Optimal Energy-Efficient Cooperative Spectrum Sensing in Cognitive Radio Networks

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Abstract. *Inspired by the green communication trend of next-generation wireless networks, we select energy-efficient throughput as optimization metric for jointly optimizing sensing time and working sensors in cooperative cognitive radio networks. Specifically, an iterative algorithm is proposed to obtain the optimal values for these two parameters. Specifically, the proposed iterative algorithm is low complexity when compares to the exhaustive search method, and very easy to be implemented. Finally, simulation results reveal that the proposed optimization improves the energy-efficient throughput significantly when the sensing time and working sensors are jointly optimized.*

Keywords

Energy-efficiency (EE), cognitive radio networks, cooperative spectrum sensing.

1. Introduction

In the past ten years, we have witnessed a dramatic growth in wireless communication due to the popularity of smart phones and other mobile devices. Meeting this huge demand for bandwidth is a challenge since most easily usable spectrum bands have been allocated. To address this issue, cognitive radio (CR) [1]-[4], firstly coined by J. Mitola, is widely viewed as a disruptive technology that can radically improve both spectrum efficiency and utilization.

One of the great challenges of implementing spectrum sensing is the hidden terminal problem, which occurs when the cognitive radio is shadowed, in severe multipath fading or inside buildings with high penetration loss, while a primary user (PU) is operating in the vicinity [5]. Therefore, a non-cooperative spectrum sensing algorithm may not work well in this case, and a cooperative spectrum sensing scheme can solve the problem by sharing the spectrum sensing information among secondary users (SU). Specifically, there are several advantages offered by cooperative spectrum sensing over the non-cooperative ones [6]-[7].

Although sensing accuracy can be improved through the use of cooperative sensing, the need for additional time for collection of local test statistics is inevitable, particularly with a large number of SUs. The added time prevents fast detection of the PU, which results in interference to the PU during the reporting time [8]-[12]. Therefore, recent research has focused on reducing the reporting time in cooperative sensing. Zhao et al. developed a Bayesian formulation for the quickest detecting mechanism based on a decision-theoretic framework [8]. Zhang et al. proposed an efficient cooperative sensing algorithm that minimizes the required number of secondary users [9]. Li et al. proposed a random broadcast scheme without any control or coordination mechanism, in which the broadcast probability is iteratively obtained to reduce detection delay [10]. Zou et al. presented a cooperative sequential detection scheme that reduces the sensing time by determining whether to stop making a measurement for each time slot [11]. G. Noh et al. proposed a scheme that controls the reporting order of the local test statistics to reduce the reporting time [12]. Young-June Choi et al. studied the overhead-throughput tradeoff in cooperative cognitive radio networks, and maximized the throughput under the detection probability constrain [13].

However, all the above-mentioned works select either throughput or overhead as optimization metric. To the best of our knowledge, exponentially increasing data traffic and demand for ubiquitous access have triggered a dramatic expansion of network infrastructure, which comes at the cost of rapidly increasing energy consumption and a considerable carbon footprint of the mobile communications industry. Therefore, increasing the energy-efficiency (EE) in cellular networks has become an important and urgent task. As such, we investigate the issue of how to achieve the maximum EE throughput in cooperative cognitive radio networks from the perspective of EE. Specifically, The sensing-sensors tradeoff problem under a cooperative sensing scenario is formulated to find a pair of sensing time and number of sensors that maximize the cognitive radio's EE throughput subject to sufficient protection that is provided to the PU.

The main contributions of this paper are twofold. Firstly, different from the previous cooperative spectrum

[1]In this paper, we focused on the optimization of optimal number of working sensors. As such, how to select the sensors is not in scope of this paper.

sensing (CSS), which adopt either throughput or overhead as optimization metric, our CSS scheme uses EE as our metric. Moreover, we select part of the secondary users to participate in detecting the PU's activity[1], and a more practical frame structure is considered. Secondly, we jointly optimize the sensing time and number of working sensors subject to sufficient protection of the PU. Moreover, we propose an iterative algorithm with low complexity to solve it effectively.

The remainder of this paper is organized as follows. Section II briefly describes the system model. Section III proposes an iterative algorithm to derive the optimal sensing time and number of working sensors. The numerical results are presented and discussed in Section IV, and our conclusion remarks are offered in Section V.

2. System Model

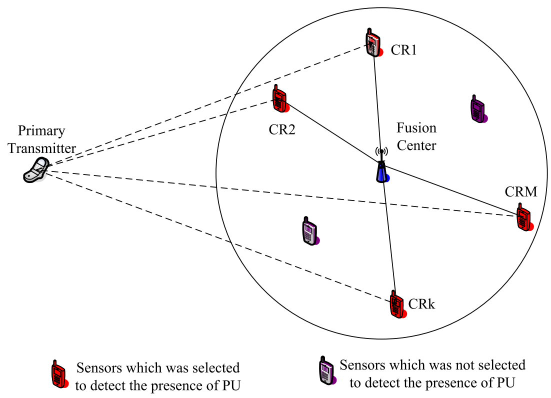

Fig. 1. System model.

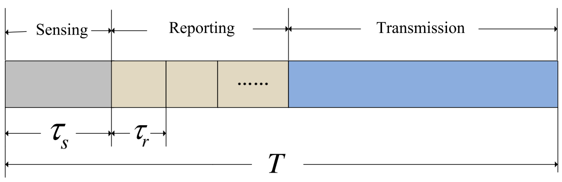

Fig. 2. Frame Structure.

We consider a cognitive radio system that consists of a fusion center and M secondary users (SUs). The SUs are deployed to detect the activity of a primary user (PU) on a given spectrum band, as shown in Fig. 1. Each working SU receives the primary signal with an instant signal-to-noise ratio (SNR) γ_i. Similar to [14], we assume that the distances between any SUs are small compared to the primary transmitter. Therefore, it is assumed that each channel gain is Rayleigh-distributed with same variance and the average received SNR is same at each sensor. Consider that each of the SUs employ an energy detector and measure their received powers during the sensing period. We assume that primary signal is a complex-valued phase-shift keying signal. As such, the probability of detection and probability of false alarm at each SU are approximated as

$$p_{d,j}(\tau_s) = Q\left(\left(\frac{\varepsilon}{\sigma^2} - \gamma - 1\right)\sqrt{\frac{\tau_s f_s}{2\gamma+1}}\right), \quad j = 1,2,...,M, \tag{1}$$

and

$$p_{f,j}(\tau_s) = Q\left(\left(\frac{\varepsilon}{\sigma_u^2} - 1\right)\sqrt{\tau_s f_s}\right), \quad j = 1,2,...,M \tag{2}$$

where ε denotes the threshold parameter of the energy detector at the SU, σ_u^2 represents the variance of additive white Gaussian noise (AWGN), τ_s and f_s denote the sensing time and sampling frequency, respectively, $Q(.)$ is the right-tail probability of a normalized Gaussian distribution.

Frame structure used in this paper is illustrated in Fig. 2. As it is clearly shown in Fig. 2, at the beginning, the working sensors spend τ_s time to perform spectrum sensing. After spectrum sensing, the working sensors report their sensing results to the fusion center. Each sensor will consume τ_r time overhead. The fusion center will merge a final decision according to the "OR" rule after collecting all the sensing information.

In cooperative spectrum sensing, local sensing information are reported to the fusion center and merged into one final decision according to some fusion rule. In this paper, we adopt the simple logic "OR" rule. By performing the "OR" rule, the probabilities of false alarm Q_f and detection Q_d for cooperative sensing are then formulated as follows

$$Q_d(k,\tau_s) = 1 - \prod_{j=1}^{k}\left(1 - p_{d,j}(\tau_s)\right) = 1 - \left(1 - p_d(\tau_s)\right)^k, \tag{3}$$

and

$$Q_f(k,\tau_s) = 1 - \prod_{j=1}^{k}\left(1 - p_{f,j}(\tau_s)\right) = 1 - \left(1 - p_f(\tau_s)\right)^k \tag{4}$$

where k is the number of the working sensors to report the sensing results. This scheme shows that when k increases, Q_d will increase and as a consequence the accuracy of the PU being detected also increases. However, the higher the value of k, the higher the cooperative false alarm probability Q_f which in turn causes a higher chance that a spectrum opportunity will be missed. In addition, the more secondary sensors participate in detecting the primary user's activity, the more time and energy are consumed for cooperative spectrum sensing, which is undesirable since the sensors have limit power resource. Hence, in this paper, we jointly optimize the sensing time and the number of working sensors to maximize the EE throughput of cognitive system subject to adequate protection to PU.

3. Problem Formulations

In this paper, we jointly optimize the sensing time and number of working sensors to maximize the EE throughput in the cooperative cognitive radio system. As such, we are focused on EE throughput, which is defined as

$$\rho = \frac{Average\ Number\ of\ Bits\ Transmitted}{Average\ Energy\ Consumed}. \tag{5}$$

Without loss of generality, the cognitive system achievable throughput in one cycle is given by

$$C(k,\tau_s) = (T - k\tau_r - \tau_s)R(1 - Q_f(k,\tau_s)) \tag{6}$$

where T denotes the length of one cycle, k represents the number of working sensors, R denotes the transmitted rate when the decision results of fusion center is that the PU is in idle state[2]. For simplicity of analysis, τ_r and R are constants. In the same way, the energy consumed in the one cycle can be given by

$$E(k,\tau_s) = E_s k\tau_s + E_r k\tau_r + E_t(T - k\tau_r - \tau_s) \tag{7}$$

where E_s denotes the energy consumption per unit time in sensing stage, E_r and E_t represent the energy consumption per unit time in reporting stage and transmitting stage, respectively. In reality, the E_s is much smaller than that of E_r and E_t. As such, the optimization problem can be formulated as follows

$$\begin{aligned}\max_{k,\tau_s} \rho(k,\tau_s) &= \frac{C(k,\tau_s)}{E(k,\tau_s)} \\ &= \frac{(T-k\tau_r-\tau_s)(1-Q_f(k,\tau_s))R}{E_s k\tau_s + E_r k\tau_r + E_t(T-k\tau_r-\tau_s)},\end{aligned} \tag{8}$$

$$s.t.\ \ k = 1,2,...,M, \tag{9}$$

$$Q_d(k,\tau_s) \geq \theta, \tag{10}$$

$$0 \leq \tau_s \leq T - k\tau_r \tag{11}$$

where θ is the predefined threshold for the detection probability which is the requirement of the PU.

Lemma 1: For a given sensing time and number of working sensors, the optimal solution to (8) occurs with equality constraint in (10).

Proof is given in Appendix A.

Lemma 2: Q_f is a monotonously increasing function of Q_d.

Proof: As we know, Q function and inverse Q function are decreasing functions. According to results in [5], we have

$$p_f = Q(\sqrt{2\gamma+1}Q^{-1}(p_d) + \sqrt{\tau_s f_s}\gamma), \tag{12}$$

$$p_d = 1 - \sqrt[k]{(1 - Q_d)}, \tag{13}$$

$$Q_f = 1 - (1 - p_f)^k. \tag{14}$$

Therefore, Q_d increasing will result in p_d increasing, and then p_f will increase. As such, Q_f will increase when the Q_d increases.

Lemma 3: Based on Lemma 1 and Lemma 2, $\rho(k,\tau_s)$ is concave of τ_s for a given k. Therefore, there exists an optimal sensing time to maximize the energy-efficient throughput.

Proof: The first differential of $\rho(k,\tau_s)$ to τ_s is given as (15) at the top of next page.

Therefore, the second differential is

$$\frac{\partial^2 \rho(k,\tau_s)}{\partial^2 \tau_s} = A + B + C \tag{16}$$

where

$$A = \frac{2\frac{\partial Q_f}{\partial \tau_s}[kE_s(T-k\tau_r)+E_r k\tau_r]}{[kE_s\tau_s+E_r k\tau_r+E_t(T-k\tau_r-\tau_s)]^2} \tag{17}$$

and

$$B = -\frac{\frac{\partial^2 Q_f}{\partial^2 \tau_s}(T-k\tau_r-\tau_s)}{[kE_s\tau_s+E_r k\tau_r+E_t(T-k\tau_r-\tau_s)]} \tag{18}$$

and

$$C = \frac{2(1-Q_f)[E_s(T-k\tau_r)+E_r k\tau_r][E_s-E_t]}{[kE_s\tau_s+E_r k\tau_r+E_t(T-k\tau_r-\tau_s)]^3}. \tag{19}$$

According to the results in [15], we have

$$A < 0, B < 0, C < 0. \tag{20}$$

Therefore, the $\rho(k,\tau_s)$ is concave of τ_s.

It is shown in (8) that there exists a tradeoff between the sensing time and number of sensors for a given overhead. Moreover, it is difficult to directly solving the two variables optimization problem (8). As such, we decouple it into two single-variable sub-optimization problem. Specifically, we propose an iterative algorithm to solve it effectively.

First, we treat the sensing time to be a constant. As such, the first sub-optimization problem which is decoupled from the (8) reduces to

$$\begin{aligned}\textbf{OP. 1}\ \ \max_{k} \rho(k) &= \frac{C(k)}{E(k)}\Big|_{\tau_s=\tau_s^*} \\ &= \frac{(T-k\tau_r-\tau_s^*)(1-Q_f(k,\tau_s^*))R}{E_s k\tau_s^* + E_r k\tau_r + E_t(T-k\tau_r-\tau_s^*)},\end{aligned} \tag{21}$$

$$s.t.\ \ k = 1,2,...,M. \tag{22}$$

According to (21), it is very difficult to reach the close-form solution for k. However, k is an integer and ranges from the 1 to M. As such, it is not computationally expensive to search for the optimal number of sensors k^*.

[2]In this work, we are interested in frequency bands that are underutilized. As such, the case when the fusion center fails to detect the primary user's presence is omitted.

$$\frac{\partial \rho(k,\tau_s)}{\partial \tau_s} = \frac{-[(1-Q_f)R + (T-k\tau_r-\tau_s)\frac{\partial Q_f}{\partial \tau_s}R]}{E_s k\tau_s + kE_r\tau_r + E_t(T-k\tau_r-\tau_s)} - \frac{(T-k\tau_r-\tau_s)R(1-Q_f(k,\tau_s))(kE_s-E_t)}{[E_s k\tau_s + kE_r\tau_r + E_t(T-k\tau_r-\tau_s)]^2} \tag{15}$$

The second sub-optimization problem is that, for a given k^*, we find the optimal sensing time τ_s^*. As such, the optimization problem reduces to

$$\textbf{OP. 2} \quad \max_{\tau_s} \rho(\tau_s) = \frac{C(\tau_s)}{E(\tau_s)}|_{k=k^*} = \frac{(T-k^*\tau_r-\tau_s)(1-Q_f(k^*,\tau_s))R}{E_s k^*\tau_s + E_r k^*\tau_r + E_t(T-k^*\tau_r-\tau_s)}, \tag{23}$$

$$0 \le \tau_s \le T - k^*\tau_r. \tag{24}$$

However, no closed-form solution for optimal sensing time τ_s^* is available for this sub-optimization problem. As such, for any given k^*, we select the Newton's method [16] to search the "optimal" sensing time τ_s^*.

Based on the two decoupled sub-optimization problems, we propose an iterative algorithm to solve it, as depicted in **Algorithm 1**. As can be clearly seen from the **Algorithm 1**, the objective function $\rho(k,\tau_s)$ is non-deceasing at any iteration. As such, we can directly conclude that

$$\rho(\tau_s(j),k(j)) \le \rho(\tau_s(j),k(j+1)) \le \rho(\tau_s(j+1),k(j+1)). \tag{25}$$

Algorithm 1*: Find optimal sensing time τ_s^* and number of sensors k^* that maximize $\rho(\tau_s,k)$*

Input: $k(1)$, any value of k in between 1 and M
Initialization: $j \Leftarrow 1$;
Repeat
Step 1: Given $k(j)$, find the τ_s^* using Newton's method.
Step 2: $\tau_s(j+1) \Leftarrow \tau_s^*$.
Step 3: Given $\tau_s(j+1)$, find k^* that solves (21) by computing $\rho(k,\tau_s)$ from 1 to M.
Step 4: $k(j+1) \Leftarrow k^*$.
Step 5: $j \Leftarrow j+1$.
Until $\tau_s(j) == \tau_s(j-1)$ and $k^{(j)} == k^{(j+1)}$.
Output: $\tau_s(j)$; $k(j)$

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4. Numerical Results

To get insight into the effectiveness of the proposed sensing methods and validate some related theorems, extensive computer simulations have been conducted in this section. We select maximum throughput scheme in [7] [13] as the referenced scheme. The default parameters used in the evaluations are set as follows: the length of time slot is 180 ms, the reporting time per each sensor is 1 ms, the sampling frequency of the received signal is assumed to 1 MHz, the energy consumption per unit time of sensing is $E_s = 1$, similarly, $E_t = 10$, $E_r = 10$.

First, in order to investigate how the sensing time and number of working sensors work in cooperative sensing, we simulate the adaptive sensing time and number of working sensors. From the Fig. 3, we can clearly see that there exist an optimal sensing time or number of working sensors, subject to adequate protection to the primary network. As such, jointly optimizing the sensing time and number of working sensors is very critical for cognitive system. Moreover, the energy-efficient (EE) throughput is a unimodal function in the range of $1 \le k \le M$ and $0 \le \tau_s \le T - k * \tau_r$.

Second, in Fig. 4, we compare the maximum EE throughput scheme to maximum throughput scheme. Optimal sensing time and optimal number of working sensors are used in each scheme. As clearly shown by Fig. 4, the proposed scheme can improve the EE of the cognitive system greatly subject to the protection requirement of primary network. Moreover, the increasing protection requirement of PU will deteriorate the EE performance of cognitive radio networks. Specifically, the proposed Algorithm can achieve the well performance with low complexity compared with exhaustive searching method.

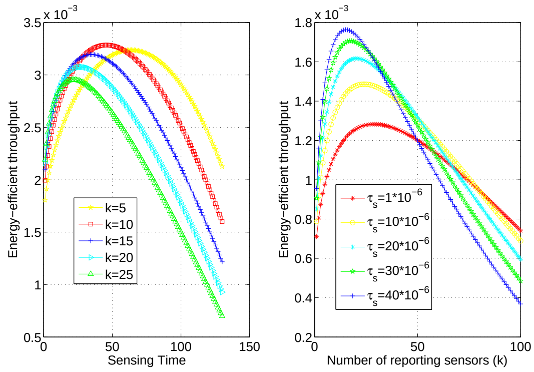

Fig. 3. Energy-efficient performance of cognitive system with adjustable sensing time or number of working sensors.

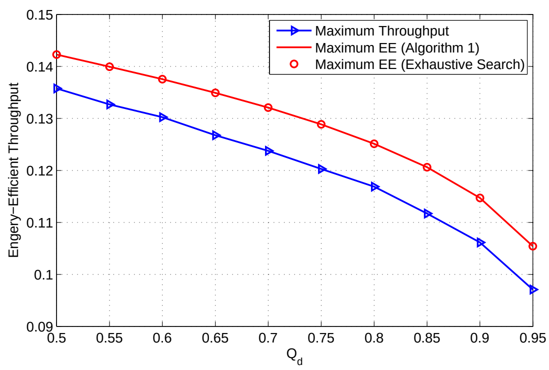

Fig. 4. Energy-efficient performance of two schemes with different detection probability when the sensing time and number of sensors are jointly optimized.

To evaluate the performance of optimal sensing time and number of working sensors, we use the same simulation. From Fig. 5, we can clearly see that the proposed scheme is prone to spend more time on sensing and less time on reporting. This is different from the maximum throughput scheme. Specifically, the higher the protection requirement is, the more overhead is needed. This can be interpreted as follows: the protection requirement of PU increases, the more overhead is needed to improve the detection probability.

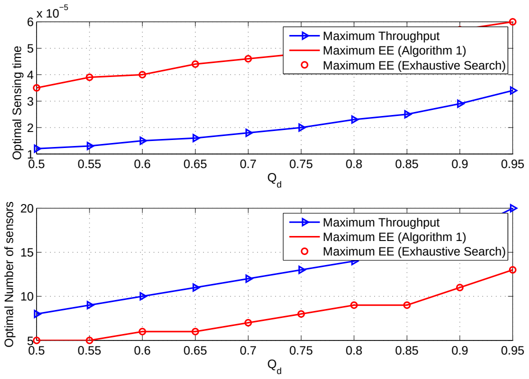

Fig. 5. Optimal sensing time performance with adjustable detection probability.

Remarks: According to the Algorithm 1, it may converge to a local maximum point. However, this local point is actually the global optimal point which has been found from the simulations. This can be interpreted as follows: According to the proposed iterative algorithm, we can conclude that, at the converged points τ_s^* and k^*, $\rho(\tau_s^*, k^*)$ is the largest across the τ_s dimension, and $\rho(\tau_s^*, k^*)$ is the largest across the k dimension. Specifically, the optimal point can be achieved for any initial value $k(1)$. As such, the proposed algorithm is not related to initial value $k(1)$ and always converges to the maximum point. Moreover, the proposed iterative algorithm is low complexity when compared to the exhaustive search method, and very easy to be implemented.

5. Conclusion

In this paper, the optimal cooperative spectrum sensing settings to maximize the system EE throughput, which is one of great practical interest than other sensing objectives, have been proposed. Subject to adequate protection to PU, there is a tradeoff between the sensing time and number of working sensors. As such, we have proposed an iterative algorithm to maximize the EE throughput. The results of the proposed iterative algorithm have been verified to be optimal by comparing them to exhaustive search results. We find that significant improvement in the EE throughput of cognitive radio system has been achieved when both the parameters for the sensing time and number of working sensors are jointly optimized.

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Appendix A

Proof: For a given sensing time and number of working sensors, based on the (1) and (2), we select a threshold ε_0 which satisfies $p_d(\varepsilon_0, \tau_s, k) = \widetilde{p}_d$. We may also select a threshold $\varepsilon_1 < \varepsilon_0$. As such, we have

$$p_d(\varepsilon_1, \tau_s, k) > p_d(\varepsilon_0, \tau_s, k) = \widetilde{p}_d, \tag{26}$$

$$p_f(\varepsilon_1, \tau_s, k) > p_f(\varepsilon_0, \tau_s, k). \tag{27}$$

Therefore, we have

$$Q_f(\varepsilon_1, \tau_s, k) > Q_f(\varepsilon_0, \tau_s, k). \tag{28}$$

According to (8) and (28), we have

$$\rho(\varepsilon_1, \tau_s, k) < \rho(\varepsilon_0, \tau_s, k). \tag{29}$$

As such, the optimal solution to (8) is achieved with equality constraint in (10).

References

[1] WU, Q., ZHANG, Z., WANG, J. Outage analysis of cognitive relay networks with relay selection under imperfect CSI environment. *IEEE Communications Letters*, 2013, vol. 17, no. 7, p. 1297 - 1300.

[2] XU, Y., WANG, J., WU, Q., ZHANG, Z., ANPALAGAN, A., SHEN, L. Optimal energy-efficient channel exploration for opportunistic spectrum usage. *IEEE Wireless Commmunication Letters*, 2012, vol. 1, no. 2, p. 77 - 80.

[3] ZHANG, Z., HUI, Q., WANG, J. Energy-efficient power allocation strategy in cognitive relay networks. *Radioengineering*, 2012, vol. 21, no. 3, p. 809 - 814.

[4] WU, Q., HAN, H., WANG, J., ZHAO, Z., ZHANG, Z. Sensing task allocation for heterogeneous channels in cooperative spectrum sensing. *Radioengineering*, 2010, vol.19, no. 4, p. 544 - 551.

[5] UNNIKRISHNAN, J., VEERAVALLI, V. V. Cooperative sensing for primary detection in cognitive radio. *IEEE Journal on Selected Topics in Signal Processing*, 2008, vol. 2, no. 1, p. 18 - 27.

[6] GHASEMI, A., SOUSA, E. Collaborative spectrum sensing for opportunistic access in fading environments. In *Proceedings IEEE DySPAN'05*. Baltimore (USA), 2005, p. 131 - 136.

[7] LIANG, Y.-C., ZENG, Y., PEH, E. C. Y., HOANG, A. T. Sensing-throughput tradeoff for cognitive radio networks. *IEEE Transactions on Wireless Communications*, 2008, vol. 7, no. 4, p. 1326 - 1337.

[8] ZHAO, Q., YE, J. When to quit for a new job: Quickest detection of spectrum opportunities in multiple channels. In *Proceedings of IEEE MILCOM Conference*. San Diego (USA), 2008, p. 1 - 6.

[9] ZHANG, W., MALLIK, R. K., LETAIEF, K. B. Optimization of cooperative spectrum sensing with energy detection in cognitive radio entworks. *IEEE Transactions on Wireless Communications*, 2009, vol. 8, no. 12, p. 5761 - 5766.

[10] LI, H., DAI, H., LI, C. Collaborative quickest spectrum sensing via random broadcast in cognitive radio systems. *IEEE Transactions on Wireless Communications*, 2010, vol. 9, no. 7, p. 2238 - 2348.

[11] ZOU, Q., ZHENG, S., SAYED, A. H. Cooperative spectrum sensing via sequential detection for cognitive radio networks. In *Proceedings of IEEE Workshop SPAWC*. Perugia (Italy), 2009, p. 121 - 125.

[12] GOSAN NOH, HANO WANG, JUNHO JO, BYOUNG-HOON KIM, DAESIK HONG. Reporting order control for fast primary detection in cooperative spectrum sensing. *IEEE Transactions on Vehicular Technology*, 2011, vol. 60, no. 8, p. 4058 - 4063.

[13] CHOI, Y., XIN, Y., S. RANGARAJAN, S. Overhead-throughput tradeoff in cooperative cognitive radio networks. In *IEEE Wireless Communications and Networking Conference (WCNC).* Budapest (Hungary), 2009, p. 1 - 6.

[14] ZHANG, W., MALLIK, R. K., LETAIEF, K. B. Cooperative spectrum sensing optimization in cognitive radio networks. In *Proceedings of IEEE ICC*. Beijing (China), 2008, p. 3411 - 3415.

[15] BOKHARAIEE, S., NGUYEN, H. H., SHWEDYK, E. Cooperative spectrum sensing in cognitive radio networks with noncoherent transmission. *IEEE Transactions on Vehicular Technology*, 2012, vol. 61, no. 6, p. 2478 - 2489.

[16] LUENBERGER, D. G. *Linear and Nonlinear Programming*, 2nd ed. Reading (MA, USA): Addison-Wesley, 1984.

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