q_{\mathrm{f,\,required}}$, is given, γ_{c} can be obtained from

$$\gamma_{\mathrm{c}} = Q^{-1}(Q_{\mathrm{f,\,required}}) \times \sqrt{2N\sum_{j=1}^{K} w_j^2 \sigma_j^4} + N\sum_{j=1}^{K} w_j \sigma_j^2 . \quad (9)$$

And then, the decision is made according to (6), and the detection probability of the linear combination-based collaborative spectrum sensing scheme is evaluated.

From (7)-(9), we observe that if the required false alarm probability, $Q_{\mathrm{f,\,required}}$, is given, the detection performance of the linear combination-based collaborative spectrum sensing scheme only depends on the set of coefficients $\{w_j|j=1, 2, \ldots, K\}$ to weight the received sensing results from CR users.

As same as in [10], we assume that each CR user in CRNs has a reputation degree used to weight corresponding sensing result in the linear combination process at the central controller. The weighted coefficients can be calculated as

$$w_j = r_j \Big/ \sum_{k=1}^{K} r_k \;, j=1, 2, \ldots, K, \quad (10)$$

where r_j is the reputation degree of the jth CR user.

B. Reputation degree adjusting method based on the ROCQ model

From the reputation-based collaborative spectrum sensing scheme in the Section III.A, we observe that the detection performance of this scheme only depends on the reputation degrees of CR users, $\{r_j|j=1, 2, \ldots, K\}$ with a given $Q_{\mathrm{f,\,required}}$. Hence, it is important to present a robust method for adjusting the reputation degrees of CR users, which can not only track unreliable CR users experiencing deep fading or hidden terminal problem, but also track quickly changing channel condition.

In this work, we introduce the ROCQ reputation management system into the spectrum sensing in CRNs. Since the ROCQ model is initially designed for decentralized networks, we revise the model in order that it is suitable for linear weighted fusion with a central controller in CRNs. Based on the improved ROCQ model, we propose a novel reputation degree adjusting method in which the reputation degrees of CR users are adjusted according to sensing result (Opinion), sensing correctness (Credibility) and result consistency (Quality).

1) Opinion

Opinion is directly taken as the sensing result of the CR user. That is,

$$O_j(l) \equiv Z_j(l), \quad (11)$$

where l is the number of spectrum sensing a CR user taking part in, $O_j(l)$ denotes the opinion about the lth sensing result from the jth CR user, $Z_j(l)$ is the lth sensing result from the jth CR user.

The central controller may also keep a record of the jth CR user's first-hand experiences in terms of the average opinion and variance, and $\varepsilon_j(l)$ and $\delta_j(l)$ represent the mean and variance of previous l sensing results from the jth CR user.

2) Credibility

Credibility is used to evaluate the sensing correctness of a CR user's sensing result. When a CR user attends the collaboration in CRNs for the first time, its credibility is initialized by the central controller. Then, at each detection interval, the central controller compares the sensing result from each CR user to the decision threshold, and updates its credibility as follows

$$C_j(l) = \begin{cases} C_j(l-1) + [1 - C_j(l-1)]Q_j(l)\Delta & O_j(l) \ge \gamma_{\mathrm{c}}(l) \\ C_j(l-1) - C_j(l-1)Q_j(l)\Delta & O_j(l) < \gamma_{\mathrm{c}}(l) \end{cases}, \quad (12)$$

where $C_j(l)$ represents the credibility of the jth CR user when it takes part in the collaborative detection l times. $Q_j(l)$ is the associated quality of l sensing results from the jth CR user, Δ is a change factor for each update.

From (12), if a CR user is unreliable, its credibility is reduced since its opinion does not match the global decision.

3) Quality

Quality is used to determine the confidence of a CR user's sensing results. Since $O_j(l)$ is normally distributed random variable and its actual mean and standard deviation are unknown, we adopt the *student's t distribution* to compute the confidence level.

The t-value for the *student's t distribution* is

$$t = \frac{\theta}{100} \cdot \frac{\varepsilon_j(l)\sqrt{l}}{\delta_j(l)} , \quad (13)$$

where θ denotes the size of the confidence interval.

And the quality of the jth CR user at the lth detection interval, $Q_j(l)$, is calculated as

$$Q_j(l) = 1 - B\left(\frac{l-1}{l-1+t^2};\; \frac{1}{2}(l-1), \frac{1}{2}\right), \quad (14)$$

where $B(\;;\;,\;)$ is an *Incomplete Beta Function* defined as $B(z;a,b) \equiv \int_0^z u^{a-1}(1-u)^{b-1}du$.

Hence, the quality is decided by the result consistency and the number of sensing results.

4) Reputation

Reputation is the final result of aggregated sensing results. In this paper, we compute the reputation of the jth CR user at the lth detection interval using L most recent transactions as

$$r_j(l) = \begin{cases} \left(\dfrac{\sum_{m=1}^{l} \rho^{l-m} \times O_j(m) \times C_j(m) \times Q_j(m)}{\sum_{m=1}^{l} \rho^{l-m} \times O_j(m) \times Q_j(m)}\right)^{\alpha} & l \le L \\ \left(\dfrac{\sum_{m=l-L+1}^{l} \rho^{l-m} \times O_j(m) \times C_j(m) \times Q_j(m)}{\sum_{m=l-L+1}^{l} \rho^{l-m} \times O_j(m) \times Q_j(m)}\right)^{\alpha} & l > L \end{cases}, \quad (15)$$

where ρ, an attenuation factor, is used to eliminate the detection inaccuracy of previous sensing results, α is used to ensure the convergence performance of the model. The calculated $\{r_j(l)|j=1, 2, \ldots, K\}$ will be used to compute $\{w_j|j=1, 2, \ldots, K\}$ for the next detection interval using (10).

In our proposed reliable collaborative spectrum sensing scheme based on ROCQ reputation model, once the quality and credibility of current sensing result of the jth CR user is low, its reputation degree will be declined, and its sensing result received by the central controller has less effect on the global decision because of its low weighted coefficient. The ROCQ reputation management model gives a system-wide view of the satisfaction of a CR user.

Since the calculation of the reputation degrees of CR users can be performed between two detection intervals and is not instantaneous, the computational complexity of the method mentioned above is tolerable. Moreover, compared to the optimal linear collaborative spectrum sensing scheme in [7-9], this model does not need instantaneous SNRs of CR users for computing the weighted coefficients.

IV. SIMULATION RESULTS AND DISSCUSSIONS

In this section, we evaluate the performance of our proposed reliable collaborative spectrum sensing scheme based on the ROCQ reputation model. We also compare our proposed scheme to other three schemes, the traditional equal gain combination (EGC) scheme, the cooperation scheme in [11] and the optimal cooperation scheme in [8] The proposed ROCQ-based collaborative sensing scheme, the traditional EGC scheme, the cooperation scheme in [11] and the optimal cooperation scheme in [8] are denoted by 'ROCQ-based collaboration scheme', 'EGC-based cooperation scheme', 'Reputation-based linear cooperation scheme in [10]' and 'Optimal cooperation scheme', respectively. Simulations were carried out in a CR network with 10 CR users and σ_j=1 (j=1,2, …, 10). After careful verification, we choose L=10, Δ=1/10, ρ=0.95, α=1.2, and θ=1 for the ROCQ reputation model, and the initial credibility for each CR user is 0.5. Moreover, in each detection interval, a CR user samples the local observation N times, N=20. $\{\mu\}$ represent local SNRs of 10 CR users. The results are obtained from simulations over 100000 random noise realization for the given set of noise variances and channel gains.

Fig. 2 shows the comparison of the missed detection probability against the false alarm probability. We set $\{\mu\}$={-3.0, -6.6, -3.5, -10.1, -3.7, -3.2, -6.2, -5.3, -5.9, -9.5} in dB. From Fig. 2, we observe that the reliable collaborative spectrum sensing scheme based on the ROCQ reputation model suffers only a little performance deterioration compared to the optimal cooperation scheme, and performs much better than the EGC-based cooperation scheme. Compared to the reputation-based cooperation scheme in [10], our proposed reputation-based collaborative scheme based on the ROCQ model has a little performance improvement. Although the optimal cooperation scheme performs a little better than our proposed scheme, it needs instantaneous SNRs which are usually very difficult to estimate accurately, which makes the optimal cooperation scheme is not applicable.

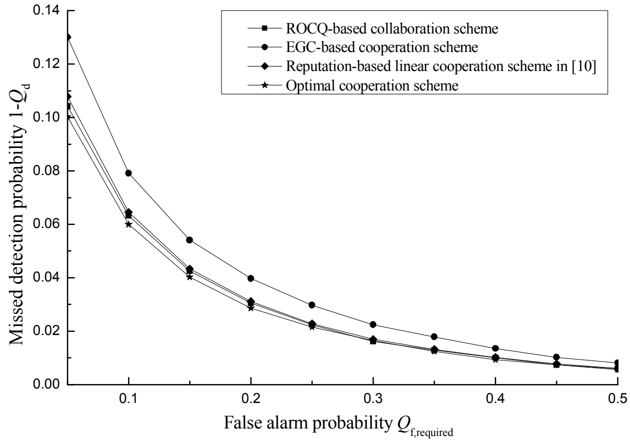


Fig. 2 The comparison of the detection performance for different schemes

Fig. 3 depicts the impact of the average SNR on the detection performance, where the average SNRs of 10 CR users are set to be -5.7dB and -6.7dB, respectively. From Fig. 3, we observe that for all three cooperation schemes, the detection performance degrades significantly when the average SNR decreases. However, the detection performance of our proposed scheme is better than the EGC-based cooperation scheme, and is close to the optimal cooperation scheme. Therefore, our proposed scheme exhibits good performance in low SNRs.

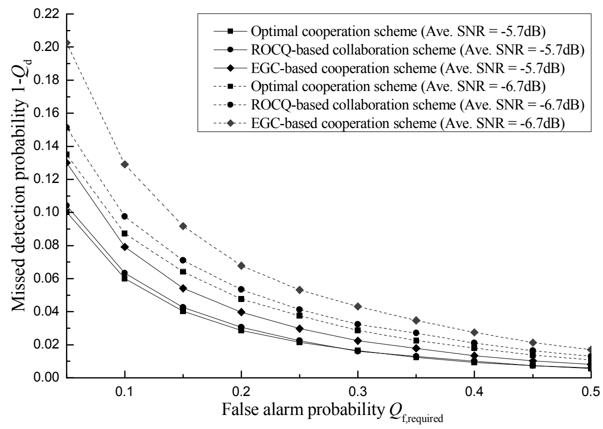
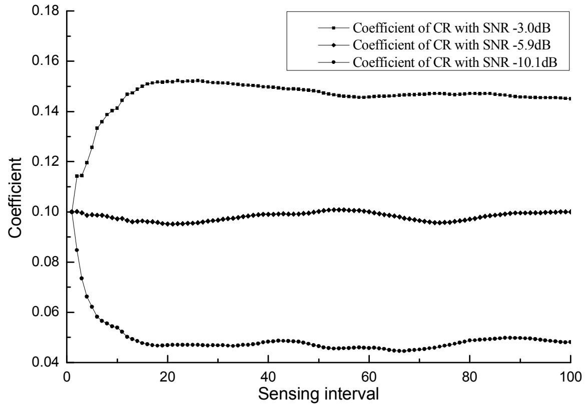


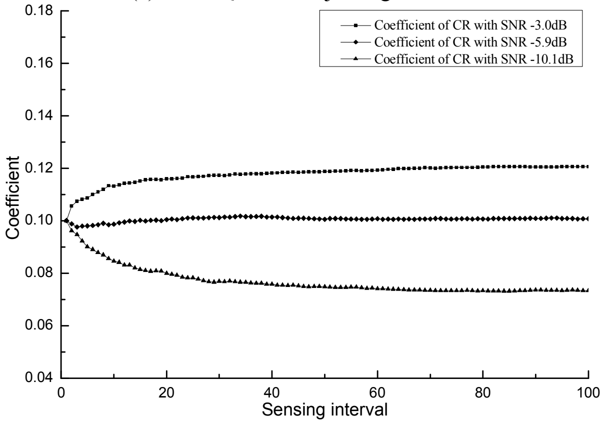
Fig. 3 The comparison of the impact of the average SNR on the detection performance

Fig. 4 shows the variation tendency of weighted coefficients at $Q_{f,required}$=0.1 for 3 CR users with different SNRs chosen from 10 CR users with $\{\mu_j\}$={-3.0, -6.6, -3.5, -10.1, -3.7, -3.2, -6.2, -5.3, -5.9, -9.5} in dB, where Fig. 4(a) is the weighted coefficients for the ROCQ-based adjusting method, and Fig. 4(b) is the weighted coefficients for the adjusting method proposed in [10]. From Fig. 4, we observe that the weighted coefficients of CR users with high SNRs are significantly greater than CR users with low SNRs. Moreover, the degree adjusting method based on improved ROCQ model outperforms the method proposed in [10], and is more effective in CRNs with rapidly changing channel condition.

Therefore, the proposed ROCQ-based collaborative scheme can alleviate the harmful influence by unreliable CR users.



(a). ROCQ-based adjusting method



(b). The adjusting method presented in [10]

Fig. 4 The coefficients of different CR users with different SNRs

V. CONCLUSIONS

In this paper, we proposed a reliable collaborative spectrum sensing scheme based on the ROCQ reputation management model for CRNs. This scheme is aimed to improve the detection performance and the convergence performance over the existing collaborative spectrum sensing scheme when the instantaneous SNRs are difficult to estimate in time-variant channels. In the ROCQ reputation management system, CR users suffering multipath fading and shadowing have lower sensing correctness and report consistency, the corresponding weighted coefficients are declined, therefore the harmful influence caused by these CR users on the global decision is alleviated. Simulation results show that the detection performance of the proposed scheme is much better than the EGC scheme and approximates to the optimal cooperation scheme. Furthermore, this scheme is more practical because it does not need knowledge of the channel statistics for computing the weighted coefficient of each CR user.

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