Energy-efficient spectrum sensing for cognitive sensor networks

Sina Maleki†, Ashish Pandharipande⋆ and Geert Leus†
⋆Philips Research Europe - Eindhoven,
High Tech Campus, 5656 AE Eindhoven, The Netherlands
Email: ashish.p@philips.com
†Faculty of Electrical Engineering, Mathematics and Computer Science,
Delft University of Technology, The Netherlands
Email: {s.maleki, g.j.t.leus}@tudelft.nl

***Abstract*—We consider a combined sleeping and censoring scheme for energy-efficient spectrum sensing in cognitive sensor networks. We analyze the detection performance of this scheme by theoretically deriving the global probabilities of detection and false-alarm. Our goal is to minimize the energy consumption incurred in distributed sensing, given constraints on the global probabilities of detection and false-alarm, by optimally designing the sleeping rate and the censoring thresholds. Using specific transceiver models for sensors based on IEEE 802.15.4/ZigBee, we show the energy savings achieved under an optimum choice of the design parameters.**

I. Introduction

The family of wireless networks - sensor networks, personal area networks, local area networks, cellular networks etc has seen tremendous growth recently, resulting in demand for radio spectrum. Traditionally, radio spectrum allocation has been based on exclusive, licensed use of portions of spectrum to wireless systems. This has resulted in a perceived dearth of spectrum available for use for newer wireless networks and applications. Radio spectrum measurements [13] however indicate that large portions of spectrum licensed to wireless systems remain under-utilized. Consequently there is a growing interest in unlicensed use of empty portions in order to improve spectrum utilization [3], [5], [17]. A promising approach for such secondary spectrum access is the use of cognitive radios. A cognitive radio can alter its radio transmission parameters autonomously based on active monitoring of spectrum in order to access spectrum on a secondary basis while coexisting with licensed systems or other unlicensed systems.

In this paper, we consider a cognitive sensor network that performs spectrum sensing in order to determine empty radio channels and limits its transmissions on channels that are found vacant in order to reduce harmful interference to licensed systems. Our study is motivated by recent developments in regulatory and standardization bodies aimed at permitting the use of portable devices and low-power sensors to operate on a secondary basis in VHF-UHF bands licensed to television broadcasting systems. In this context, reliable spectrum sensing that is energy efficient is critical.

The cognitive sensor network comprises of a fusion center (FC) and a number of cognitive sensors that carry out sensing in dedicated, periodic sensing slots. Channel sensing is done using energy detection, which is a common approach to the detection of unknown signals [3], [8]. The results of the sensing are collected at a fusion center that makes a global decision using an OR fusion rule on the occupancy of the channel. Distributed spectrum sensing aims at exploiting the inherent spatial diversity to alleviate local shadowing conditions that may result in unreliable detection at an individual cognitive sensor. Distributed spectrum sensing schemes based on soft and hard fusion have been considered in the past [10] (the reader is also referred to literature in distributed detection [14]). Although the global detection performance improves, so does the energy consumption in the cognitive sensor network. There is considerable literature on different distributed spectrum sensing schemes and their performance, limited attention has however been paid to schemes that are energy-efficient. A clustering-based approach to energy-efficient distributed sensing was proposed in [9]. However this approach is only suitable for tree-structured cognitive sensor networks.

We propose a combination of sleeping and censoring as an energy saving mechanism in spectrum sensing. When in sleep mode, a cognitive sensor switches off its sensing transceiver and incurs no observation costs or transmission costs. Censoring involves transmitting detection results only when they are in a certain information region. Our goal is to minimize the average energy incurred by the cognitive sensor network to perform spectrum sensing while maintaining a global detection performance by determining the optimum sleeping rate and censoring region. The constraint on detection performance is specified by a minimum target probability of detection and a maximum permissible probability of false-alarm. We first provide a theoretical framework to analyze the combined sleeping and censoring scheme and obtain the optimum design parameters. We then consider a sensor network based on IEEE 802.15.4/ZigBee radios to validate the theoretical analysis. Simulation results show orders of magnitude in energy savings in comparison to traditional spectrum sensing schemes.

In the context of wireless sensor networks, sleeping and censoring schemes have been individually shown as effective ways to achieve energy efficiency, with the exception of [16].

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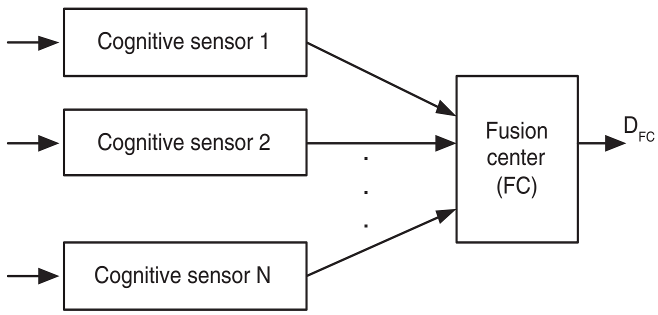

Fig. 1. Distributed spectrum sensing topology.

The design of censoring regions under different optimization settings related to detection performance has been considered in [2], [12]. In [16], the problem of maximizing the mutual information between the state of signal occupancy and the decision state of the fusion center by choosing an appropriate sleeping and censoring policy was considered. As shall be shown, the optimization problem resulting in our work differs from these past works.

The remainder of the paper is organized as follows. In Section II, we describe distributed spectrum sensing based on sleeping and censoring and formulate energy-efficient distributed sensing as an optimization problem. Expressions for the global probability of detection and probability of false-alarm are then derived in Section III. We then show that network energy minimization is a convex optimization problem. We present simulation results to show the energy savings obtained by the proposed scheme in Section IV. Conclusions are presented in Section V.

II. System Model

The cognitive sensor network comprises of N cognitive sensors and an FC in a parallel fusion topology as shown in Figure 1. Under this setting, using local decisions made by the cognitive sensors, the FC has to solve a binary hypothesis testing problem, i.e. determine whether a licensed system is transmitting, given by hypothesis $\mathcal{H}_1$, or not, given by hypothesis $\mathcal{H}_0$. Each of the cognitive sensors is controlled by two policies. A sleeping policy determines whether or not it is awake and a censoring policy determines whether or not it transmits its detection result, given that it is awake. Denote μ to be the sleeping rate, i.e. the probability that a cognitive sensor is in the "off" state. Each cognitive sensor that is awake performs detection in a dedicated sensing slot using T_0 observation samples. Energy detection with censoring is employed at each cognitive sensor. Censoring thresholds λ_1 and λ_2 are applied at each of the cognitive sensors. At the i-th cognitive sensor, denoting E_i to be the received energy measured using the T_0 observation samples, the local censoring decision rule is given as follows:

$$\begin{cases} \text{send 1, declaring } \mathcal{H}_1 & \text{if } E_i \geq \lambda_2 \\ \text{no decision} & \text{if } \lambda_1 < E_i < \lambda_2 \\ \text{send 0, declaring } \mathcal{H}_0 & \text{if } E_i \leq \lambda_1. \end{cases} \quad (1)$$

We assume that the received signal-to-noise ratio (SNR) at each cognitive sensor is the same, denoted by γ. Consequently the probabilities of false-alarm and detection for each cognitive sensor are the same, denoted respectively by P_f and P_d. It is well known [8] that E_i follows a central chi-square distribution with $2T_0$ degrees of freedom under $\mathcal{H}_0$ and a non-central chi-square distribution with $2T_0$ degrees of freedom and non-centrality parameter 2γ under $\mathcal{H}_1$.

Based on the above decision rule, the probabilities of false alarm and detection can be respectively written as

$$P_f = Pr(E_i \geq \lambda_2|\mathcal{H}_0) = \frac{\Gamma(T_0, \frac{\lambda_2}{2})}{\Gamma(T_0)} \quad (2)$$

and

$$P_d = Pr(E_i \geq \lambda_2|\mathcal{H}_1) = Q_{T_0}(\sqrt{2\gamma}, \sqrt{\lambda_2}), \quad (3)$$

where $\Gamma(a,x)$ is the incomplete gamma function given by $\Gamma(a,x) = \int_x^\infty t^{a-1}e^{-t}dt$, with $\Gamma(a,0) = \Gamma(a)$ representing the gamma function and $Q_u(a,x)$ is the generalized Marcum Q-function, $Q_u(a,x) = \frac{1}{a^{u-1}}\int_x^\infty t^u e^{-\frac{t^2+a^2}{2}} I_{u-1}(at)dt$, with $I_{u-1}(.)$ being the modified Bessel function of the first kind and order $u-1$.

We assume that the respective prior probabilities, $\pi_0 = Pr(\mathcal{H}_0)$ and $\pi_1 = Pr(\mathcal{H}_1)$, of the hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ are known. In practice, estimates of π_0 and π_1 can be obtained via spectrum measurements. In this case, we can follow the definition of [12] for the censoring rate

$$\begin{aligned} \rho &= Pr(\lambda_1 < E_i < \lambda_2) \\ &= \pi_0 Pr(\lambda_1 < E_i < \lambda_2|\mathcal{H}_0) + \pi_1 Pr(\lambda_1 < E_i < \lambda_2|\mathcal{H}_1) \\ &= \pi_0\delta_0 + \pi_1\delta_1 \end{aligned} \quad (4)$$

where δ_0 and δ_1 can be written using (2) and (3) as

$$\begin{aligned} \delta_0 &= Pr(\lambda_1 < E_i < \lambda_2|\mathcal{H}_0) \\ &= \frac{\Gamma(T_0, \frac{\lambda_1}{2})}{\Gamma(T_0)} - \frac{\Gamma(T_0, \frac{\lambda_2}{2})}{\Gamma(T_0)}, \end{aligned} \quad (5)$$

$$\begin{aligned} \delta_1 &= Pr(\lambda_1 < E_i < \lambda_2|\mathcal{H}_1) \\ &= Q_{T_0}(\sqrt{2\gamma}, \sqrt{\lambda_1}) - Q_{T_0}(\sqrt{2\gamma}, \sqrt{\lambda_2}). \end{aligned} \quad (6)$$

Denote C_{s_i} and C_{t_i} to be the energy consumed by the i-th cognitive sensor in sensing and transmission respectively. Our cost function is given by the average energy consumed in distributed sensing in the network,

$$C_T = (1-\mu)\sum_{i=1}^{N}(C_{s_i} + C_{t_i}(1-\rho)). \quad (7)$$

The sensing energy C_{s_i} constitutes the energy consumed in listening and collecting the T_0 observation samples, as well as the signal processing involved in making a local decision. The transmission energy C_{t_i} is the energy required to transmit the one-bit local decision to the FC.

Denote Q_D and Q_F to be the respective global probability of detection and global probability of false-alarm. The target detection performance is then quantified by: $Q_F \leq \alpha$ and $Q_D \geq \beta$. Here, α and β are pre-specified detection design parameters. For reliable detection, it is desirable to have α close to zero and β close to unity. Our goal is to determine the optimum sleeping rate μ and the censoring thresholds λ_1 and λ_2 such that C_T in (7) is minimized subject to the constraints $Q_F \leq \alpha$ and $Q_D \geq \beta$. Hence our optimization problem can be reformulated as follows:

$$\begin{aligned} &\min_{(\mu,\lambda_1,\lambda_2)} \; C_T \\ &\text{s.t. } Q_F \leq \alpha, \; Q_D \geq \beta. \end{aligned} \tag{8}$$

In the following section, we derive analytically the expressions for Q_D and Q_F.

III. Distributed detection performance analysis

Each cognitive sensor that is awake listens on the channel periodically in dedicated sensing slots. An awake cognitive sensor computes the received signal energy and locally decides on the presence or absence of the licensed system based on the decision rule in (1). If it comes up with a decision, then it sends its decision result to the FC. The FC employs an OR rule to make the final decision. That is, $D_{FC} = 1$ if the FC receives at least one local decision declaring 1, else $D_{FC} = 0$. Let the number of awake cognitive sensors be K, and let L out of K such cognitive sensors send their decision to the FC.

The global probability of false-alarm, Q_F, can now be written as

$$\begin{aligned} Q_F &= Pr(D_{FC}=1, L \geq 1, K \geq 1 | \mathcal{H}_0) \\ &= \sum_{K=1}^{N} Pr(D_{FC}=1, L \geq 1, K | \mathcal{H}_0) \\ &= \sum_{K=1}^{N} Pr(K|\mathcal{H}_0) Pr(D_{FC}=1, L \geq 1 | \mathcal{H}_0, K) \\ &= \sum_{K=1}^{N} \binom{N}{K} \mu^{N-K}(1-\mu)^K \\ &\times \sum_{L=1}^{K} Pr(D_{FC}=1, L|\mathcal{H}_0, K) \\ &= \sum_{K=1}^{N} \binom{N}{K} \mu^{N-K}(1-\mu)^K \\ &\times \sum_{L=1}^{K} Pr(L|\mathcal{H}_0, K) Pr(D_{FC}=1|\mathcal{H}_0, K, L) \\ &= \sum_{K=1}^{N} \binom{N}{K} \mu^{N-K}(1-\mu)^K \\ &\times \sum_{L=1}^{K} \binom{K}{L} \delta_0^{K-L}(1-\delta_0)^L [1-(1-P_f)^L] \end{aligned} \tag{9}$$

where P_f is given by (2).

Equation (10) can be further simplified using the binomial expansion theorem. After some algebraic manipulation, we obtain

$$Q_F = 1 - \{1-(1-\mu)(1-\delta_0)P_f\}^N. \tag{10}$$

The global probability of detection, Q_D, can be derived in a similar way. We have

$$\begin{aligned} Q_D &= Pr(D_{FC}=1, L \geq 1, K \geq 1 | \mathcal{H}_1) \\ &= \sum_{K=1}^{N} Pr(D_{FC}=1, L \geq 1, K | \mathcal{H}_1) \\ &= \sum_{K=1}^{N} Pr(K|\mathcal{H}_1) Pr(D_{FC}=1, L \geq 1 | \mathcal{H}_1, K) \\ &= \sum_{K=1}^{N} \binom{N}{K} \mu^{N-K}(1-\mu)^K \\ &\times \sum_{L=1}^{K} Pr(D_{FC}=1, L|\mathcal{H}_1, K) \\ &= \sum_{K=1}^{N} \binom{N}{K} \mu^{N-K}(1-\mu)^K \\ &\times \sum_{L=1}^{K} Pr(L|\mathcal{H}_1, K) Pr(D_{FC}=1|\mathcal{H}_1, K, L) \\ &= \sum_{K=1}^{N} \binom{N}{K} \mu^{N-K}(1-\mu)^K \\ &\times \sum_{L=1}^{K} \binom{K}{L} \delta_1^{K-L}(1-\delta_1)^L [1-(1-P_d)^L] \\ &= 1 - \{1-(1-\mu)(1-\delta_1)P_d\}^N. \end{aligned} \tag{11}$$

where P_d is given by (3).

The optimization problem (8) can now be rewritten as follows.

$$\begin{aligned} &\min_{(\mu,\lambda_1,\lambda_2)} \; (1-\mu)\textstyle\sum_{i=1}^{N} [C_{s_i} + C_{t_i}(1-\rho)] \\ &\text{s.t. } 1 - \{1-(1-\mu)(1-\delta_0)P_f\}^N \leq \alpha, \\ &\quad\; 1 - \{1-(1-\mu)(1-\delta_1)P_d\}^N \geq \beta. \end{aligned} \tag{12}$$

Efficient algorithms for solving inequality-constrained optimization problems can be found in [11].

IV. Simulation results

We consider an example transceiver, which is a Chipcon CC2420 chip based on the IEEE 802.15.4/ZigBee standard [7], to compute the energy consumption in sensing and transmission. This low-power radio is designed for wireless personal area networks to provide a data rate up to 250 Kbps in the range of 10 m - 70 m. Our cognitive sensor network comprises of such radios arranged in a circular field with a radius of 70 m, uniformly distributed along the circumference with the FC located in the center. We model the wireless channel between the cognitive sensor and the FC using a free-space path loss model. That is, the signal power attenuation is inversely proportional to the square of the distance d between the transmitter and receiver.

We employ the transceiver model developed in [6] for our analysis on energy consumption. The sensing energy for each decision consists of two parts: the energy consumption involved in listening over the channel and making the decision and the energy consumption of the signal processing part for modulation, signal shaping, etc. The former contribution depends on the number of samples taken during the detection time. We choose $T_0 = 5$, corresponding to a detection time of 1 μs. The typical circuit power consumption of ZigBee is approximately 40 mW. Therefore, the energy consumed for listening is approximately 40 nJ. The processing energy related to the signal processing part in the transmit mode for a data rate of 250 kbps, a voltage of 2.1 V and current of 17.4 mA is approximately 150 nJ/bit. Since we use one bit per decision, the sensing energy of each cognitive sensor is $C_s = 190$ nJ.

The transmitter dissipates the energy to run the radio electronics and the power amplifier. Following the model in [6] and [1], to transmit one bit over a distance d, the radio spends:

$$C_t(d) = C_{t-elec} + e_{amp} d^2 \tag{13}$$

where C_{t-elec} is the transmitter electronics energy and e_{amp} is the amplification required to satisfy a given receiver sensitivity level. Assuming a data rate of 250 kbps and a transmit power of 20 mW, $C_{t-elec} = 80$ nJ/bit. The e_{amp} to satisfy a receiver sensitivity of -90 dBm at an SNR of 10 dB is 40.4 pJ/bit/m^2.

Every simulation result in this section is averaged over 10000 realizations. Two sets of values were chosen for the a priori probabilities: $\pi_0 = 0.2, \pi_1 = 0.8$ and $\pi_0 = 0.8, \pi_1 = 0.2$. In Figure 2, we show the energy consumed in spectrum sensing for different values of probability of detection, Q_D. Here, $N = 5$, SNR $= 10$ dB and $\alpha = 0.1$. As is clear, a combined sleeping and censoring scheme consumes less than half the energy as would be consumed if a distributed spectrum sensing such as in [10] were employed. In Figure 3, we show the average energy consumed as the number of cognitive sensors in the network is increased. Here, $\alpha = 0.1$ and $\beta = 0.99$. Without sleeping or censoring, the energy consumed in spectrum sensing scales linearly with the number of cognitive sensors. However with a sleeping and censoring scheme, the energy consumption saturates to a level that is several orders of magnitude lower. We clearly see that to attain this desired detection performance level, only a small fraction of the cognitive sensors need to participate in spectrum sensing.

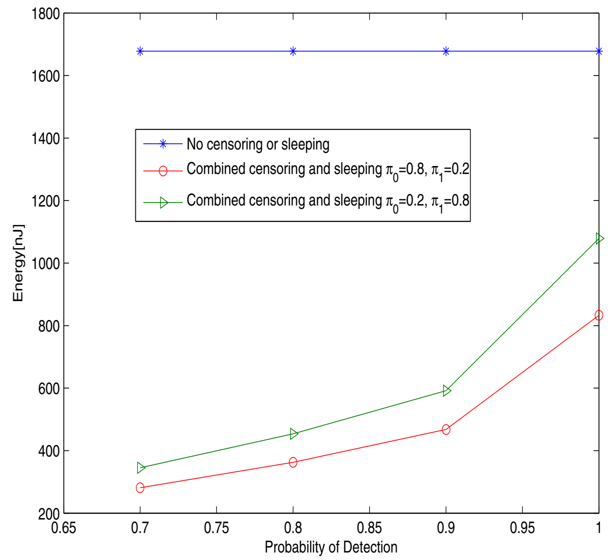

Fig. 2. Comparison of energy consumption.

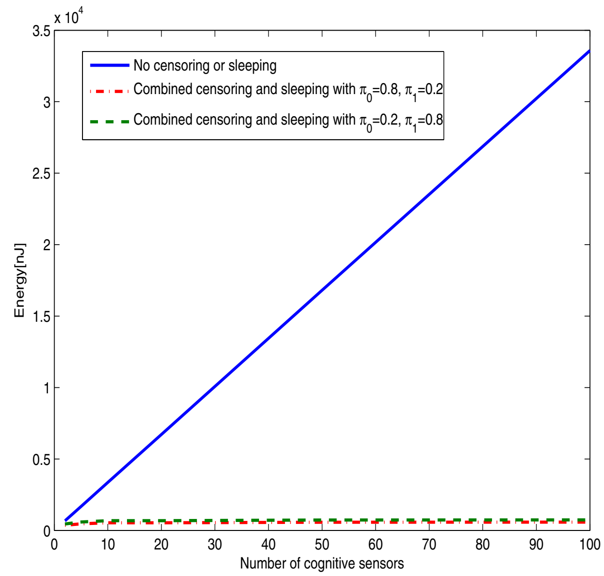

Fig. 3. Energy scaling with number of sensors.

V. Conclusions and Remarks

We designed the optimum sleeping rate and censoring thresholds in order to minimize the average energy consumed in distributed spectrum sensing, under the constraint that desired probabilities of detection and false-alarm are satisfied. We showed that with an optimum choice of parameters, our proposed scheme results in substantial energy savings in comparison to a scheme where no sleeping or censoring is employed.

In this work, we did not address the design of protocols employed in the cognitive sensor network - in particular, the protocol that individual sensors use to transmit their detection results to the FC. Optimizing the design of the protocol with the sensing and censoring policies could lead to additional energy savings.

Our analysis was based on the OR hard fusion rule. The design of sleeping and censoring schemes with extensions to other fusion rules and soft fusion is a subject of further study.

References

[1] J. Ammer and J. Rabaey, "The energy-per-useful-bit metric for evaluating and optimizing sensor network physical layers," *IEEE International Workshop on Wireless Ad-Hoc and Sensor Networks*, 2006.

[2] S. Appadwedula, V. V. Veeravalli and D. L. Jones, "Decentralized Detection With Censoring Sensors," *IEEE Transactions on Signal Processing*, pp 1362-1373, Apr 2008.

[3] D. Cabric, S. M. Mishra and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," *Asilomar Conference on Signals, Systems and Computers*, pp 772-776, Nov 2004.
[4] C. R. C. da Silva, B. Choi and K. Kim, "Cooperative Sensing among Cognitive Radios," *Information Theory and Applications Workshop*, pp 120-123, 2007.
[5] Federal Communications Commission - Second Report and Order and Memorandum Opinion and Order, "Unlicensed operation in the TV broadcast bands," *FCC 08-260*, Nov 2008.
[6] W. Heinzelman, A. P. Chandrakasan and H. Balakrishnan, "An Application-Specific Protocol Architecture for Wireless Microsensor," *IEEE Transactions on Wireless Networking*, pp 660-670, Oct 2002.
[7] IEEE 802.15.4 standard, *Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (WPANs)*, 2006.
[8] S. M. Kay, *Fundamentals of Statistical Signal Processing, Volume 2: Detection Theory*, Prentice Hall, 1998.
[9] C.-H. Lee and W. Wolf, "Energy Efficient Techniques for Cooperative Spectrum Sensing in Cognitive Radios," *IEEE Consumer Communications and Networking Conference*, pp 968-972, Jan 2008.
[10] S. M. Mishra, A. Sahai and R. W. Brodersen, "Cooperative Sensing among Cognitive Radios," *IEEE International Conference on Communications*, pp 1658-1663, June 2006.
[11] J. Nocedal and S. Wright, *Numerical Optimization*, Springer, 2000.
[12] C. Rago, P. Willett and Y. Bar-Shalom, "Censoring sensors: a low-communication-rate scheme for distributed detection," *IEEE Transactions on Aerospace and Electronic Systems*, pp 554-568, Apr 1996.
[13] D. A. Roberson, C. S. Hood, J. L. LoCicero and J. T. MacDonald, "Spectral Occupancy and Interference Studies in support of Cognitive Radio Technology Deployment," *IEEE Workshop on Networking Technologies for Software Defined Radio Networks*, pp 26-35, Sept 2006.
[14] P. K. Varshney, *Distributed Detection and Data Fusion*, Springer, 1996.
[15] A. Y. Wang and C. G. Sodini, "On the Energy Efficiency of Wireless Transceivers", *IEEE International Conference on Communications*, pp 3783-3788, June 2006.
[16] K. Yamasaki and T. Ohtsuki, "Design of energy-efficient wireless sensor networks with censoring, on-off, and censoring and on-off sensors based on mutual information," *IEEE Vehicular Technology Conference*, pp 1312-1316, 2005.
[17] Q. Zhao and B. M. Sadler, "A Survey of Dynamic Spectrum Access," *IEEE Signal Processing Magazine*, pp 79-89, May 2007.