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Sensing Optimization in Cooperative Cognitive Radio Networks

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Abstract

Cooperative spectrum sensing is a key function in cognitive radio networks in order to provide unused spectrum access opportunities and mitigate the impact of interference to the primary networks. Cooperative sensing can incur additional cooperation overhead, increased energy consumption, extra sensing time and delay in heterogeneous networks. In this paper, the sensing time period is optimized to minimize energy consumption in a diverse cooperative network using square law combining decision rule. The evaluation results confirm significant improvement in the sensing time and sensing task energy consumption.

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Keywords: Cooperative Sensing; cognitive network; square law combining

1. Introduction

The anticipated growth and proliferation of wireless devices with multifarious network's standards require advanced and intelligent devices to overcome the challenges of spectrum scarcity, power consumption, interoperability and users' demands for higher data rates and better quality of service. Cognitive Radio (CR) is a promising technology to enhance better spectrum utilization by enabling secondary users (SU) have access to intermittently available unoccupied spectrum band referred to as spectrum holes without interfering with the operations of the primary or licensed users **[1]**, **[2]**. Spectrum sensing is an important functionality in cognitive radio. Its main objective is to detect the transmission of licensed users and avoid interference to them while identifying any unused portions in the frequency bands. Sensing process can be categorized into two mechanisms namely: non-cooperative and cooperative sensing. In the former, each cognitive user senses its radio environment, and makes an independent decision based on collected radio information. In the later, cognitive users observe their

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radio environment, collects radio state information which is shared to make a cooperative decision (central/distributed strategies) [3], [4], [5]. In cooperative centralized decision, different fusion techniques such as hard decision (i.e. OR, AND and majority scheme) and soft decision such as: square-law combining (SLC) and maximal ratio combining (MRC) can be applied. Cooperative sensing **[6]** has the benefit of overcoming the hidden node problem and hardware simplicity, as each node does not need much computational processing capacity. However, cooperative sensing consumes a high level of energy and energy saving thus becomes a critical challenge. Sensing time allocation is also crucial in cooperative sensing. Increasing sensing time results in high-level of energy consumption and also causes significant delay in the network. This paper focuses on a sensing time optimization scheme to reduce the energy consumption of a cognitive network at the sensing period. In the proposed scheme, the fusion center collects energy of the primary users' signal and makes the final decision on the availability of the monitored spectrum by using the SLC technique. The rest of this paper is organized as follows: Section 2 presents related work on energy optimization in cooperative networks. The system model, primary and secondary user activity, signal detection and cooperative model are described in Section 3, square law combining and sensing time optimization are analyzed in Section 4. The numerical evaluation of the proposed scheme is presented in Section 5. Finally, the conclusions are drawn in Section 6.

2. Related Work

There have been many research activities on proposing optimal spectrum-sensing strategies. In [7], authors introduced an energy-efficient cooperative spectrum-sensing scheme in sensor-aided cognitive radio networks. Authors addressed the energy minimization problem under accuracy constraint of the detection and false alarm probabilities. The bounds for the number of sensors to simultaneously guarantee the thresholds for high detection probability and low false alarm probability are derived. With these bounds, the optimization problem is formulated to find the optimal sensing interval and the optimal number of sensor that minimize the energy consumption. In [8] an optimal scheduling of each sensor active time is presented to extend the network lifetime. Authors divide the sensors into a number of feasible subsets, such that only one subset of sensors is turned on at a period of time under the necessary detection and false alarm thresholds constraints. Each subset is activated successively and non-activated sensors are put in a low-energy sleep mode, so as to extend the network lifetime.

In [9] [10] the problem of energy minimization in cooperative network under threshold level of detection and false alarm probabilities is addressed where optimal sensing interval and number of sensors to minimize energy consumption are derived. In [11], authors developed a new model for the PU in its idle state. The multi-idle states, each with specific length and known probability of staying in it. This model is used to find minimum sensing time, energy detection threshold of each channel, and false alarm probability of the channel being sensed in monitoring. Authors in [12] optimized monitoring time to maximize the achievable throughput of the CR nodes under the constraint of the PU interference level. Authors in [13] discussed the issue of the optimal detection time selection that leads to the highest channel efficiency. Authors in [14] proposed a detection probability called the time-constrained detection probability (TDP) and investigated the effect of the sensing interval on the TDP. This sensing interval consists of a sensing duration and transmission duration. The optimal sensing interval and transmission duration satisfy the interference threshold level of the primary user, and maximize the achievable throughput for secondary users. Our work is differ from them by using SLC technique and the probability of detection and false alarm constraint to optimize sensing time and reduce energy consumption.

3. System Model

This paper considers an open licensed spectrum network consisting of several static wireless nodes communicating with each other using N licensed channels, while a multi-user cognitive radio network is located within the licensed coverage area. The coverage area of the secondary network is small compared to the distance between the secondary users and the primary transmitter such that the effect of primary signal at the secondary user can be ignored (see figure 1). In the considered cooperative sensing scenario, each cognitive user detects primary signal energy and sends the energy to the fusion centre via the reporting channels [3], [4]. At the fusion center, square-law combining

(SLC) technique is employed to find the appropriate spectrum hole and sensing time under detection and false alarm probabilities constraint. The common notations used throughout this paper are summarized in Table 1.

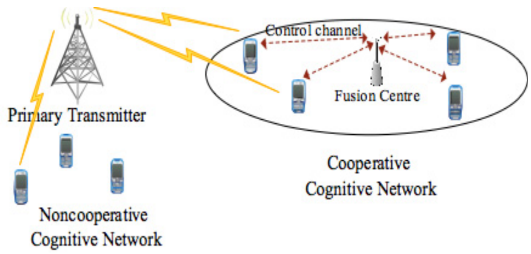


Fig.1. Network topology; secondary users report sensing information to the fusion centre

Table 1. Network notation

Parameter	Description	Parameter	Description
Q_f	Cooperative false alarm probability	$\overline{Q_f}$	Upper limit of false alarm probability
Q_d	Cooperative detection probability	$\overline{Q_d}$	Lower limit of detection probability
$T_{ex.}$	Cooperative overhead time	P_{fa}	False alarm probability
W	Bandwidth	P_d	Detection probability
τ	Local sensing time	γ	Received SNR of primary user
P_{md}	Miss detection probability	$\hat{T}_s$	Optimized sensing time
N	Number of SU	f_s	Sampling frequency
σ_w^2	AWGN variance	T_T	Data transmission time
δ^i	Threshold value for sensor i		

3.1. Primary and Secondary User Activity Model

The licensed bands utilization is modeled as a Poisson process and the channel model can be estimated as an ON/OFF alternating process with different transit probabilities. The ON and OFF periods are identical independent distribution (i.i.d) random variables with an exponential distribution of constant busy and idle periods during system analysis. While the secondary user data transmission activity within a typical spectrum hole includes sensing, exchanging, data delivery/transmission interval times. The SU utilizes the receiving power level during the sensing functions and utilizes the transmit power level at the reporting and data delivery/transmission functions [15].

3.2. Spectrum Sensing and Cooperation Mechanism

Each cognitive device performs spectrum sensing independently and the sensing outcomes are sent to the fusion centre. According to the collected information received at the fusion centre, the SLC scheme can be employed to explore unoccupied licensed channels (spectrum hole) in a cooperative manner. Assuming licensed channels are identical and independent, received signals at the SU node i during sensing period of time slot (n) can be given by;

$$Y_i(n) = \begin{cases} \omega_i(n) \\ h_i(n)S_i(n) + \omega_i(n) \end{cases} \tag{1}$$

Where $Y_i(n)$ is the received signal by the i^{th} secondary user. The signal $S_i(n)$ is distorted by the channel gain $h_i(n)$, which is assumed to be constant during the detection interval, and is further corrupted by the zero-mean Additive White Gaussian Noise (AWGN). ω_i is the receiver noise for the i^{th} secondary user, which is assumed to be an i.i.d random process with zero mean and variance σ^2. Each secondary user calculates a summary statistic over observation time, $E_i = \sum_{n=0}^{N-1}|y_i(n)|^2$, i=1, 2, 3…K. Where N represents the number of observed samples in the observation time interval τ. $E_i \sim \begin{cases} \Upsilon_{2\upsilon}^2 & , H_0 \\ \Upsilon_{2\upsilon}^2(2\gamma^i) & , H_1 \end{cases}$ The random variable E follows a central chi-square distribution with $2\tau W$ degree of freedom and a non-central chi-square distribution with τW degree of freedom. In the case of soft decision, each cognitive user forwards the entire energy result E_i to the FC. For hard decision, cognitive users make one bit local decision based on comparing the received energy of the primary signal with a threshold level (δ). Therefore, the local probability of detection (P_d^i) and probability of false alarm $\left(P_{fa}^i\right)$ of the detector can be approximated as;

$$P_d^i = P(E_i > \delta^i | H_1) = Q\left(\frac{\delta^i - \tau f_s\left(|h|^2\sigma_s^2 + \sigma_\omega^2\right)}{\sqrt{2\tau f_s}\left(|h|^2\sigma_s^2 + \sigma_\omega^2\right)}\right) \tag{2}$$

$$P_{fa}^i = P(E_i > \delta^i | H_0) = Q\left(\frac{\delta^i - \tau f_s \sigma_\omega^2}{\sqrt{2\tau f_s}\sigma_\omega^2}\right) \tag{3}$$

Where $Q(.)$ denotes the right-tail probability of a normalized Gaussian distribution $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{\frac{-t^2}{2}}dt$, f_s is the sampling frequency and τ represents the sensing time slot. The equations above show that the probability of detection and probability of false alarm are related to the detection threshold, sensing time, SNR and sampling frequency. From equations (2) and (3), the minimum required sensing time on secondary user i to satisfy desired P_{fa} and P_{md} is given by:

$$\tau^i = \frac{2}{f_s {\gamma^i}^2}\left[Q^{-1}\left(p_{fa}^i\right) - Q^{-1}\left(1 - p_{md}^i\right)\sqrt{1 + 2\gamma^i}\right]^2 \tag{4}$$

The equations above show that increasing the SNR level reduces the sensing time, while increasing the sensing time increases the probability of detection and reduces the probability of false alarm. It also shows that increasing the sensing time duration increases the energy consumption and delay at the secondary user.

4. Fusion Centre Decision

Hard decision and soft decision are two prominent decision mechanisms at the fusion center. In the former, each cognitive user detects the primary signal and makes an individual binary decision about spectrum occupancy. The binary decisions are then transmitted to the fusion centre via common control channel. The final decision is made employing OR, AND and majority voting schemes at the fusion centre [6]. In soft data fusion, cognitive users report the sensing result E_i to the fusion centre without making local decisions. The final decision is made by using appropriate combining rules such as: square law combining (SLC), maximal ratio combining (MRC) and selection combining (SC). Soft decision requires larger bandwidth for control channels than hard decision and also generates more overhead than hard decision. In this work, the square law combining is utilized. In the SLC scheme, each secondary user observes primary signal energy and sends the estimated energy to the fusion centre where they will be added to provide the average energy. This average energy is then compared to a threshold level to decide on the presence of the PU. The summation of received energy of primary user at fusion centre is $Y_{SLC} = \sum_{i=1}^{K} E_i$.
Equations (5) and (6) show the cooperative false alarm probability and cooperative detection probability utilizing the square law combining respectively;

$$Q_{f,SLC} = P(Y_{SLC} > \lambda | H_0) = \frac{\Gamma\left(\upsilon K, \frac{\lambda}{2}\right)}{\Gamma(\upsilon K)} \tag{5}$$

$$\mathbf{Q_{d,SLC} = P(Y_{SLC} > \lambda | H_1) = Q_{\upsilon K}\left(\sqrt{2\bar{\gamma}}, \sqrt{\lambda}\right)} \tag{6}$$

Where $\bar{\gamma}$ is $\bar{\gamma} = \sum_{i=1}^{K}\gamma_i$, and γ_i is the received PU's SNR at the K^{th} cognitive radio user, $Q_x(.,.)$ is the generalized Marcum Q-function, δ is the decision threshold, $\Gamma(.)$ and $\Gamma(.,.)$ are the gamma and the incomplete gamma function.

5. Optimal Cooperative Sensing

This section considers an optimal sensing time algorithm, which results in the minimum energy consumption during the entire sensing period. In this scenario, each SU observes PU's target channel independently during local sensing period and the received SNR levels will be reported to the fusion centre. In Algorithm 1, the first line is the objective function, which has to be minimized and $\boldsymbol{t_i}$ represents a set of sensing time that satisfies the probability of detection and false detection constraints. The second and third lines in algorithm 1 are constraints to satisfy the conditions of PU detection. In Algorithm 2, once all secondary users report their local sensing time to the fusion centre, the minimum sensing time is selected using reported information. In this scheme, each SU computes its local sensing time subject to the probability of detection and probability of false detection constraints (using equation 4).

Algorithm 1. Exploring optimal sensing time

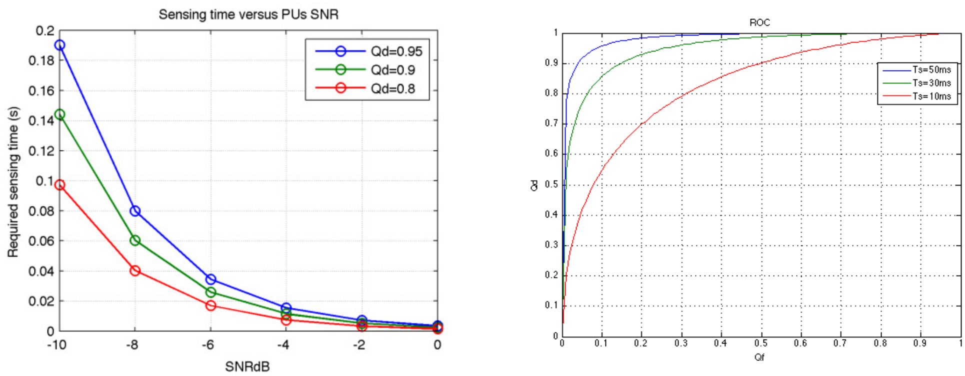
$\widehat{\mathrm{T}}_s = \min(t_i)$
st.
$\mathrm{Q_{d,SLC}} \geq \overline{\mathrm{Q_d}}$
$\mathrm{Q_{f,SLC}} \leq \overline{\mathrm{Q_f}}$

Algorithm 2. Local minimum sensing time selection

SU^i $estimates$ τ^i $using$ $local$ $information$
τ^i is $reported$ to $fusion$ $centre$
$\widehat{\mathrm{T}} = \{\tau^i\}, \quad i = 1, 2, \dots, K$
$\widehat{\mathrm{T}}_s = \min\{\tau^i\}$
$\widehat{\mathrm{T}}_s$ is $broadcasted$ to SUs

6. Numerical Analysis

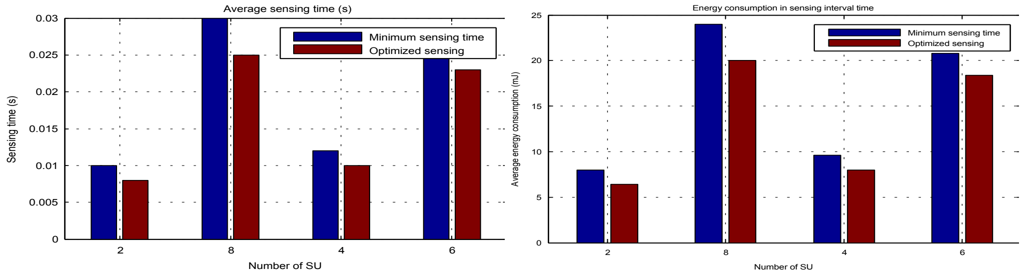
This section presents the performance of the proposed scheme through its complementary Receiver Operating Characteristic (ROC) curves (Q_d versus Q_f) for different situations of the network. Assuming the sampling frequency f_s= 1 kHz, the upper limit of false alarm probability 0.1 and the lower limit of detection probability 0.9. Fig.2a shows the sensing time versus received SNR of the primary user at the SU. The results show that low level SNR causes SU to spend more time on the sensing phase which will result to its associated increase in energy consumed and delay within the network. Fig. 2b indicates the ROC curves for soft SLC fusion rules under AWGN channel. The average received SNR of the PU is assumed to be -10dB. The results depict that increase the sensing time improves probability of detection of primary signal. The sensing time takes the value of 50ms, 30ms and 10ms.



a) b)

Figure 2. a) Sensing time versus primary user SNR ($\bar{Q}_d = 0.95$, $\bar{Q}_f = 0.1$). b) Q_d versus Q_f of the cognitive users with diverse sensing time

Fig.3a presents the comparison of the average sensing time within a typical cognitive network and the proposed optimized scheme. For the simulation, each cognitive user reports a different SNR for the primary user's signal. it is observed from this figure that there is a 16% improvement in sensing time with regard to false alarm and detection probabilities ($\bar{Q}_f = 0.1, \bar{Q}_d = 0.95$) in a cooperative cognitive radio of eight users. Fig. 3b depicts the energy consumption of the proposed scheme and minimum sensing time scenario. The outcomes show that the proposed scheme improves energy consumption of the sensing interval time of a cooperative cognitive network. Considering that the average received SNR equals to -5dB. The outcomes reveal an improvement of 17.6%, 16.6%, 15.7% and 13.6% in the cognitive network comprising of two, eight, four and six user respectively.



a) **b)**

Fig. 3. Average sensing time versus number of SUs. b) The average energy consumption of assumed cognitive network

7. Conclusion

This paper has considered a diverse cooperative cognitive radio network with cooperative sensing where cognitive users' sense licensed spectrum bands and report the received PU's SNR to the fusion centre. Each cognitive user reports a different SNR level for the primary users' signals. The final decision is made by employing the square law combining scheme at the fusion centre. Our proposed scheme results in the sensing time to be optimized and also an improvement in the energy efficiency of the cognitive network by optimization programming. The simulation results showed that there is a significant improvement on sensing time and energy consumption with our proposed optimized sensing time algorithms when compared to a typical minimum sensing time. To this end, sensing time allocation and optimization is a crucial challenge in cooperative cognitive radio networks and needs to be considered by standardization work groups on cognitive radio technology and cooperative spectrum sensing.

6. References

[1] Simon Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE journal on selected areas in communications*, vol. 23, no. 2, pp. 201-220, Feburary 2005.

[2] Joseph Mitola III, "Cognitive radio: An integrated agent architecture for software defined radio," KTH Royal Institue of Technology, 2000.

[3] R.Fan and H.Jiang, "Optimal multi-channel cooperative sensing incognitive radio networks," *IEEE Transaction in Wireless Communication*, vol. 9, no. 3, pp. 1128-1138, March 2010.

[4] W. Zhang and K. B. Letaief, "Cooperative communications for cognitive radio networks," *Proceeding of the IEEE*, vol. 97, pp. 878–893, 2009.

[5] Nan Zhao, Fei Richard Yu, Hongjian Sun and Arumugam Nallanathan, "Energy-efficient cooperative spectrum sensing schemes for cognitive radio networks," *EURASIP Journal onWireless Communications and Networking* , pp. 1-13, 2013.

[6] Ian F. Akyildiz, Brandon F. Lo, Ravikumar Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Physical Communication*, vol. 4, pp. 40-62, 2011.

[7] H.N. Pham, Y. Zhang, P. Engelstad, T. Skeie, F. Eliassen, "Energy minimization approach for optimal cooperative spectrum sensing in sensor-aided cognitive radio networks," in *ICST WiCON 2010*, 2010, pp. 1-9.

[8] Ruilong Deng, Jiming Chen, Chau Yuen, Peng Cheng, Youxian Sun, "Energy-Efficient Cooperative Spectrum Sensing by Optimal Scheduling in Sensor-Aided Cognitive Radio Networks," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 2, Feburary 2012.

[9] Hai Ngoc Pham ,Yan Zhang ,Paal E. Engelstad,Tor Skeie ,Frank Eliassen, "Optimal Cooperative Spectrum Sensing in Cognitive Sensor Networks ," in *International Conference on Wireless Communications and Mobile Computing*, New York, 2009, pp. 1073-1079.

[10] Hai Ngoc Pham ,Yan Zhang ,Paal E. Engelstad,Tor Skeie,Frank Eliassen, "Energy minimization approach for optimal cooperative spectrum sensing in sensor-aided cognitive radio networks," in *IEEE WICON*, Singapor, 2010, pp. 1-9.

[11] Ramzi Saifan , Ahmed E. Kamal , Yong Guan, "Efficient Spectrum Searching and Monitoring in Cognitive Radio Network," *Mobile adhoc and Sensor Networks*, 2011.

[12] Y. Pei, A.T. Hoang, Y.C. Liang, "Sensing-throughput tradeoff in cognitive radio networks: how frequently should spectrum sensing be carried out?," in *IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications*, 2007, pp. 1-5.

[13] P. Wang, L. Xiao, S. Zhou, J. Wang, "Optimization of detection time for channel efficiency in cognitive radio systems," in *Wireless Communications and Networking Conference*, 2007, pp. 111-115.

[14] Jae-Kark Choi, Sang-Jo Yoo, "Time-constrained detection probability and sensing parameter optimization in cognitive radio networks," *EURASIP Journal on Wireless Communications and Networking*, 2013.

[15] M.pirmoradian, O.Adigun, C.politis, "An analytical evaluation of energy consumption in cognitive radio networks," in *International Telecommunication Union(ITU)-Kaleidoscope 2013*, Kyoto, 2013.