Opportunistic Reporting-based Sensing-Reporting-Throughput Optimization Scheme for Cooperative Cognitive Radio Networks

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Abstract

This paper proposes an opportunistic reporting-based sensing-reporting-throughput optimization scheme that maximizes the spectral efficiency of secondary users (SUs) in cooperative cognitive radio networks with a soft combining rule. The performance of cooperative spectrum sensing depends on the sensing time, the reporting time of transmitting sensing results, and the fusion scheme. While longer sensing time and reporting time improve the sensing performance, this shortens the allowable data transmission time, which in turn degrades the spectral efficiency of SUs. The proposed scheme adopts an opportunistic reporting scheme to restrain the reporting overhead and it jointly controls the sensing-reporting overhead in order to increase the spectral efficiency of SUs. We show that there is a trade-off between the spectral efficiency of SUs and the overheads of cooperative spectrum sensing. The numerical results demonstrate that the proposed scheme significantly outperforms the conventional sensing-throughput optimization schemes when there are many SUs. Moreover, the numerical results show that the sensing-reporting time should be jointly optimized in order to maximize the spectral efficiency of SUs.

Keywords: Cognitive radio, sensing-reporting optimization, cooperative spectrum sensing, opportunistic reporting

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1. Introduction

Cognitive radio (CR) is a promising technology that allows unlicensed secondary users (SUs) to sense and use any vacant licensed frequency bands of primary users (PUs) at a given time. Spectrum sensing is an important function in CR networks for SUs to opportunistically access the unused frequency bands of PUs. However, the multi-path fading and hidden terminal problem significantly deteriorate the performance of the spectrum sensing with a single SU. Recently, cooperation among multiple SUs has been extensively investigated in order to increase the sensing performance via multiuser diversity [1]–[3]. In cooperative spectrum sensing, SUs report their local sensing results to a fusion center (FC) and the FC determines the presence of a PU through combining the sensing results from SUs, where the fusion scheme to combine the sensing results can be categorized into soft combination schemes and hard combination schemes [4], [5]. In cooperative CR networks, there is a trade-off among the following three phases of SUs: sensing, reporting, and data transmission. A longer sensing and reporting time will improve the sensing performance; however, this shortens the allowable data transmission time, which degrades the throughput of the SUs. Moreover, the cooperative fusion scheme affects the throughput of SUs. In general, soft combination schemes exhibit better sensing performance than hard combination schemes (e.g. OR-rule, AND-rule, and k-out-of-N rule) [4], [6].

Many researchers have endeavored to increase the throughput of SUs in cooperative CR networks using a hard combining rule [7]–[10]. In [7] and [8], a sensing-throughput optimization (STO) problem was formulated to determine the optimal sensing time that maximizes the throughput of the SUs. However, the previous studies of [7] and [8] failed to jointly and effectively control the sensing and reporting time in order to increase the throughput of the SUs. In [9], [10], a sensing-reporting optimization (SRO) problem was investigated in order to jointly control the sensing and reporting time. The authors of [9] found the optimal division of time between the sensing time and reporting time under the assumption that the sum of the sensing time and reporting time is fixed. The authors of [10] considered the reporting time as well as the sensing time when calculating the throughput of the SUs. Other researchers have focused on fusion schemes [5], [11]–[13]. The authors of [5] considered the joint optimization of the sensing time and the weighted-based k-out-of-N fusion rule. The authors of [11] improved the sensing performance of the OR-rule based fusion scheme through differentiating the sensing time of the SUs. The authors of [12] derived the optimal voting rule for the k-out-of-N fusion scheme and optimized the detection threshold. The authors of [13] derived the optimal individual thresholds of the SUs in the OR-rule based fusion scheme. However, the above studies of [5], [7]–[13] did not attempt to increase the throughput of the SUs through reducing the reporting overhead. Moreover, they adopted a hard combination-based fusion rule, an OR-rule or a k-out-of-N rule, which exhibit lower sensing performance than the soft combination-based fusion rule.

Few studies have successfully reduced the reporting overhead in cooperative CR networks with a soft combining rule. In contrast, in cellular networks, there have been numerous studies on reducing the reporting overhead for multiuser diversity in the downlink services [14]–[17]. However, there is a key difference between cooperative CR networks and multiuser diversity cellular networks. In cellular networks with multiuser diversity, a base station selects the user who has the best channel condition among multiple users for every frame. In contrast, in cooperative CR networks, an FC combines multiple sensing results reported from the SUs.

Hence, the reporting reduction schemes proposed in the cellular networks cannot be directly applied to cooperative CR networks.

This paper proposes an opportunistic reporting-based sensing-reporting-throughput optimization (OR-SRTO) scheme that jointly controls the sensing and reporting time in order to increase the spectral efficiency of the SUs. The contribution of this paper is twofold. First, this paper extensively studies the effects of the throughput of SUs caused by the sensing time, the reporting time, and the fusion scheme. However, the previous work reported in [7]-[10] focused on finding the sensing time or the sensing-reporting time that maximizes the throughput of SUs without taking the fusion scheme into consideration. Although some groups [11]-[13] have focused on the fusion scheme in order to increase the sensing performance, they failed to find the optimal sensing-reporting time and moreover they failed to reduce the reporting overhead. Second, this paper integrates the opportunistic reporting scheme into the cooperative spectrum sensing in order to reduce the reporting overhead by allowing SUs to access the contention-based reporting channels. It also mathematically analyzes the performance of the proposed reporting scheme in the cooperative CR network with a soft combination rule. Third, this paper formulates a sensing-reporting-throughput optimization problem that determines the following parameters: the sensing time, the reporting time, and the parameters of the proposed reporting scheme.

The remainder of this paper is organized as follows: Section 2 describes the system model, where the opportunistic reporting scheme is introduced. Section 3 analyzes the sensing performance and formulates the sensing-reporting-throughput problem that determines the optimization parameters. Section 4 presents an iterative algorithm that solves the optimization problem. Section 5 analyzes the computational complexity of the proposed scheme and Section 6 presents the numerical results. Finally, Section 7 concludes the paper.

2. System Model

We consider a centralized CR network with K SUs, where a CR base station functions as an FC and each SU functions as a sensing node. SUs sense a licensed frequency of PUs. In a primary network, because a primary base station controls the transmissions of PUs, we assume that a single PU is present or absent in a primary frequency band. Hence, in the CR network that monitors a single primary band, an FC determines the presence or absence of a single PU at a primary band.

As described in **Fig. 1**, each frame in a CR network consists of a sensing duration (T_s), a reporting duration (T_r), and a data transmission duration (T_d); the frame duration is $T_f = T_s + T_r + T_d$. In the sensing duration, each SU senses the PU signal during l samples through energy detection, where the observed energy of SU k is denoted by Y_k and the PU's signal-to-noise ratio (SNR) received by SU k within the observation period is denoted by γ_k. Assuming a small-sized CR network, the γ_k values of the SUs are assumed to be independent and identically distributed (i.i.d.) [18]. The probability density function (pdf) and cumulative distribution function (cdf) of the received PU's SNR of each SU are denoted by $f_\gamma(\gamma)$ and $F_\gamma(\gamma)$, respectively.

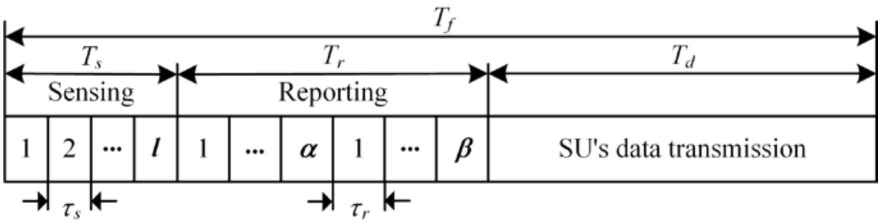

Fig. 1. Frame structure

In the reporting duration, SUs report their local sensing results to the FC. The FC determines the presence of a PU by combining the multiple sensing results from SUs, where the FC uses a maximal ratio combination (MRC)-based fusion rule [6]. In order to reduce the reporting overhead, we adopt a modified version of the opportunistic reporting scheme that has been proposed for cellular networks [16]. The reporting process consists of the dedicated reporting phase and the contention-based reporting phase. The dedicated reporting phase consists of α reporting channels and the contention-based reporting phase consists of β reporting channels, where the total number of reporting channels is limited to $\alpha + \beta \leq K$. The FC randomly selects α SUs out of K SUs and allocates the α dedicated reporting channels to the selected SUs. Hence, the randomly selected α SUs report their sensing results via their dedicated reporting channels without collision. The dedicated reporting phase guarantees that the FC can achieve at least α sensing results, which improves the sensing performance when the number of SUs is small. The other (K-α) SUs report their sensing results with a random access probability of p via β contention-based reporting channels if their observed SNRs are greater than the threshold of λ[1]. If two or more SUs simultaneously report their sensing results at a contention-based reporting channel, their messages collide. However, we assume that the FC can capture the strongest signal from the multiple received signals although multiple SUs simultaneously report their sensing results [17], [19]. When the FC receives x multiple reporting signals under a Rayleigh channel, the probability of a signal being captured is given as $\pi(x) = x/2^{x-1}$, where the derivation of the capture probability is given in the Appendix.

If the FC decides the absence of a PU at a primary band, the FC selects one SU to transmit data in the data transmission duration, where the FC can use various scheduling policies as follows: maximum rate scheduling, proportional fair scheduling, round-robin scheduling, etc. However, some scheduling policies, such as maximum rate scheduling and proportional fair scheduling, require that the CR base station obtains the channel state information from all SUs. Although this improves the system performance, it also increases the signaling overhead. A low-complexity scheduling scheme for a clustering CR network was also proposed [20]. Because the scheduling issue in the data transmission phase of the CR network is outside of the scope of this paper, we simply assume that the FC selects an SU in the data transmission phase according to the round-robin scheduling policy.

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[1] In the contention-based reporting phase, an SU may access the reporting channel several times because it does not know if the transmitted reporting message is successfully received at the FC, which deteriorates the reporting efficiency. However, it is difficult for the FC to send an acknowledgement to SUs whenever it successfully receives a reporting message at a contention-based reporting channel because of the delay between the FC and SUs. Hence, an SU may repeatedly access the contention-based reporting channels with a random access probability. Consequently, in the contention-based reporting phase, it is important to determine the parameters, p and λ, in order to decrease the collision probability and restrain the excessive access of SUs. The optimal parameters are obtained in Section 4.

3. Opportunistic Reporting-based Sensing-Reporting-Throughput Optimization Scheme

When an FC successfully receives m sensing results from SUs, the MRC-based summation at the FC is $Y = \sum_{j=1}^{m} w_j Y_j$, where Y_j is the jth received sensing result. Let γ_j denote the PU's SNR at the jth received sensing result and the set of γ_j be denoted by $\boldsymbol{\gamma}_m = \{\gamma_1, \gamma_2, \ldots, \gamma_m\}$. The weight factor can then be approximated as $w_j \approx \gamma_j / \sqrt{\sum_{i=1}^{m} \gamma_i^2}$ [6]. Given a detection probability, P_D, the false alarm probability is given as follows [21]:

$$P_f(\boldsymbol{\gamma}_m) = Q\left(Q^{-1}(P_D) \sqrt{\sum_{j=1}^{m} w_j^2 (1 + 2\gamma_j)} + \sqrt{\frac{l}{2}} \sum_{j=1}^{m} w_j \gamma_j \right), \tag{1}$$

where $Q(y) = \int_y^\infty \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$ and l is the number of samples in the sensing duration.

The probability that there are n SUs that have an observed SNR higher than λ out of $(K - \alpha)$ SUs is given as follows:

$$P(n) = \binom{K-\alpha}{n} (1 - F_\gamma(\lambda))^n F_\gamma(\lambda)^{K-\alpha-n}. \tag{2}$$

Because an FC can capture one signal among multiple received signals, the probability that one SU out of n SUs successfully reports its sensing result at each reporting channel is given as follows:

$$q_s(n) = \sum_{x=1}^{n} \binom{n}{x} p^x (1-p)^{n-x} \frac{x}{2^{x-1}}. \tag{3}$$

Then, the probability that the FC successfully receives k sensing results during β reporting channels can be expressed as follows:

$$p_s(k \mid n) = \binom{\beta}{k} q_s(n)^k (1 - q_s(n))^{n-k}. \tag{4}$$

However, because an SU does not know if the reported signal is correctly received at the FC, the SU may report its sensing result several times during the β reporting channels and the FC may receive multiple sensing results from the same SU. Hence, the probability that there are m different sensing results out of k successfully received sensing results is given as follows:

$$\varphi(k, m) = \binom{k}{m} \mathrm{suj}(k, m) / k^k, \tag{5}$$

where suj(k, m), which is the number of surjections from a k-set to an m-set, is given as follows: $\mathrm{suj}(k,m)=\sum_{i=0}^{m-1}(-1)^i\binom{m}{i}(m-i)^k$ [22]. Consequently, the probability that the FC successfully receives m different sensing results from n SUs during the β contention-based reporting channels can be expressed as follows:

$$P(n,m)=P(n)\sum_{k=m}^{\beta}p_s(k\,|\,n)\varphi(k,m)\text{, for } m\le\min(n,\beta). \tag{6}$$

When (α + m) different sensing results are successfully obtained via (α + β) reporting channels, let γ_j represent the PU's SNR in the reporting message and the set of γ_j be denoted by $\boldsymbol{\gamma}_{\alpha+m}=\{\gamma_1,\gamma_2,\ldots,\gamma_{\alpha+m}\}$, where for $1\le j\le\alpha$, γ_j denotes the PU's SNR in the reporting message obtained via α dedicated reporting channels and for $\alpha<j\le\alpha+m$, γ_j denotes the PU's SNR in the jth reporting message obtained via β contention-based reporting channels. Given that m different sensing results are successfully obtained via the β reporting channels, the conditional false alarm probability is given as follows:

$$q_f(m)=\underbrace{\int_0^{\infty}\cdots\int_0^{\infty}}_{\alpha}\underbrace{\int_{\lambda}^{\infty}\cdots\int_{\lambda}^{\infty}}_{m}P_f(\boldsymbol{\gamma}_{\alpha+m})\prod_{i=1}^{\alpha}f_\gamma(\gamma_i)\prod_{j=\alpha+1}^{\alpha+m}\frac{f_\gamma(\gamma_j)}{1-F_\gamma(\lambda)}d\gamma_1 d\gamma_2\cdots d\gamma_{\alpha+m}\ . \tag{7}$$

Consequently, the average false alarm probability can be expressed as follows:

$$\overline{P}_F=\sum_{n=0}^{K-\alpha}\sum_{m=0}^{\min(n,\beta)}P(n,m)q_f(m)\,. \tag{8}$$

Let H_0 be the hypothesis that PUs are absent and H_1 be the hypothesis that PUs are present. Because the sensing-reporting time is given by $l\cdot\tau_s+(\alpha+\beta)\cdot\tau_r$, the average spectral efficiency of an SU is given as follows:

$$\overline{R}(\boldsymbol{\chi})=\left(1-\frac{l\cdot\tau_s+(\alpha+\beta)\cdot\tau_r}{T_f}\right)\left(r_0(1-\overline{P}_F)P(H_0)+r_1(1-\overline{P}_D)P(H_1)\right), \tag{9}$$

where $\boldsymbol{\chi}$ represents the set of parameters (l, α, β, λ, p) used in the proposed opportunistic reporting scheme, r_0 is the spectral efficiency when the primary channel is idle, and r_1 is the spectral efficiency when the primary channel is busy.

The objective of CR networks is to maximize the average spectral efficiency of an SU while maintaining the detection probability under a predetermined value. Because $1-\overline{P}_D$ should be sufficiently small to protect the PUs and the parameters (r_0, $P(H_0)$) are uncontrollable, the optimization problem can be approximated as follows:

$$\max_{l,\alpha,\beta,\lambda,p}\tilde{R}(\boldsymbol{\chi})=(1-l\Delta_s-(\alpha+\beta)\Delta_r)\cdot(1-\overline{P}_F)\,. \tag{10}$$

$$\text{s.t. } l, \alpha, \beta, \lambda \geq 0$$
$$\overline{P}_D \geq \xi$$
$$0 < p \leq 1$$
$$0 < l\Delta_s + (\alpha + \beta)\Delta_r < 1$$

where $\Delta_s = \tau_s/T_f$ and $\Delta_r = \tau_r/T_f$.

4. Optimization Parameters

Because the problem of (10) is nonconvex, which is usually NP-hard, it is difficult to directly determine the optimal values of $\chi = (l, \alpha, \beta, \lambda, p)$. Hence, we iteratively determine the optimal values in single variable suboptimization problems that are decoupled from the original problem in terms of l, α, β, λ, and p.

First, given values of $(l, \alpha, \beta, \lambda)$, we determine the optimal value of p^*. Given values of $(l, \alpha, \beta, \lambda)$, the optimization problem of (10) is to minimize the average false alarm probability, $\overline{P}_F$; therefore, the optimal value of p^* is given by $\partial\overline{P}_F/\partial p = 0$. From (8), the solution of $\partial\overline{P}_F/\partial p = 0$ is identical to the solution of $\partial q_s(n)/\partial p = 0$, where

$$\frac{\partial q_s(n)}{\partial p} = \sum_{x=1}^{n} \binom{n}{x} x(x - np)\left(\frac{p}{2(1-p)}\right)^{x-1} (1-p)^{n-2}. \tag{11}$$

The solution of the above equation is given by $p = 2/n$. However, because the value of n fluctuates for every frame and the FC cannot precisely estimate this, we approximate the optimal value of p^* based on the distribution of the observed SNRs, as follows:

$$p^* = \min\left(\frac{2}{(K-\alpha)(1-F_\gamma(\lambda))}, 1\right). \tag{12}$$

Let the functions $f_1(\chi)$ and $f_2(\chi)$ respectively represent $f_1(\chi) = 1 - l\Delta_s - (\alpha+\beta)\Delta_r$ and $f_2(\chi) = 1 - \overline{P}_F$; therefore, $\tilde{R}(\chi) = f_1(\chi) f_2(\chi)$.

Lemma 1: (with respect to l). *For other given parameters $(\alpha, \beta, \lambda, p)$, the function $\tilde{R}(\chi)$ is a concave function with respect to l.*

Proof: We define the discrete derivative of a function $f(x)$ as follows: for the first forward difference, $\Delta f(x) = f(x+h) - f(x)$, and for the second forward difference, $\Delta^2 f(x) = f(x + 2h) + f(x) - 2f(x + h)$.

For simplicity of notation, we use $f_1(l)$ and $f_2(l)$ instead of $f_1(\chi)$ and $f_2(\chi)$, respectively. For $l' = l + h > l$, we have

$$\Delta f_1(l) = f_1(l') - f_1(l) = -h\Delta_s < 0 \tag{13}$$
$$\Delta^2 f_1(l) = f_1(l+2h) + f_1(l) - 2 f_1(l+h) = 0. \tag{14}$$

Moreover, we have

$$\begin{aligned}\Delta f_2(l) &= f_2(l') - f_2(l) \\ &= -\left[\overline{P}_F(l') - \overline{P}_F(l)\right] \\ &= -\sum_{n=0}^{K-\alpha}\sum_{m=0}^{\min(n,\beta)} P(n,m)\left\{\underbrace{q_f(m \mid l') - q_f(m \mid l)}_{\equiv \Delta q_f(m|l)}\right\}.\end{aligned} \tag{15}$$

In (15), $\Delta q_f(m \mid l)$ is less than 0, as follows:

$$\begin{aligned}\Delta q_f(m \mid l) = &\underbrace{\int\cdots\int}_{\alpha+m} \underbrace{\left\{P_f(\boldsymbol{\gamma}_{\alpha+m}; l') - P_f(\boldsymbol{\gamma}_{\alpha+m}; l)\right\}}_{<\ 0,\text{ because } Q(l) \text{ of (1) is a decreasing function w.r.t. } l} \\ &\times \prod_{i=1}^{\alpha} f_\gamma(\gamma_i) \prod_{j=\alpha+1}^{\alpha+m} \frac{f_\gamma(\gamma_j)}{1-F_\gamma(\lambda)} d^{\alpha+m}\boldsymbol{\gamma}_{\alpha+m} < 0.\end{aligned} \tag{16}$$

where $\boldsymbol{\gamma}_{\alpha+m}$ represents the $(\alpha+m)$-tuple $(\gamma_1, ..., \gamma_{\alpha+m})$ and $d^{\alpha+m}\,\boldsymbol{\gamma}_{\alpha+m}$ is the $(\alpha+m)$-dimensional differential. Hence, we have $\Delta f_2(l) > 0$. Additionally, $\Delta^2 f_2(l) < 0$ because $P_f(\boldsymbol{\gamma}_{\alpha+m}; l)$ is a function of $Q(l)$ in (1), as follows:

$$\begin{aligned}\Delta^2 f_2(l) &= f_2(l+2h) + f_2(l) - 2f_2(l+h) \\ &= \underbrace{\left\{f_2(l'+h) - f_2(l')\right\}}_{>0} - \underbrace{\left\{f_2(l+h) - f_2(l)\right\}}_{>0} \\ &= \Delta f_2(l') - \Delta f_2(l) < 0\end{aligned} \tag{17}$$

Consequently,

$$\Delta^2\left(f_1(l)f_2(l)\right) = \underbrace{\Delta^2 f_1(l)}_{=0} f_2(l) + 2\underbrace{\Delta f_1(l)}_{<0}\underbrace{\Delta f_2(l)}_{>0} + \underbrace{f_1(l)}_{0<.f_1(l)<1}\underbrace{\Delta^2 f_2(l)}_{<0} < 0. \tag{18}$$

Hence, because $\Delta^2(f_1(l)f_2(l)) < 0$, $f_1(l)f_2(l)$ is a concave function with respect to l. ■

Lemma 2: (with respect to β). *For other given parameters (l, α, λ, p), the function* $\tilde{R}(\boldsymbol{\chi})$ *is a concave function with respect to* β*.*

Proof: For simplicity of notation, we use $f_1(\beta)$ and $f_2(\beta)$ instead of $f_1(\boldsymbol{\chi})$ and $f_2(\boldsymbol{\chi})$, respectively.

For $\beta' = \beta + h > \beta$, we have

$$\Delta f_1(\beta) = f_1(\beta') - f_1(\beta) = -h\Delta_r < 0 \tag{19}$$

$$\Delta^2 f_1(\beta) = f_1(\beta+2h) + f_1(\beta) - 2f_1(\beta+h) = 0. \tag{20}$$

Moreover, we have $\Delta f_2(\beta) = \overline{P}_F(\beta) - \overline{P}_F(\beta') > 0$ because the false alarm probability decreases as the number of reporting channels increases. Additionally, $\Delta^2 f_2(l)$ = $\Delta f_2(l') - \Delta f_2(l) < 0$ because $\Delta f_2(l) > \Delta f_2(l') > 0$.

Consequently,

$$\Delta^2\left(f_1(\beta) f_2(\beta)\right) = \Delta^2 f_1(\beta) f_2(\beta) + 2\Delta f_1(\beta)\Delta f_2(\beta) + f_1(\beta)\Delta^2 f_2(\beta) < 0 \tag{21}$$

Hence, $f_1(\beta)f_2(\beta)$ is a concave function with respect to β. ■

Lemma 3: (with respect to λ). *For other given parameters (l, α, β, p), the function $\tilde{R}(\chi)$ is a quasiconcave function with respect to λ.*

Proof: In (8), the average false alarm probability of $\overline{P}_F$ depends on two parameters, (m, γ_m), where m is the number of different sensing results at the FC and γ_m is the PU's SNR list of m different sensing results. Moreover, we have

$$\begin{aligned} \overline{P}_F &= \sum_{n=0}^{K-\alpha} \sum_{m=0}^{\min(n,\beta)} P(n,m) q_f(m) \\ &< P(n=0, m=0) q_f(m=0) \\ &= P(n=0, m=0) \int_0^{\infty} \cdots \int_0^{\infty} P_f(\gamma_\alpha) d^\alpha \gamma_\alpha, \end{aligned} \tag{22}$$

where γ_α is the PU's SNR list of the sensing results obtained via α dedicated reporting channels.

Let n denote the number of SUs that have an observed SNR higher than λ. Then, in (2), the expected value of n is a decreasing function with respect to λ, as follows:

$$E(n) = (K-\alpha)(1 - F_\gamma(\lambda)). \tag{23}$$

That is, as the value of λ increases, the number of SUs that have an observed SNR higher than λ decreases. Hence, the values of the distribution of m decrease as the value of λ increases.

Moreover, in (1), the false alarm probability of $P_f(\gamma_m)$ is a decreasing function with respect to the parameters, (m, γ_m), because $Q(\bullet)$ is a decreasing function with respect to the parameters, (m, γ_m). As the value of λ increases, the values of the distribution of γ_m increase because only the SUs that have an observed SNR higher than λ are allowed to report their sensing results.

Consequently, as the value of λ increases, the values of the distribution of γ_m increase but the values of the distribution of m decrease. However, if the value of n is sufficiently large, the average false alarm probability $\overline{P}_F$ decreases as the value of λ increases because the value of m is dynamically controlled due to the random access probability of each SU. Whereas, if the value of n is sufficiently small, the average false alarm probability $\overline{P}_F$ approaches $\lim_{n\to 0} \overline{P}_F = \int_0^{\infty} \cdots \int_0^{\infty} P_f(\gamma_\alpha) d^\alpha \gamma_\alpha$. Hence, from (22), the average false alarm probability $\overline{P}_F$ is a quasiconvex function with respect to λ. Consequently, $\tilde{R}(\chi)$ in (10) is a quasiconcave function with respect to λ.

From Lemmas 1, 2, and 3, given a value of p^*, we can iteratively determine the optimal values of (l^*, α^*, β^*, λ^*) using the bisection search method or the Golden section method in the four single variable suboptimization problems that are decoupled from the original problem in terms of l, α, β, and λ [23]. The proposed iterative algorithm is summarized in Algorithm 1.

Algorithm 1 Find the optimal parameters $\chi^* = (l^*, \alpha^*, \beta^*, \lambda^*, p^*)$ that maximize $\tilde{R}(\chi)$

initialize

$i \leftarrow 0$ // iteration count

$l^{(i)} \leftarrow 1$, $\alpha^{(i)} \leftarrow 1$, $\beta^{(i)} \leftarrow 0$, $\lambda^{(i)} \leftarrow 0$

repeat

1. Given $(\alpha^{(i)}, \lambda^{(i)})$, find p^* from (12).
2. Given $(\alpha^{(i)}, \beta^{(i)}, \lambda^{(i)}, p^*)$, find l^* that maximizes $\tilde{R}$ from l = 1 to $\left\lfloor \frac{1-(\alpha^{(i)}+\beta^{(i)})\Delta_r}{\Delta_s} \right\rfloor$ using the Golden section method.
3. Given $(l^*, \beta^{(i)}, \lambda^{(i)}, p^*)$, find α^* that maximizes $\tilde{R}$ from $\alpha = 0$ to $\left\lfloor \frac{1-l^*\Delta_s}{\Delta_r} - \beta^{(i)} \right\rfloor$ using the Golden section method.
4. Given $(l^*, \alpha^*, \lambda^{(i)}, p^*)$, find β^* that maximizes $\tilde{R}$ from $\beta = 0$ to $\left\lfloor \frac{1-l^*\Delta_s}{\Delta_r} - \alpha^* \right\rfloor$ using the Golden section method.
5. Given $(l^*, \alpha^*, \beta^*, p^*)$, find λ^* that maximizes $\tilde{R}$ from λ = -15 dB to -5 dB using the Golden section method.
6. Update: $l^{(i+1)} \leftarrow l^*$, $\alpha^{(i+1)} \leftarrow \alpha^*$, $\beta^{(i+1)} \leftarrow \beta^*$, $\lambda^{(i+1)} \leftarrow \lambda^*$, $p^{(i+1)} \leftarrow p^*$, and $i \leftarrow i + 1$.

until $|\tilde{R}(\chi^{(i)}) - \tilde{R}(\chi^{(i-1)})| \leq \varepsilon$

return $\chi^* = (l^*, \alpha^*, \beta^*, \lambda^*, p^*)$

5. Complexity Analysis

The computational complexity can be classified into two complexities, O_1 and O_2, where O_1 is the calculation complexity to calculate the average spectral efficiency from (9) given optimization parameters; and O_2 is the search complexity to find the optimization parameters. Let $[x]$ denote the range of x (or the cardinality of the set of x), e.g., if $x \in \mathbf{X} = \{1, 2, ..., 10\}$, $[x] = |\mathbf{X}| = 10$.

- Complexity of O_1: From (9), the average spectral efficiency of an SU is dependent on calculating the false alarm probability. To calculate the multi-fold integration in (7), we reduce the multiple integral to an iterated integral (i.e., a series of integrals of one variable) and use a trapezoidal rule for approximating each definite integral. The computational complexity of (7) can then be denoted by $O([\gamma]^{\alpha+m})$ and the computational complexity of (6) can be approximated as $O(\beta)$. Hence, from (8) and (9), given the parameter set of χ, the computational complexity of O_1 can be simplified as $O_1 = O((K\text{-}\alpha)\bullet\beta^2\bullet[\gamma]^{\alpha+\beta})$.
- Complexity of O_2: The search complexity to find the optimization parameters of χ is dependent on the iterative search algorithm. For simplicity of the complexity analysis, we

consider a naive exhaustive search method to find the optimal parameters and moreover we focus on the number of iterations to find the parameters. Assuming that the optimal parameters are iteratively and independently found, the search complexity is given by $O_2 = O([l]\bullet[\alpha]\bullet[\beta]\bullet[\lambda])$.

The FC periodically finds the optimal parameters of χ and broadcasts the parameters to SUs. However, the FC does not have to calculate and broadcast for every frame. The parameters vary depending on the number of cooperative SUs. Because the number of cooperative SUs slowly varies in comparison with the frame duration, the FC may lessen the computational complexity and reduce the effect of the signaling overhead on the throughput of SUs.

6. Numerical Results

We evaluate the average spectral efficiency of an SU under the constraint of a detection probability of $\xi = 0.9$. The PU's SNR is independent and identically Rayleigh distributed with $f_\gamma(\gamma) = 1/\bar{\gamma}\exp(-\gamma/\bar{\gamma})$, where $\bar{\gamma} = -10$ dB. The other simulation parameters are as follows: $P(H_0) = 0.8$, $P(H_1) = 0.2$, $r_0 = 2.6$ bps/Hz, $r_1 = 1.9$ bps/Hz, $\Delta_s = 0.002$, and $\Delta_r = 0.01$.

Fig. 2 to **4** present the average spectral efficiency of an SU for each l, β, and λ in the proposed OR-SRTO scheme, where we verify the convexity of the average spectral efficiency of an SU in Lemmas 1 and 2. **Fig. 2** presents the average spectral efficiency, the sensing overhead, and the average false alarm probability as the value of l increases, where the other parameters are fixed at $\alpha = 5$, $\beta = 10$, and $\lambda = -8$ dB. As the value of l increases, the average false alarm probability decreases whereas the sensing time overhead linearly increases. Hence, as expected from Lemma 1, the figure illustrates that the average spectral efficiency of an SU is concave with respect to l. Moreover, the figure demonstrates that the number of sensing time samples that maximizes the average spectral efficiency should decrease as the number of SUs increases in order to reduce the sensing overhead.

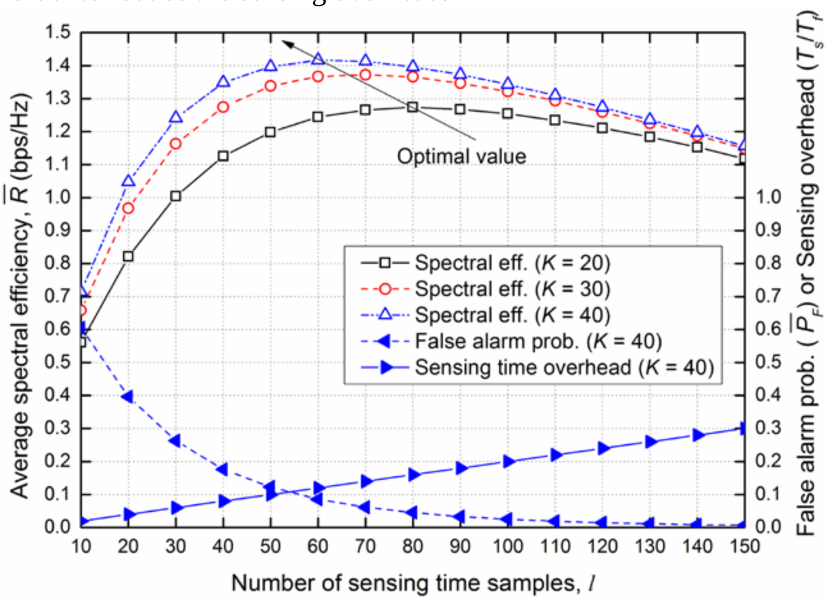

Fig. 2. The average spectral efficiency, sensing time overhead, and average false alarm probability plotted against the sensing time

Fig. 3 presents the average spectral efficiency of an SU as the number of the contention-based reporting channels increases, where the other parameters are fixed at l = 60, α = 5, and λ = -8 dB. As expected from Lemma 2, the figure demonstrates that the average spectral efficiency of an SU is concave with respect to β. When the value of β is fixed, as the number of SUs increases, the average spectral efficiency of an SU increases due to the multiuser diversity.

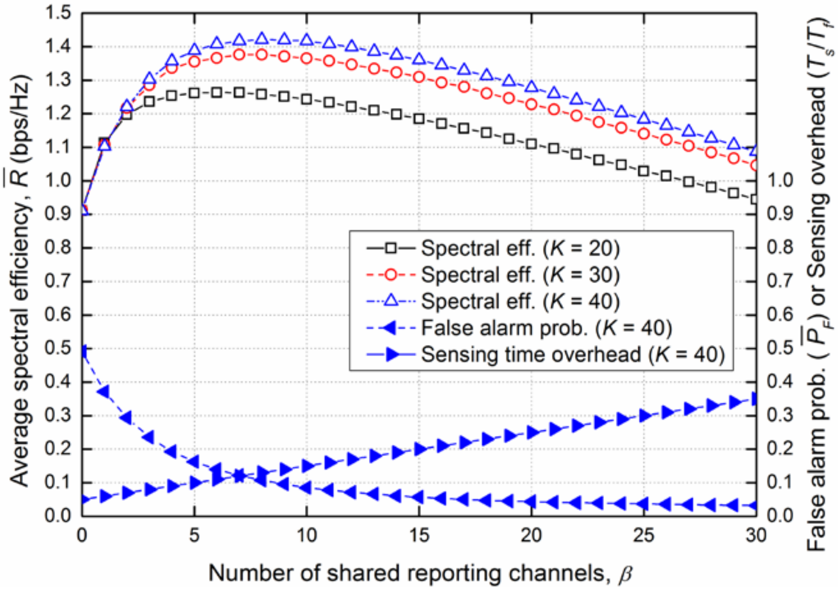

Fig. 3. The average spectral efficiency, sensing time overhead, and average false alarm probability plotted against the number of reporting channels

Fig. 4 presents the average spectral efficiency of an SU as the access threshold of λ increases, where the other parameters are fixed at l = 60, α = 5, and β = 10. A higher threshold enables the FC to receive sensing results with higher SNR values via the shared reporting channels. Hence, as the value of λ increases, the average false alarm probability decreases and the average spectral efficiency increases. However, an excessively high threshold significantly reduces the number of SUs that can access the shared reporting channels. Therefore, as the value of λ increases above a critical value, e.g. -9.5 dB when K = 20, -8.5 dB when K = 30, and -7.5 dB when K = 40 under this simulation environment, the average spectral efficiency of the SU rapidly deteriorates. The figure also demonstrates that the threshold of λ should be increased as the number of SUs increases in order to increase the multiuser diversity gain. Consequently, the selection of the appropriate threshold of λ is important because the threshold-based opportunistic reporting may statistically bias the performance of the fusion scheme.

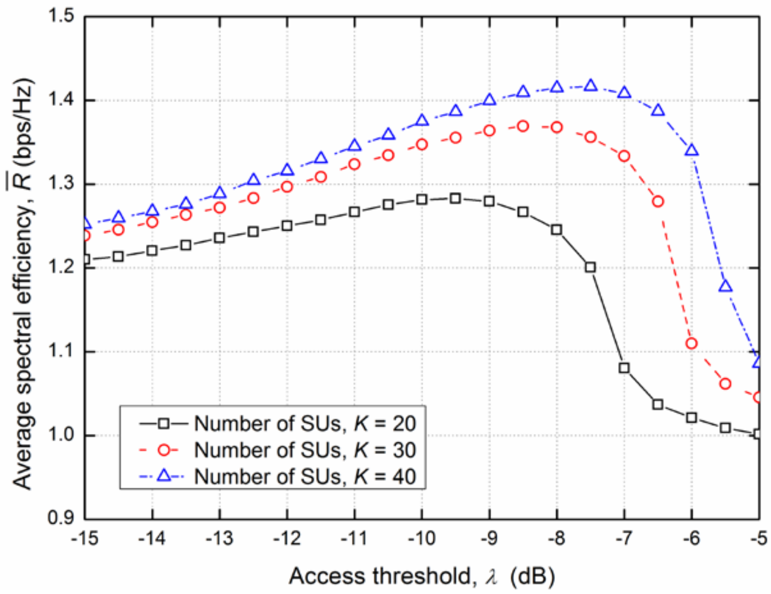

Fig. 4. The average spectral efficiency vs. the threshold of λ

Fig. 5 presents the average spectral efficiency of an SU according to the number of SUs in the following four cooperative spectrum sensing schemes: (i) a conventional STO scheme, where the sensing time is optimally adjusted in order to maximize the spectrum efficiency of an SU but the reporting time linearly increases with the number of SUs [7]; (ii) a conventional sensing-reporting-throughput optimization (SRTO) scheme, where the sensing time and number of reporting SUs are jointly controlled in order to maximize the spectrum efficiency of an SU [10], [12]; (iii) an opportunistic reporting-based throughput optimization (OR-TO) scheme, where the FC uses a fixed number of contention-based reporting channels shared by all SUs while the sensing time is fixed; and (iv) the proposed OR-SRTO scheme, where the sensing time and reporting time are jointly controlled and the FC dynamically uses both dedicated reporting channels and shared reporting channels. **Fig. 5** demonstrates that the proposed OR-SRTO scheme outperforms the other schemes. The STO scheme has a concave plot because many SUs make excessive reporting overheads that shorten the allowable data transmission. As the number of SUs increases, the SRTO scheme increases the average spectral efficiency and then maintains the average spectral efficiency for K = 15 because it controls the number of reporting SUs. The OR-TO scheme with the fixed sensing time exhibited the worst performance when the number of SUs was low as a result of the collision due to the shared reporting channels and the fixed sensing time. However, because the contention-based reporting scheme increases the multiuser diversity with the number of SUs, the average spectral efficiency increases as the number of SUs increases. The multiuser gain is low when the number of SUs is low and it is high when the number SUs is high. Therefore, in the OR-TO scheme, when the number of SUs is low, the sensing time should be increased in order to increase the sensing accuracy of the SUs, and when the number of SUs is high, the sensing time should be decreased in order to reduce the sensing overhead. The proposed OR-SRTO scheme increases the average spectral efficiency of an SU as the number of SUs increases through efficiently controlling the sensing and reporting time. When the number of SUs is 50, the proposed OR-SRTO scheme increases the average spectral efficiency by approximately 62 %**,** 10 %, and 5 %, in comparison with the STO, SRTO, and OR-TO (l = 110) schemes, respectively.

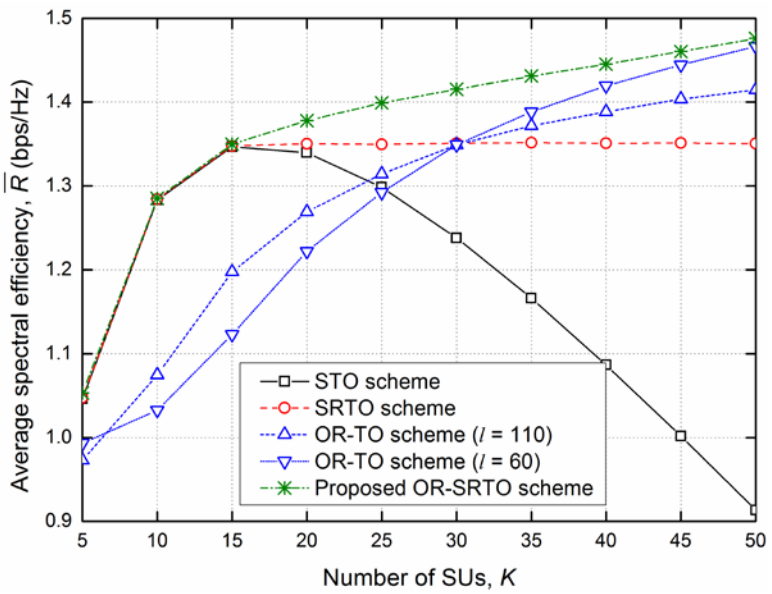

Fig. 5. The average spectral efficiency vs. the number of SUs according to the cooperative spectrum schemes

7. Conclusion

This paper proposed an opportunistic reporting-based sensing-reporting-throughput optimization scheme for cooperative cognitive radio networks and compared the average spectral efficiency of the proposed scheme with that of the conventional cooperative spectrum sensing schemes. In particular, we have demonstrated that the sensing time and reporting time should be adjusted together in order to increase the spectral efficiency of an SU and that it is important to restrain the reporting overhead as the number of secondary users increases. When there are 50 secondary users, the proposed scheme increases the average spectrum efficiency by approximately 62 % and 10 % in comparison with the conventional sensing-throughput and sensing-reporting-throughput optimization schemes, respectively. In the proposed scheme, in order to determine the optimal parameters of a mixed integer nonconvex optimization problem, we have applied an iterative algorithm that solves the problem by dividing it into four single variable suboptimization problems, where each suboptimization problem was proven to be concave or quasiconcave.

Appendix

Derivation of the capture probability, $\pi(x)$

The capture probability of $\pi(x)$ is the probability that one signal is captured given that x SUs report signals in one reporting channel. Let t_k be the received signal power at the FC from the kth SU. $\{t_k\}$ is assumed to be i.i.d. [17]. Let $f(t)$ and $F(t)$ be the pdf and cdf of $\{t_k\}$, respectively. $\pi(x)$ can then be expressed as follows [Eq. (11) of [17]]:

$$\pi(x) = \begin{cases} 0, & \text{if } x = 0 \\ 1, & \text{if } x = 1 \\ x\int_0^\infty (1 - F(t)) f^{(x-1)}(t)dt, & \text{if } x \geq 2, \end{cases} \tag{24}$$

where $f^{(x)}(t)$ is x-fold convolution of $f(t)$, i.e., $f^{(x)}(t) = \int_0^t f^{(x-1)}(y) f(t-y)dy$.

Under Rayleigh fading, we assume $f(t) = a\exp(-at)$ and $F(t) = 1 - \exp(-at)$, where $1/a$ is the average value of t_k. From [Eq. (6) of [24]], the x-fold convolution can be represented as follows: $f^{(x)}(t) = a^x e^{-at}\psi_x(t)$, where $\psi_x(t) = \dfrac{t^{x-1}}{(x-1)!}$. For $x \geq 2$, we can then formulate as follows:

$$\begin{aligned} \pi(x) &= x\int_0^\infty (1 - F(t)) \cdot f^{(x-1)}(t)dt \\ &= x\int_0^\infty e^{-at} \cdot \frac{a^{x-1}}{(x-2)!} e^{-at} t^{x-2} dt \\ &= x\frac{a^{x-1}}{(x-2)!} \times \int_0^\infty t^{x-2} e^{-2at} dt \end{aligned}$$

Let $u(t) = t^{x-2}$ and $v'(t) = e^{-2at}$. From integration by parts, i.e., $\int u(t)v'(t)dt = u(t)v(t) - \int u'(t)v(t)dt$, we obtain

$$= x\frac{a^{x-1}}{(x-2)!} \times \left\{ \underbrace{-\frac{1}{2a} t^{x-2} e^{-2at} \Big|_0^\infty}_{=0} - \frac{(x-2)}{-2a} \int_0^\infty t^{x-3} e^{-2at} dt \right\}$$

Let $u(t) = t^{x-3}$ and $v'(t) = e^{-2at}$. By applying integration by parts again, we obtain

$$= x\frac{a^{x-1}}{(x-2)!} \times \frac{(x-2)}{2a} \times \left\{ \underbrace{-\frac{1}{2a} t^{x-3} e^{-2at} \Big|_0^\infty}_{=0} - \frac{(x-3)}{-2a} \int_0^\infty t^{x-4} e^{-2at} dt \right\}$$

By applying integration by parts repeatedly, we finally obtain

$$\begin{aligned} &= x\frac{a^{x-1}}{(x-2)!} \times \frac{(x-2)(x-3)\cdots 1}{(2a)^{x-1}} \\ &= \frac{x}{2^{x-1}}. \end{aligned}$$

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