Super-allocation and Cluster-based Cooperative Spectrum Sensing in Cognitive Radio Networks

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Received June 5, 2014; revised September 12, 2014; accepted October 9, 2014; published October 31, 2014

Abstract

An allocation of sensing and reporting times is proposed to improve the sensing performance by scheduling them in an efficient way for cognitive radio networks with cluster-based cooperative spectrum sensing. In the conventional cooperative sensing scheme, all secondary users (SUs) detect the primary user (PU) signal to check the availability of the spectrum during a fixed sensing time slot. The sensing results from the SUs are reported to cluster heads (CHs) during the reporting time slots of the SUs and the CHs forward them to a fusion center (FC) during the reporting time slots of the CHs through the common control channels for the global decision, respectively. However, the delivery of the local decision from SUs and CHs to a CH and FC requires a time which does not contribute to the performance of spectrum sensing and system throughput. In this paper, a super-allocation technique, which merges reporting time slots of SUs and CHs to sensing time slots of SUs by re-scheduling the reporting time slots, has been proposed to sense the spectrum more accurately. In this regard, SUs in each cluster can obtain a longer sensing duration depending on their reporting order and their clusters except for the first SU belonged to the first cluster. The proposed scheme, therefore, can achieve better sensing performance under -28 dB to -10 dB environments and will thus reduce reporting overhead.

Keywords: cognitive radio network, super-allocation, cluster head, fusion center

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This work was supported in part by the Information and Communication Technology (ICT) Division, Ministry of Post, Telecommunication and ICT, Bangladesh, and in part by the National Research Foundation of Korea through the Basic Science Research Program funded by the Ministry of Science, ICT and Future Planning (NRF-2014R1A1A1002179).

http://dx.doi.org/10.3837/tiis.2014.10.001

1. Introduction

Cognitive radio (CR) is a new technology in the wireless communications era that has changed the policy of spectrum allocation from a static to a more flexible paradigm [1]. Recently, CRs that enable opportunistic access to under-utilized licensed bands have been proposed as a promising technology for the improvement of spectrum operations. In an overlay cognitive radio networks, an overlay waveform is used to exploit idle spectra and transmit information data within these unused regions. On the other hand, in an underlay cognitive radio networks, an underlay waveform with low transmit power used to transmit data without harmful effects on the primary network [2]. In this paper, we focus on overlay networks where secondary users find the idle channel with spectrum sensing. A precondition of secondary access is that there shall be no interference with the primary system [3]. This means spectrum sensing has a vital role in a CR network (CRN).

There are a number of spectrum sensing techniques, including matched filter detection, cyclostationary detection, and energy detection [4-6]. Matched filter detection is known as the optimum method for detection of the primary users when the transmitted signal is known. The main advantage of matched filtering is that it takes a short time to achieve spectrum sensing below a certain value for the probability of false alarm or the probability of detection, compared to the other methods. However, it requires complete knowledge of the primary user's signaling features, such as bandwidth, operating frequency, modulation type and order, pulse shaping, and packet format. Cyclostationary detection offers good performance but requires knowledge of the PU cyclic frequencies and requires a long time to complete sensing. On the other hand, energy detection is an attractive and suitable method due to its easy implementation and low computation complexity. However, it is vulnerable to the uncertainty of noise power, and cannot distinguish between noise and signal. Conversely, its major limitation is that the received signal strength can be dangerously weakened at a particular geographic location due to multi-path fading and the shadow effect [7].

In order to improve the reliability of spectrum sensing, cooperative spectrum sensing was proposed [8-11]. Each SU performs local spectrum sensing independently, and then forwards the sensing results to the fusion centre (FC) through the noise-free reporting channels between the SUs and the FC. However, the reporting channels are always subject to fading effects in real environments [12]. When reporting channels become very noisy, cooperative sensing offers no advantages [13-14]. To overcome this problem, Zhang et al. [15] and Xia et al. [16] proposed a cluster-based cooperative sensing scheme by dividing all the SUs into a number of clusters and selecting the most favorable SU in each cluster as a CH to report the sensing results, which can dramatically lessen the performance deterioration caused by fading of the wireless channels. In these schemes, the SU selected as the CH has to fuse sensing data from all cluster members (the SUs in this cluster). However, in these schemes, each SU's reporting time slot and the CH reporting time slot offer no contribution to spectrum sensing, while SU sensing and reporting times and CH reporting time are in different time slots.

Jing et al. proposed a superposition-based cooperative spectrum sensing scheme that increases the sensing duration by superpositing the SUs' reporting duration into the sensing duration [17]. However, this scheme adopts various individual reporting durations. In this case, synchronization problems occur at the FC. Moreover, the data processing burden at the FC increases for a large CR network.

In this paper, we propose a super-allocation and cluster-based cooperative spectrum sensing scheme to provide more efficient spectrum sensing. In this scheme, each SU achieves a non-fixed and longer sensing time for sensing the PU signal bandwidth, because both the SUs and the CHs are super-allocated to different reporting time slots. On the other hand, both the SU and the CH reporting time slots are of fixed length because the synchronization problem for the FC is relieved. In addition, this proposed scheme decreases the data processing burden of the FC while all the SUs in the CRN are divided into fewer clusters, such that each SU reports its local decision to the corresponding CH, which then reports to the FC. Simulation results show that the proposed scheme can improve sensing performance in low signal-to-noise ratio (SNR) environment (i.e., -28 dB) and also greatly reduces reporting overhead, in comparison with conventional cluster-based cooperative spectrum sensing schemes.

The remainder of the paper is organized as follows. Section 2 describes the system model. Section 3 offers an overview of energy detection. Section 4 describes the conventional cluster-based cooperative spectrum sensing scheme. The proposed a super-allocation and cluster-based cooperative spectrum sensing scheme is presented in Section 5. Some simulations and comparisons are given in Section 6. Finally, our conclusion is in Section 7.

2. System Model

Spectrum sensing can be formulated as a binary hypothesis-testing problem as follows:

$$\begin{cases} H_1 : \text{PU signal is present}, \\ H_0 : \text{PU signal is absent}. \end{cases} \tag{1}$$

Each SU implements a spectrum sensing process which is called local spectrum sensing, to detect the PU's signal. According to the status of the PU, the received signal of an SU can be formulated as follows:

$$y_j(t) = \begin{cases} \eta_j(t), & H_0 \\ h_j(t)x(t) + \eta_j(t), & H_1 \end{cases} \tag{2}$$

where $y_j(t)$ represents the received signal at the j-th SU, $h_j(t)$ denotes the gain of the channel between the j-th SU and the PU, $x(t)$ with varance of σ_x^2 represents the signal transmitted by the PU, and $\eta_j(t)$ is a circularly symmetric complex Gaussian (CSCG) with variance of $\sigma_{\eta,j}^2$ at the j-th SU.

In addition, we make the following assumptions [18]:

- $x(t)$ is a binary phase shift keying (BPSK) modulated signal.
- $x(t)$ and $\eta_j(t)$ are mutually independent random variables.
- the SU has complete knowledge of noise and signal power.

Cluster-based cooperative spectrum sensing in a CR network is shown in **Fig. 1** which contains N SUs, K clusters, and one FC. In this network, all the SUs are separated into K

clusters, in which each cluster contains N_c SUs, and the cluster head CH_k , k=1,2, …, K, is selected to process the collected sensing results from all SUs in the same cluster.

For sensing duration, first, each SU calculates the energy of its received signal in the frequency band of interest. Local decisions are then transmitted to the corresponding CH through a control channel, which will combine local decisions to make a cluster decision. Secondly, all cluster decisions will be forwarded to the FC through a control channel. At the FC, all cluster decisions from the CHs will be combined to make a global decision about the presence or absence of the PU signal.

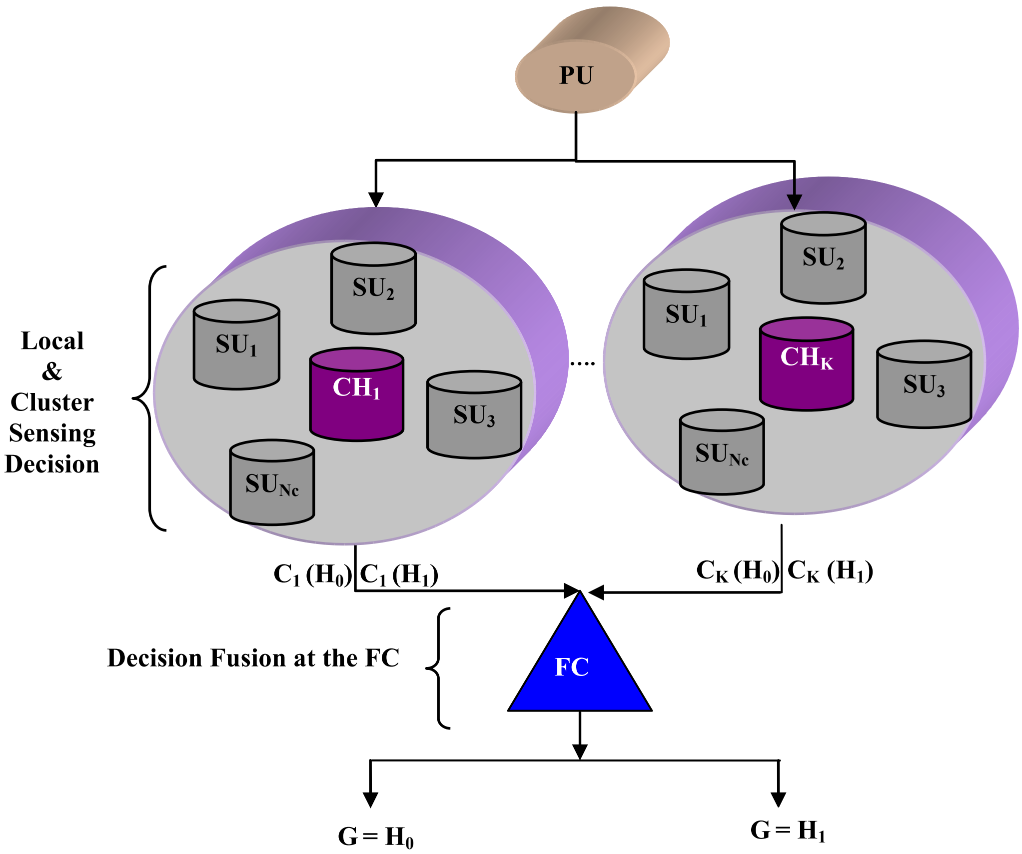

Fig. 1. Cluster-based cooperative spectrum sensing in cognitive radio network

3. Overview of Energy Detection

The energy detection method has been demonstrated to be simple, quick and able to detect primary signals, even if prior knowledge of the signal is unknown [19-22]. A block diagram of the energy detection method in the time domain is shown in **Fig. 2**. To measure the energy of the signal in the frequency band of interest, a band-pass filter is first applied to the received signal, which is then converted into discrete samples with an analog-to-digital (A/D) converter.

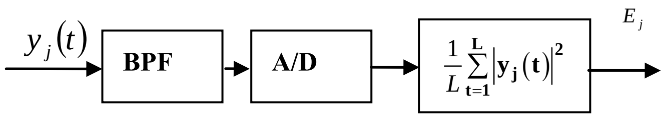

Fig. 2. Block diagram of the energy detection scheme

An estimation of the received signal power is given by each SU with the following equation:

$$E_j = \frac{1}{L}\sum_{t=1}^{L}\left|y_j(t)\right|^2 \tag{3}$$

where $y_j(t)$ is the t-th sample of a received signal at the j-th SU, and L is the total number of samples. $L = T_s F_s$, where T_s and F_s are the sensing time and signal bandwidth in hertz, respectively. According to the central limit theorem, for a large number of samples, e.g., $L > 250$, the probability distribution function (PDF) of E_j, which is a chi-square distribution under both hypothesis H_0 and hypothesis H_1, can be well approximated as a Gaussian random variable, such that

$$E_j = \begin{cases} \boldsymbol{N}\left(\mu_{0,j}, \sigma_{0,j}^2\right) \\ \boldsymbol{N}\left(\mu_{1,j}, \sigma_{1,j}^2\right) \end{cases} \tag{4}$$

where $\boldsymbol{N}\left(\mu, \sigma^2\right)$ deontes a Gaussian distribution with mean of μ and variacne of σ^2, $\mu_{0,j}$ and $\sigma_{0,j}^2$ represent the mean and variance, respectively, for hypothesis H_0, and $\mu_{1,j}$ and $\sigma_{1,j}^2$ represent the mean and variance for hypothesis H_1.

Lemma 1. When the primary signal is a BPSK modulated signal and noise is a CSCG, the decision rule in Eq. (4) is modified as follows:

$$E_j = \begin{cases} \boldsymbol{N}\left(\sigma_\eta^2, \frac{1}{L}\sigma_\eta^4\right) \\ \boldsymbol{N}\left(\sigma_\eta^2(1+\gamma), \frac{1}{L}(1+2\gamma)\sigma_\eta^4\right) \end{cases} \tag{5}$$

where $\gamma = \frac{\sigma_x^2}{\sigma_\eta^2}$ which is the SNR of the primary signal at the j-th SU. The SNR is a constant in the non-fading additive white Gaussian noise environment [23]. Here, we omit the subscript of j in $\sigma_{\eta,j}^2$, which denotes that index of SU, to simplify the notation.

Proof: For hypothesis H_1, the mean $\mu_{1,j}$ is expressed as

$$\mu_{1,j} = \sigma_x^2 + \sigma_\eta^2 = \sigma_\eta^2\left(1 + \frac{\sigma_x^2}{\sigma_\eta^2}\right) \\ = (1+\gamma)\sigma_\eta^2. \tag{6}$$

From Boyd and Vandenberghe [23], variance $\sigma_{1,j}^2$ is

$$\sigma_{1,j}^2 = \frac{1}{L}\left[E|x(t)|^4 + E|\eta(t)|^4 - \left(\sigma_x^2 - \sigma_\eta^2\right)^2\right]. \tag{7}$$

For a complex M-ary quadrature amplitude modulation signal [24], $E|x(t)|^4$ is given as

$$E|x(t)|^4 = \left(3 - \frac{2}{5}\frac{(4M-1)}{(M-1)}\right)\sigma_x^4. \tag{8}$$

For the BPSK signal [24], then we set $M=4$. By substituting the value $M=4$ in Eq. (8).

$$E|x(t)|^4 = \sigma_x^4. \tag{9}$$

For the CSCG noise signal [23], $E|\eta(t)|^4$ is given as

$$E|\eta(t)|^4 = 2\sigma_\eta^4. \tag{10}$$

Substituting the values $E|x(t)|^4$ and $E|\eta(t)|^4$ in Eq. (7), we get

$$\sigma_{1,j}^2 = \frac{1}{L}\left[\sigma_x^4 + 2\sigma_\eta^4 - \left(\sigma_x^4 - 2\sigma_x^2\sigma_\eta^2 + \sigma_\eta^4\right)\right] \\ = \frac{1}{L}\left[\sigma_\eta^4 + 2\sigma_x^2\sigma_\eta^2\right] = \frac{1}{L}\left[1 + 2\frac{\sigma_x^2}{\sigma_\eta^2}\right]\sigma_\eta^4 \\ = \frac{1}{L}[1+2\gamma]\sigma_\eta^4. \tag{11}$$

For hypothesis H_0, substituting the value $\sigma_x^2 = 0$ in Eq. (6), mean $\mu_{0,j}$ is

$$\mu_{0,j} = \sigma_\eta^2. \tag{12}$$

Again, substituting the value $\sigma_x^2 = 0$ in Eq. (7), variance $\sigma_{0,j}^2$ is

$$\begin{aligned}\sigma_{0,j}^2 &= \frac{1}{L}\left[E\left|\eta(t)\right|^4 - \left(\sigma_\eta^2\right)^2\right] \\ &= \frac{1}{L}\left[2\sigma_\eta^4 - \sigma_\eta^4\right] \\ &= \frac{1}{L}\sigma_\eta^4.\end{aligned} \tag{13}$$

Then, we can have distributions of a decision statistic under null and alternative hypotheses as in Eq. (5).

By the definition of a false alarm probability in a hypothesis testing with a decision statistic of E_j depending on T_s, and a decision threshold of λ_j, the probability of false alarm for the *j*-th SU is given by

$$\begin{aligned}P_f^j\left(T_s,\lambda_j\right) &= \Pr[E_j \geq \lambda_j \mid H_0] \\ &= Q\left(\frac{\lambda_j - \mu_{0,j}}{\sqrt{\sigma_{0,j}^2}}\right)\end{aligned} \tag{14}$$

where $Q(x)$ is the Gaussian tail function given by $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty \exp\left(-\frac{t^2}{2}\right)dt$. Form the Lemma 1, the probability of false alarm under a CSCG noise is given by

$$P_f^j\left(T_s,\lambda_j\right) = Q\left(\left(\frac{\lambda_j}{\sigma_\eta^2} - 1\right)\sqrt{T_s F_s}\right). \tag{15}$$

By the definition of a probability of detection in hypothesis testing and Lemma 1, the detection probability for the BPSK modulated primary signal under a CSCG noise for the *j*-th SU is given by

$$\begin{aligned}P_d^j\left(T_s,\lambda_j\right) &= \Pr[E_j \geq \lambda_j \mid H_1] \\ &= Q\left(\frac{\lambda_j - \mu_{1,j}}{\sqrt{\sigma_{1,j}^2}}\right) \\ &= Q\left(\left(\frac{\lambda_j}{\sigma_\eta^2} - \gamma - 1\right)\sqrt{\frac{T_s F_s}{(1+2\gamma)}}\right).\end{aligned} \tag{16}$$

The last equality is obtained by using Eq. (5).

With Eqs. (15) and (16), the probabilities of false alarm and detection for PU signal can be calculated when the duration of sensing time T_s is given.

4. Conventional Cluster-based Cooperative Spectrum Sensing

A general frame structure for conventional cluster-based cooperative spectrum sensing is shown in **Fig. 3**. With this frame structure, all local decisions are forwarded to the CHs in the scheduled SU reporting time slots and are then forwarded to the FC in the scheduled CH reporting time slots.

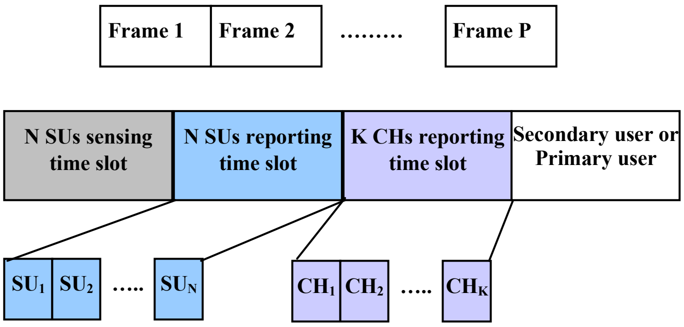

Fig. 3. A conventional cluster-based cooperative spectrum sensing scheme [16]

Lemma 2. In conventional cluster-based cooperative spectrum sensing, the N SUs in the network adopt fixed sensing time slot T_s^{con} given by

$$T_s^{con} = \frac{1}{F_s\gamma^2}\left[Q^{-1}\left(P_f^j\right) - Q^{-1}\left(P_d^j\right)\sqrt{(1+2\gamma)}\right]^2 \tag{17}$$

to sense the PU's signal with false alarm and detection probabilities of P_f^j and P_d^j, respectively.

Proof: We focus on the BPSK signal and CSCG noise. The probability of detection can be obtained with Eq. (18) by using the Eq. (17).

$$\left(\frac{\lambda_j}{\sigma_\eta^2} - \gamma - 1\right)\sqrt{\frac{T_s F_s}{(1+2\gamma)}} = Q^{-1}\left(P_d^j\right). \tag{18}$$

From Eq. (15), the probability of false alarm can be obtained with

$$\left(\frac{\lambda_j}{\sigma_\eta^2} - 1\right)\sqrt{T_s F_s} = Q^{-1}\left(P_f^j\right). \tag{19}$$

By substituting Eq. (19) into Eq. (18) and rewriting this equation, we have

$$\left(\frac{Q^{-1}\left(P_f^j\right)}{\sqrt{T_s F_s}} - \gamma\right)\sqrt{T_s F_s} = Q^{-1}\left(P_d^j\right)\sqrt{(1+2\gamma)}$$
$$Q^{-1}\left(P_f^j\right) - \gamma\sqrt{T_s F_s} = Q^{-1}\left(P_d^j\right)\sqrt{(1+2\gamma)}$$

$$\sqrt{T_s F_s} = \frac{1}{\gamma}\left[Q^{-1}\left(P_f^j\right) - Q^{-1}\left(P_d^j\right)\sqrt{(1+2\gamma)}\right]$$
$$T_s = \frac{1}{F_s \gamma^2}\left[Q^{-1}\left(P_f^j\right) - Q^{-1}\left(P_d^j\right)\sqrt{(1+2\gamma)}\right]^2 \tag{20}$$

Defining the sensing time with the last equation in (20), i.e., $T_s^{con} = T_s$, we can meet the requirement on false alarm and detection probabilities.

Because all SUs in k clusters have the same fixed sensing time slot, T_s^{con}, the sensing performance, i.e., false alarm and detection probabilities depend on SNR of a SU. Therefore, sensing performance is not improved with a fixed sensing time slot. In addition, the reporting time slot for the SU and the CH are not utilized.

5. Proposed Super-allocation and Cluster-based Cooperative Spectrum Sensing Scheme

In the conventional approach, sensing time slots, reporting time slots of SUs, and reporting time slots of CHs are strictly devided as shown in **Fig. 3**. Due to this rigid structure in the conventionanl approach, the reporting time slots of other SUs and CHs are not used for spectrum sensing. However, these reporting time slots can be used in sensing the specturm by other SUs by scheduling sensing and reporting time slots effectively. To this end, a super-allocation and cluster-based cooperative spectrum sensing scheme is proposed by increasing the sensing time slot. In the proposed scheme, each SU can obtain longer sensing time slot because the other SU reporting times and the CH reporting times are merged to the SU sensing time. Therefore, the sensing time slots for SUs in the proposed scheme can be logner than those in the conventional scheme.

Fig. 4 shows the proposed schduling method of sening and reproting time slots in the super-allocation for cluster-based cooperative spectrum sensing. In the figure, SU_{nk} means the k-th SU in the n-th cluster in the network. To explain the duration of sensing time slot for SU_{nk}, we define the durations of the sensing and reporting time for SU_{nk} with T_s^{nk} and T_r^{nk} , respectively.

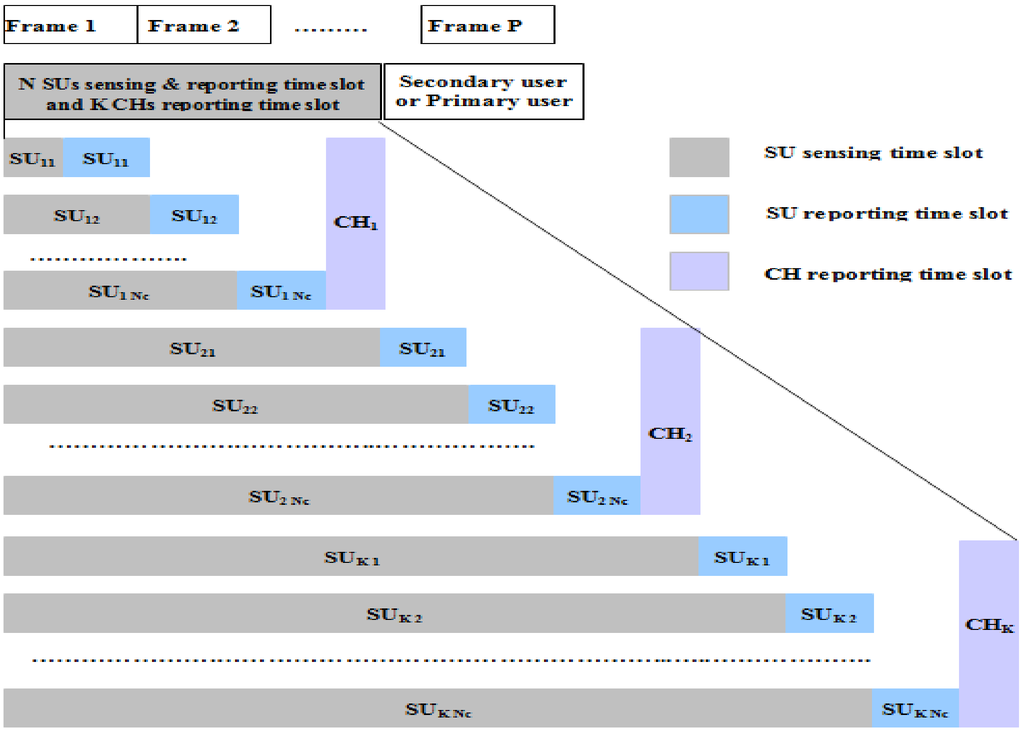

Fig. 4. A super-allocation and cluster-based cooperative spectrum sensing scheme

In this proposed scheme, the sensing time slot for the first SU in the first cluster, i.e. SU_{11}, is equal to the sensing time slot in the conventional scheme, i.e., $T_s^{11} = T_s^{con} = T_s$. Except for SU_{11}, other SUs can obtain longer sensing time slots by scheduling SU resproting slots followed by the repoting slot for the CH of that cluster. With such a schedulig method, SUs can sense the specurm during the resprting time slots of other SUs and CHs. For example, the sensing time slot of SU_{12}, T_s^{12}, is equal to the total duration of sensing time slot and the reporting time slot of the SU_{11}, i.e., $T_s^{12} = T_s + T_r^{11}$. Similarly, T_s^{13} becomes the sum of the sensing duration of SU_{12} and the reporting duration of SU_{12}, i.e., $T_s^{13} = T_s^{12} + T_r^{12} = T_s + \sum_{i=1}^{2} T_r^{1i}$. Obviously, the relationship of the sensing time slot $T_s^{1(j+1)}$ of the $SU_{1(j+1)}$ with the sensing time slot and the reporting time slot of the previous SUs can be given by

$$T_s^{1(j+1)} = T_s^{1j} + T_r^{1j} = T_s + \sum_{i=1}^{j} T_r^{1i} \tag{21}$$

for $j = 1, 2, 3, ..., N_c$.

When $T_r^{prop} = T_r^{1j}$ for $j = 1, 2, 3, ..., N_c$, the sensing time slot of j-th SU in the first cluster is written as

$$T_s^{1j} = T_s + (j-1)T_r^{prop} \tag{22}$$

Therefore, T_s^{1j} in first cluster is greater than or equal to T_s^{con}.

For SU in the other clusters, the reporting time slots of SUs in the previous clusters and that of the previous CH can be used for a sesing time slot of SUs in the current cluster. Thus, T_s^{nj} is given by

$$\begin{aligned} T_s^{nj} &= \sum_{i=1}^{n-1} T_s^{iN_c} + \sum_{i=1}^{k} T_r^{ni} \\ &= (n-1)(T_s + N_c T_r^{prop} + T_{r,CH}^{prop}) + T_s + (j-1)T_r^{prop}. \end{aligned} \tag{23}$$

Here, $T_{r,CH}^{prop}$ is the duration of the reporting time slot of a CH. Therefore, we can obtain longer sensing time as an index of CH increases.

5.1. Local Sensing

As shown in Eq. (16), the detection probability P_d^j is a function of parameters λ_j, γ and $T_s F_s$. For fixed F_s, γ and λ_j, P_d^j is a function of T_s, which can be represented as $P_d^j(T_s)$.

Lemma 3. In the proposed cluster-based cooperative spectrum sensing, the N SUs in the network adopts non-fixed sensing time slot T_s^{nk} $(\geq T_s^{con})$ in Eq. (23) to sense the PU's signal. Therefore, sensing performance is improved over the conventional scheme.

Proof: Let $P_{d(con)}^j$ and $P_{d(prop)}^{1j}$ denote the probability of detection for the conventional and proposed schemes, rspectively. When SU belongs to the first cluster, the CH reporting time slot is not included in its sesing time.

Substituting the values of T_s and T_s^{1j} in the Eq. (16), we have

$$P_{d(con)}^j\left(T_s, \lambda_j\right) = Q\left(\left(\frac{\lambda_j}{\sigma_\eta^2} - \gamma - 1\right)\sqrt{\frac{T_s F_s}{(1+2\gamma)}}\right) \tag{24}$$

$$P_{d(prop)}^{1j}\left(T_s^{1j}, \lambda_j\right) = Q\left(\left(\frac{\lambda_j}{\sigma_\eta^2} - \gamma - 1\right) \times \sqrt{\frac{\left(T_s + (j-1) \times T_r^{prop}\right) \times F_s}{(1+2\gamma)}}\right) \tag{25}$$

When the sensing time T_s^{1j} becomes longer, then the detection probability $P_{d(prop)}^j$ increases obviously. Then, we show that

$$P_{d(prop)}^{1j} \geq P_{d(con)}^j \tag{26}$$

Because $\left(T_s + (j-1) \times T_r^{prop}\right) \geq T_s^{con}$ for $j = 1, 2, 3, ..., N_c$. When $j = 1$, then we get $P_{d(prop)}^{1j} = P_{d(con)}^j$.

If SU is not inculded in the first cluser, $P_{d(prop)}^{nj}$ denotes the probability of detection for the proposed scheme. In this case, the sensing time slot includes the CH reporting time slots. Substituting the value of T_s^{nj} in the Eq. (16), we get,

$$P_{d(prop)}^{nj}\left(T_s^{nj},\lambda_j\right)=Q\left(\left(\frac{\lambda_j}{\sigma_\eta^2}-\gamma-1\right)\times\sqrt{\frac{\left((n-1)(T_s+N_cT_r^{prop}+T_{r,CH}^{prop})+T_s+(j-1)T_r^{prop}\right)\times F_s}{(1+2\gamma)}}\right). \quad (27)$$

Therefore, $P_{d(prop)}^{nj}\left(T_s^{nj},\lambda_j\right)>P_{d(con)}^{(n-1)N_c+j}\left(T_s,\lambda_j\right)$.

Each SU makes a local hard decision d_j^{hd} as follows.

$$d_{nj}^{hd}=\begin{cases}1, & if\ P_{d(prop)}^{nj}>P_{f(prop)}^{nj}\\ 0, & Otherwise\end{cases} \quad (28)$$

5.2 Cluster Decision

At the n-th CH, all local decisions d_{nj}^{hd} received from the SUs will be combined to make a cluster decision $Q_{d,n}^{prop}$ as follows:

$$Q_{d,n}^{prop}=\begin{cases}1, & \sum_{j=1}^{N_c}d_{nj}^{hd}>\xi\\ 0, & Otherwise\end{cases} \quad (29)$$

where ξ is the threshold for the cluster decision.

5.3 Global Decision

At the FC, all cluster decisions $\left(Q_{d,n}^{prop}\right)$ received will be combined to make a global decision (G) about the presence or absence of the PU signal by using a τ-out-of-K rule as follows:

$$G=\begin{cases}1, & if\ \sum_{n=1}^{K}Q_{d,n}^{prop}\geq\tau \quad :H_1\\ 0, & Otherwise \quad :H_0\end{cases} \quad (30)$$

where τ is the threshold for the global decision.

6. Simulation and Results Analysis

To evaluate the performance of the proposed spectrum sensing scheme, Monte-Carlo simulations were carried out under following conditions:

- The number of SUs is 12.
- The number of clusters is 3.
- The number of SUs in each cluster is 4.
- The durations of sensing, SU reproting, and CH reporting time slots are 1ms.
- Average SNR of each SU in a cluster is -17 dB.
- The PU signal is a BPSK signal.
- The noise in SUs is CSCG.
- The number of samples is 300.

First, the sensing performance of the proposed and conventional cluster-based schemes, in terms of receiver operating characteristic (ROC), were evaluated under a CSCG channel. In this simulation, each SU conducts local sensing using equal gain combining (EGC).

Fig. 5 and **Fig. 6**, respectively show ROC curves for the proposed cluster-based schemes, without and with cluster reporting time (RT). The proposed scheme outperforms in detection of the PU, compared with the conventional scheme bacause the proposed super-allocation can have longer sensing time the conventional one. Test statistics Eq. (25) was considered for the proposed scheme without reporting time for the cluster decision. Also, test statistics Eq. (27) was considered for the proposed scheme with reporting time for the cluster decision. When the index of the cluster increases from one to three, the detection probability is increased.

From the detection efficiency of cooperative spectrum sensing, the probability of detection is 0.8, and the probability of false alarm is 0.2. However, in the worst environment, we need the probability of detection to be more than 0.9 and the probability of false alarm to be less than 0.1. In the conventional scheme, we can achieve these sensing performance with a longer sensing time slotm but the throughput of the cognitive radio network decreases. In the proposed scheme, we can easily achieve more than 0.9 and less than 0.1 for the probabilities of detection and false alarm, respectively, because SU reporting time and CH reporting time merge to sense the PU signal without decreasing system throughput.

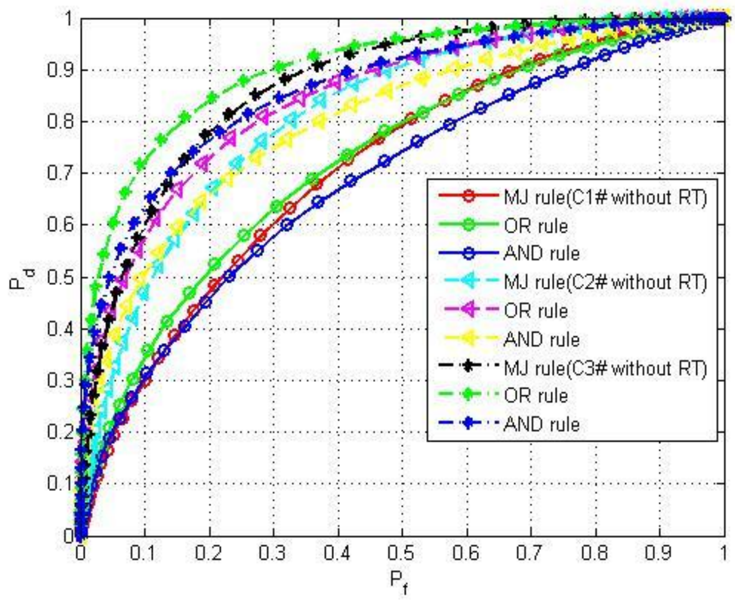

Fig. 5. ROC curves of the proposed scheme without cluster reporting time where C1#, C2# and C3# mean the first, second and third clusters

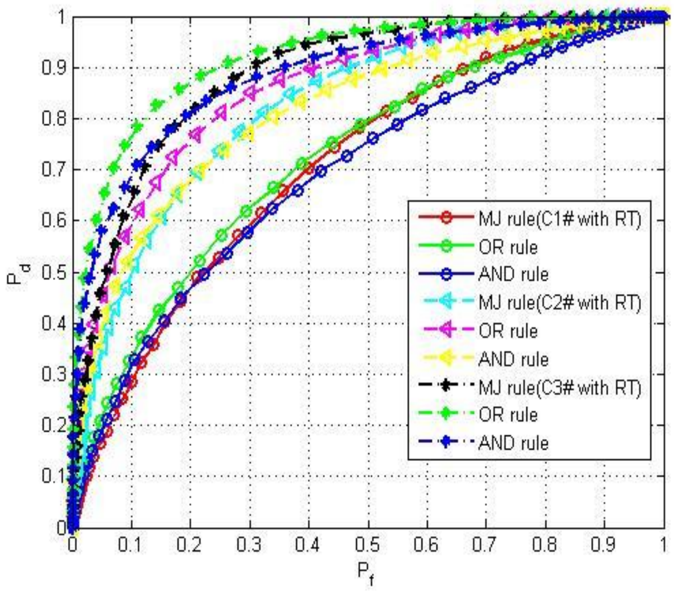

Fig. 6. ROC curves of the proposed scheme with cluster reporting time

Fig. 7 and **Fig. 8**, respectively, show ROC curves for the global decision at the FC for the proposed and conventional cluster-based schemes with and without cluster reporting time. The figures show that an OR-rule-based [25] proposed scheme can achieve the most reliable performance, with and without cluster RT, as well. Therefore, the OR-rule offers the best performances, compared with other fusion decisions (Majority-rule, AND-rule) [25]. As we can expect, the detection performance of the proposed scheme with cluster RT in **Fig. 8** is better than the proposed scheme without cluster RT in **Fig. 7**.

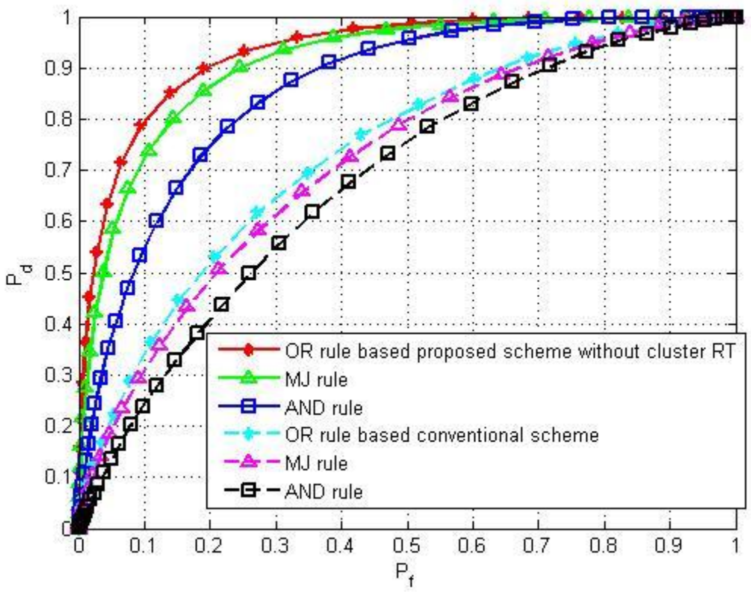

Fig. 7. ROC curves of the proposed scheme without cluster reporting time and the conventional scheme

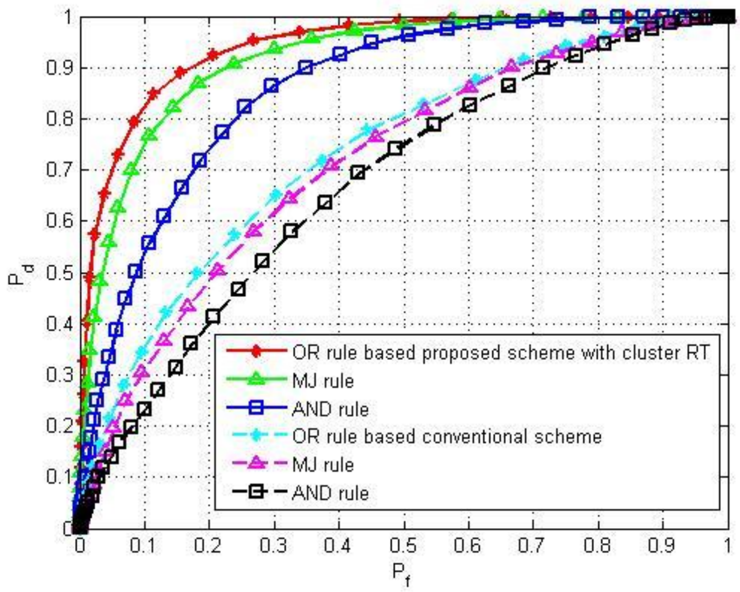

Fig. 8. ROC curves of the proposed scheme with cluster reporting time and the conventional scheme

Secondly, the simulation was carried out under conditions whereby the SNRs of the PU's signal at the nodes are from -28 to -10 dB. The ROC curves of proposed scheme without cluster reporting time and the conventional scheme are illustrated in **Fig. 9**. For our proposed scheme, it can be seen that probability of detection increases as sensing time, T_s^{nj}, increases.

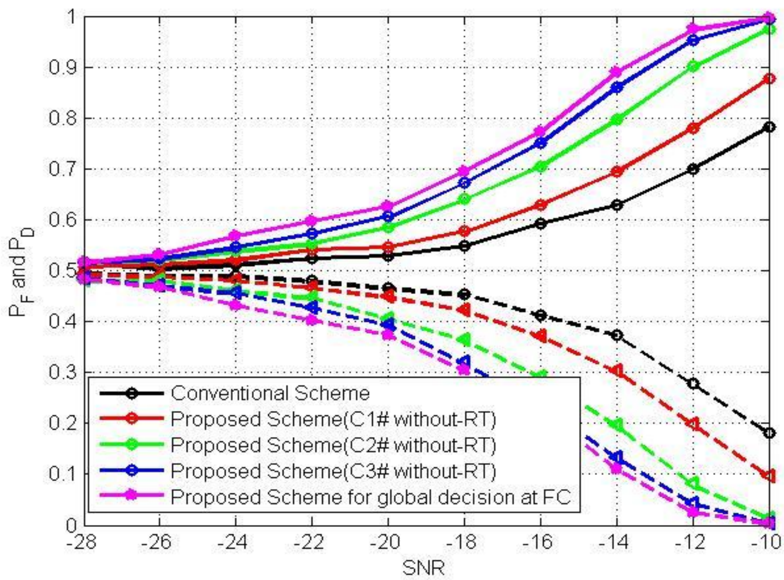

Fig. 9. ROC curves of the proposed scheme without cluster reporting time and the conventional scheme where SNRs of the PU's signal at the nodes are from -28 to -10 dB

The ROC curves of the proposed scheme with cluster reporting time versus the conventional scheme are shown in **Fig. 10**. From **Fig. 9** and **Fig. 10**, it is shown that the probability of detection in the proposed scheme with cluster reporting time is better than the proposed scheme without cluster reporting time.

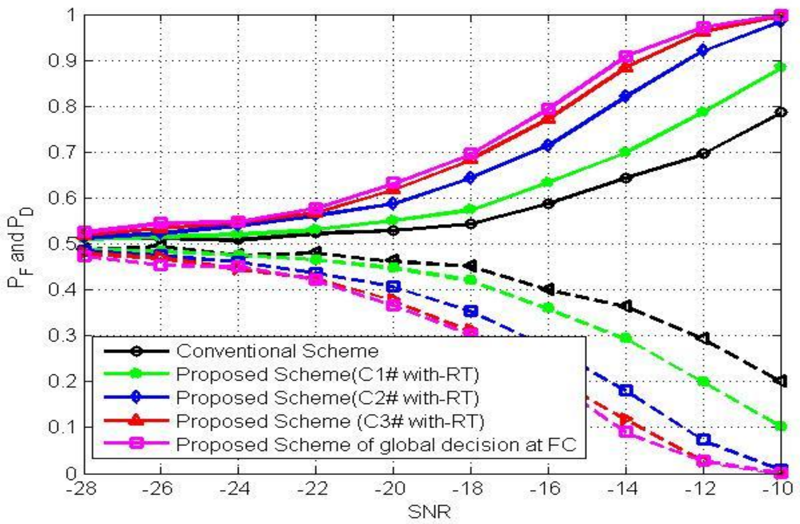

Fig. 10. ROC curves of the proposed scheme with cluster reporting time and the conventional scheme where SNRs of the PU's signal at the nodes are from -28 dB to -10 dB

In Tables 1 and 2, the exact values of detection probabilities in the proposed and conventional approaches are shown. The gain of sensing performance can be verified with the results. For example, the proposed method with a cluster reporting time can detect the spectrum with nearly 100% detection probability whereas the conventional one detects the PU's signal with 78% of detection probability in -10 dB SNR.

7. Conclusion

In this paper, we propose super-allocation and cluster-based cooperative spectrum sensing in a CR network. The proposed scheme can achieve better sensing performance in comparison with the conventional cluster-based cooperative spectrum sensing scheme. By re-scheduling the reporting time solts of SUs and CHs, a longer sensing durations are guranteed for SUs depending on the order of reporting times of SU and CH. With simulations, the gain of performance is verified.

Table 1. Probability of detection (PD) without cluster reporting time under SNR vs. number of clusters.

SNR	-28	-26	-24	-22	-20	-18	-16	-14	-12	-10
Conventional scheme	0.516	0.5042	0.5119	0.5248	0.5295	0.5487	0.5933	0.6286	0.6994	0.7825
Cluster 1	0.5073	0.5122	0.5209	0.5421	0.5473	0.5775	0.6290	0.6944	0.7810	0.8776
Cluster 2	0.5154	0.5208	0.5378	0.5533	0.5860	0.6408	0.7055	0.7973	0.9006	0.9747

Cluster 3	**0.5149**	**0.5232**	**0.5453**	**0.5737**	**0.6061**	**0.6727**	**0.7507**	**0.8605**	**0.9528**	**0.9949**
Global	**0.5160**	**0.5324**	**0.5682**	**0.5968**	**0.6264**	**0.6957**	**0.7733**	**0.8896**	**0.9734**	**0.9965**

Table 2. Probability of detection (PD) with cluster reporting time under SNR vs. number of clusters.

SNR	**-28**	**-26**	**-24**	**-22**	**-20**	**-18**	**-16**	**-14**	**-12**	**-10**
Conventional scheme	**0.516**	**0.5042**	**0.5119**	**0.5248**	**0.5295**	**0.5487**	**0.5933**	**0.6286**	**0.6994**	**0.7825**
Cluster 1	**0.5112**	**0.5170**	**0.5207**	**0.5316**	**0.5517**	**0.5743**	**0.6342**	**0.6993**	**0.7883**	**0.8835**
Cluster 2	**0.5135**	**0.5236**	**0.5407**	**0.5628**	**0.5882**	**0.6445**	**0.7153**	**0.8217**	**0.9206**	**0.9844**
Cluster 3	**0.5205**	**0.5346**	**0.5474**	**0.5684**	**0.6191**	**0.6845**	**0.7728**	**0.8849**	**0.9625**	**0.9972**
Global	**0.5261**	**0.5460**	**0.5495**	**0.5790**	**0.6327**	**0.6963**	**0.7949**	**0.9093**	**0.9722**	**0.9995**

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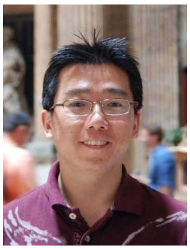

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