Optimal Cooperative Spectrum Sensing in Cognitive Sensor Networks

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ABSTRACT

This paper addresses the problem of optimal cooperative spectrum sensing in a cognitive-enabled sensor network where cognitive sensors can cooperate in the sensing of the spectrum. Such sensor networks are assumed to be power resource constrained. With a given threshold for the accuracy of the spectrum detection, we find the optimal number of cognitive sensors participating in the cooperative spectrum sensing and the optimal sensing interval that minimize the total energy consumption of the cooperative sensing. First, the mathematical lower bound and upper bound for the number of cooperative cognitive sensors are found. Then the optimization problem to minimize the total energy consumed by a group of sensors is presented. Finally, an efficient approximate solution to the optimization problem is proposed. Numerical calculations validate the accuracy and the performance of the proposed scheme. The impact of the noise uncertainty, the choice of the energy detection threshold, and the spectrum bandwidth on the detection accuracy and the minimum total energy consumption is also studied.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Wireless communication*

General Terms

Design, Performance, Reliability

Keywords

Spectrum Sensing, Optimization, Energy Consumption

1. INTRODUCTION

The Federal Communications Commission (FCC) in the US estimates that only 15% - 85% of the assigned spectrum is utilized, depending on geographical and temporal variations [2]. The main reason is that the policy of fixed or static assignment of the spectrum leads to spectrum underutilization. Therefore, cognitive radio (CR) has been envisioned by J. Mitola as the emerging technology to accommodate dynamic spectrum access [9] [1]. In a cognitive radio network, the unlicensed (secondary) devices can utilize the licensed spectrum when it is unused by any licensed (primary) devices. However, the occupied spectrum will need to be vacated instantly when a primary device starts using it in order to avoid interfering with the transmission of the primary device. Thus, spectrum sensing, which enables a CR device to detect and adapt to primary usage of the spectrum band, plays a critical role in dynamic spectrum utilization.

The use of cognitive-enabled sensors is an emerging technology for spectrum sensing. These sensors sense the spectrum band continuously and report the detection results to secondary devices that will make use of the spectrum. However, one single sensor might perform poorly when the communication channel experiences fading and shadowing. To overcome this problem, cooperative spectrum sensing by a group of collaborating sensors has been proposed to exploit multi-user diversity in the sensing process [4, 8, 12].

Spectrum sensing consumes energy for the receiver and base-band circuitry and depletes the battery life-time of a cognitive sensor. On the one hand, one wants to gain a high sensing (or detection) reliability by using many collaborating cognitive sensors and a long sensing interval. On the other hand, one wants to save as much energy as possible by using fewer sensors and a shorter sensing interval. This tradeoff is explored in this paper. To the best of our knowledge, this key problem has not been studied before.

It is assumed that each cognitive sensor performs spectrum sensing with the well-known energy detection scheme [3]. The performance of this scheme is represented by two essential parameters, i.e. the probability of detection P_d and the false alarm probability P_f. A high detection probability means a high accuracy of detecting the activity of primary users. Furthermore, a low false alarm probability translates into a high usage of available spectrum by the secondary device, due to a low chance that the spectrum is mistakenly believed to be occupied when it is actually available. The previously mentioned tradeoff means to keep a high P_d and an acceptable level of P_f and at the same time preserve the power resources of the cognitive sensors as much as possible.

The rest of the paper is organized as follows. First, the

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related work is presented in Section 2. Next, the bounds for the number of cognitive sensors in cooperative spectrum sensing is formulated in Section 3. Then, Section 4 presents the energy minimization problem and an approximation approach to efficiently solve the optimization under the given accuracy of primary user detection. In Sections 5 numerical results are used to explore the optimization and validate the performance and accuracy of the proposed scheme. Finally, conclusions and future work are drawn in Section 6.

2. RELATED WORK

There has been a high research focus on improving the accuracy of spectrum sensing as well as finding optimal spectrum sensing strategy, and a lot of literature on this issue is available. In [6], Lee and Akyildiz propose the interesting idea of optimizing the sensing parameters in order to maximize the sensing efficiency subject to interference avoidance constraints in a single spectrum band. They propose spectrum selection and scheduling methods where the best spectrum bands for sensing are selected to maximize the sensing capacity. An adaptive and cooperative spectrum sensing method where the sensing parameters are optimized adaptively to the number of cooperating users is also considered.

Furthermore, in [7], Liang et al. study the problem of designing the sensing duration to maximize the achievable throughput for the secondary network under the constraint that the primary users are sufficiently protected. They formulate the sensing-throughput tradeoff problem and use the energy detection sensing scheme in order to prove that the formulated problem has one optimal sensing time, which yields the highest throughput for the secondary network.

In [11], the authors consider sensor networks that attempt to reclaim some of the available spectrum for their own communications by using spectrum sensing to detect the absence of the primary user. Different nearby sensor networks cooperate to reduce uncertainty caused by the presence/absence of possible interference from other users.

Peh and Liang show in [10] that cooperation among *all* secondary users in the network does not necessary achieve the optimum performance. Instead, optimum is achieved with a cooperation that involves only a certain number of secondary users, i.e. those users sensing the highest signal to noise ratio of the primary transmission.

3. LOWER BOUND AND UPPER BOUND FOR THE NUMBER OF SENSORS

3.1 Energy Detector for Spectrum Sensing

Each cognitive sensor i is assumed to derive the single-node detection probability P_{di} and single-node false alarm probability P_{fi} using the energy detection scheme for spectrum sensing [3, 4]. P_{di} and P_{fi} can then be evaluated in terms of the $\mathbb{Q}$-function [5], following the approach in [6]:

$$P_{di} = \mathbb{Q}\left(\frac{\lambda - 2t_sW(\gamma_i+1)\sigma_n^2}{\sqrt{4t_sW(\gamma_i+1)\sigma_n^2}}\right) \quad (1)$$

$$P_{fi} = \mathbb{Q}\left(\frac{\lambda - 2t_sW\sigma_n^2}{\sqrt{4t_sW\sigma_n^4}}\right) \quad (2)$$

where t_s is the sensing interval, which is assumed to be the same for every sensor, W is the spectrum bandwidth, and λ is the energy detection threshold. $\sigma_{n,i}^2$ and $\sigma_{n,i}^2$ are the variance of the noise and of the received signal at sensor i, respectively. Here, the Signal-to-Noise-Ratio (SNR) at the sensor i is $\gamma_i = \sigma_{s,i}^2/\sigma_{n,i}^2$. Without loss of generality, it is assumed that the variance of the noise is the same at every sensor, and it can therefore simply be denoted as σ_n.

Observe that P_{di} is monotonically increasing with regard to the sensing interval t_s and the SNR γ_i. This means that if all sensors have the same sensing interval t_s, the sensors that experience the lowest SNR will yield the lowest detection probabilities or the least accurate detection. Thus, one might reduce the total energy consumption by excluding these sensors from the group of sensing nodes, and still keep the total detection probability above the required threshold.

In addition, the primary activity has also an effect on the spectrum sensing performance. The traffic pattern of the primary user on a channel can be modeled as a two state independent and identically distributed (i.i.d) ON-OFF random process, whose ON and OFF distributions are exponentially distributed with means equal to T_{on} and T_{off}, respectively. Hence, the probabilities of the ON and OFF periods are $P_{on} = \frac{T_{on}}{T_{on}+T_{off}}$ and $P_{off} = \frac{T_{off}}{T_{on}+T_{off}}$, respectively [6, Ref. 15]. Therefor sensor i can detect a spectrum by the single-node detection and false alarm probabilities as [6]:

$$\hat{P}_{di} = P_{on}P_{di} \quad (3)$$

$$\hat{P}_{fi} = P_{off}P_{fi} \quad (4)$$

3.2 A Cooperative Spectrum Sensing Scheme

In this paper, it is assumed that the cooperative spectrum sensing is coordinated by the common receiver. The common receiver invites a group of sensors to participate in spectrum sensing. After having received the invitation, all the cognitive sensors of the invited group, say $\mathbb{G}$, will independently start sensing the spectrum and then return their observations back to the common receiver. It is further assumed that the common receiver is employing the "OR-rule" for decision fusion and that the communication channels with the invited cognitive sensors are perfect. Hence, the cooperative detection probability Q_d and the cooperative false alarm probability Q_f are given by [4]:

$$Q_d = 1 - \prod_{i=1}^{|\mathbb{G}|}(1-\hat{P}_{di}) \quad (5)$$

$$Q_f = 1 - \prod_{i=1}^{|\mathbb{G}|}(1-\hat{P}_{fi}) \quad (6)$$

where $|\mathbb{G}|$ is the number of the invited sensors in $\mathbb{G}$ and $\hat{P}_{di}, \hat{P}_{fi}$ are the sing-node detection and false alarm probabilities estimated from sensor i according to (3) and (4), respectively. We observe from (5) and (6) that when the number of cooperative sensors for spectrum sensing, n (or $|\mathbb{G}|$), increases, then the cooperative detection probability Q_d of the group increases and as a result the accuracy of primary user being detected also increases. However, the higher $|\mathbb{G}|$, the higher cooperative false alarm probability Q_f which in turn leads to a higher chance that a spectrum opportunity will be missed.

In addition, the more sensors participate in the cooperative group for spectrum sensing, the more energy is consumed. This should be strictly avoided, since sensors are assumed to be battery-powered and have limited energy resource. That is why finding an optimal size of such cooperative spectrum sensing group is an important issue. In addition, an energy-efficient problem of how to efficiently select the actual sensors that experience the highest SNR and that are well separated to avoid correlation shadowing is also critical. This problem is considered as the future direction of the present paper.

3.3 Bound for the Size of the Cooperative Sensing Group

Given a threshold $\bar{Q}_d$ for the cooperative detection probability, the condition $Q_d \geq \bar{Q}_d$ is necessary to be confident that a primary user is detected. Hence, (5) yields:

$$1 - \bar{Q}_d \geq \prod_{i=1}^{|\mathbb{G}|}(1 - \hat{P}_{di}) \tag{7}$$

Let $\hat{P}_d^{min}$ denote the minimum of the single-node detection probability among the group of sensor such that:

$$\begin{aligned} \hat{P}_d^{min} &\triangleq \min\{\hat{P}_{di}, \quad i = [1 \ldots n]\} \\ &= P_{on}.\mathbb{Q}\left(\frac{\lambda - 2t_s W(\gamma^{min}+1)\sigma_n^2}{\sqrt{4t_s W}(\gamma^{min}+1)\sigma_n^2}\right) \end{aligned} \tag{8}$$

where, the minimum SNR is: $\gamma^{min} \triangleq \min\{\gamma_i, \quad i = [1 \ldots n]\}$.

Hence, if $|\mathbb{G}|$ is bounded by:

$$1 - \bar{Q}_d \geq (1 - \hat{P}_d^{min})^{|\mathbb{G}|} \Leftrightarrow |\mathbb{G}| \geq \frac{\log(1 - \bar{Q}_d)}{\log(1 - \hat{P}_d^{min})} \tag{9}$$

then the inequality in (7) will be satisfied as:

$$1 - \bar{Q}_d \geq (1 - \hat{P}_d^{min})^{|\mathbb{G}|} \geq \prod_{i=1}^{|\mathbb{G}|}(1 - \hat{P}_{di})$$

Similarly, given a cooperative false alarm probability threshold $\bar{Q}_f$, the condition $Q_f \leq \bar{Q}_f$ is needed to ensure that a spectrum opportunity is not missed. Likewise, (6) yields:

$$1 - \bar{Q}_f \leq \prod_{i=1}^{|\mathbb{G}|}(1 - \hat{P}_{fi}) \tag{10}$$

Here we denote $\hat{P}_f^{max}$ as the maximum single-node false alarm probability among the group such that:

$$\hat{P}_f^{max} = \max\{\hat{P}_{fi}, \quad i = [1 \ldots n]\} \tag{11}$$

Then, (10) is guaranteed when:

$$\prod_{i=1}^{|\mathbb{G}|}(1 - \hat{P}_{fi}) \geq (1 - \hat{P}_f^{max})^{|\mathbb{G}|} \geq 1 - \bar{Q}_f$$

which leads to the following upper bound:

$$1 - \bar{Q}_f \leq (1 - \hat{P}_f^{max})^{|\mathbb{G}|} \Leftrightarrow |\mathbb{G}| \leq \frac{\log(1 - \bar{Q}_f)}{\log(1 - \hat{P}_f^{max})} \tag{12}$$

Combining (9) and (12), the bound for $|\mathbb{G}|$ is derived as:

$$\left\lceil \frac{\log(1 - \bar{Q}_d)}{\log(1 - \hat{P}_d^{min})} \right\rceil \leq |\mathbb{G}| \leq \left\lfloor \frac{\log(1 - \bar{Q}_f)}{\log(1 - \hat{P}_f^{max})} \right\rfloor \tag{13}$$

where $\lceil . \rceil$ and $\lfloor . \rfloor$ denote the ceiling and flooring functions for the rounding of a real number to an integer, respectively. It is observed that the higher the single-node detection probability the fewer sensors are required to guarantee a given threshold. More importantly, the lower bound shows that the higher the minimum SNR condition among the sensors, the fewer sensors need to be included in the spectrum sensing. This gives a hint that one should only select as part of the sensing group only the sensors that experience a sufficiently high SNR. On the other hand, the upper bound indicates an invaluable physical meaning for the requirement of the false alarm probability of the cooperative group. It means the required threshold $\bar{Q}_f$ cannot be as small as possible, since a low $\bar{Q}_f$ requires a small number of sensors, which may break the detection accuracy by breaking (13).

4. ENERGY CONSUMPTION MINIMIZATION

The lower bound in (13) gives the minimum number of sensors collaborating in spectrum sensing in order to yield a given accuracy of the primary user detection. Clearly, the fewer the sensors used for cooperative spectrum sensing, the less the total sensing energy consumed. Hence, for energy efficiency, the lower bound of $|\mathbb{G}|$ in (13) is selected as the minimum number of spectrum sensing sensors of group $\mathbb{G}$:

$$|\mathbb{G}| \triangleq \left\lceil \frac{\log(1 - \bar{Q}_d)}{\log(1 - \hat{P}_d^{min})} \right\rceil \tag{14}$$

However, this formulation does not mean that the size of $\mathbb{G}$ is optimal in terms of minimizing the total sensing energy consumption for cooperative spectrum sensing. It can be seen from (1) that the detection probability depends on the sensing interval t_s. The higher the sensing interval, the more accurate the detection probability. Then, fewer sensors will need to participate in the cooperative spectrum sensing (see (14)), and consequently less energy will be spent on the spectrum sensing. On the other hand, the higher the sensing interval t_s, the more energy is consumed for spectrum sensing. As a result, there is a tradeoff in estimating t_s or $|\mathbb{G}|$ in the energy efficiency problem.

Let δE^{ss} denote the sensing energy consumption per unit of spectrum sensing interval, which is assumed to be the same for every cognitive sensor in the network. Hence, for a sensing interval t_s, each sensor i consumes the sensing energy $\Delta E_i^{ss} = (\delta E^{ss}.t_s)$. The total sensing energy consumed by the group $\mathbb{G}$ is minimized as follow:

$$\begin{aligned} &\underset{t_s}{\text{Minimize:}} \quad \sum_{i=1}^{|\mathbb{G}|} \Delta E_i^{ss} \triangleq |\mathbb{G}|.(\delta E^{ss}.t_s) \\ \Leftrightarrow \quad &\underset{t_s}{\text{Minimize:}} \quad \frac{\log(1 - \bar{Q}_d)}{\log(1 - \hat{P}_d^{min})}.(\delta E^{ss}.t_s) \end{aligned} \tag{15}$$

To refine the above optimization problem, it is argued that the absolute function $|\log(1 - \hat{P}_d^{min})|$ is monotonically increasing with regard to $\hat{P}_d^{min}$. Thus, (15) is equivalent to:

$$\begin{aligned} &\underset{t_s}{\text{Minimize:}} \quad |\log(1 - \bar{Q}_d)|.\delta E^{ss}.\frac{t_s}{|\log(1 - \hat{P}_d^{min})|} \\ \Leftrightarrow &\underset{t_s}{\text{Maximize:}} \quad \frac{1}{|\log(1 - \bar{Q}_d)|.\delta E^{ss}}.\frac{\hat{P}_d^{min}}{t_s} \\ \Leftrightarrow &\underset{t_s}{\text{Maximize:}} \quad \frac{P_{on}}{|\log(1 - \bar{Q}_d)|.\delta E^{ss}}.\frac{\mathbb{Q}\left(\frac{\lambda - 2t_s W(\gamma^{min}+1)\sigma_n^2}{\sqrt{4t_s W}(\gamma^{min}+1)\sigma_n^2}\right)}{t_s} \end{aligned}$$

Without loss of generality, it is assumed that δE^{ss} is known and that $\bar{Q}_d$ is given. $P_{on} = \frac{T_{on}}{T_{on}+T_{off}}$ is also known and independent of the sensing interval t_s. Finally, we derive the following maximization problem with regard to the sensing interval t_s for minimizing the total sensing energy consumed by the cooperative group $\mathbb{G}$ as:

$$t_s^* = \arg\max_{t_s} \frac{\mathbb{Q}\left(\frac{\lambda - 2t_sW(\gamma^{min}+1)\sigma_n^2}{\sqrt{4t_sW(\gamma^{min}+1)\sigma_n^2}}\right)}{t_s}$$
$$\triangleq \arg\max_{t_s} \frac{\mathbb{Q}(z)}{t_s} = \frac{\frac{1}{\sqrt{2\pi}}\int_z^\infty e^{-\frac{x^2}{2}}dx}{t_s} \quad (16)$$
$$\text{where: } z = \frac{\lambda - 2t_sW(\gamma^{min}+1)\sigma_n^2}{\sqrt{4t_sW(\gamma^{min}+1)\sigma_n^2}}$$

The optimality of (16) can be found by solving the roots t_s^* of the first partial derivative as follows:

$$\frac{\partial\left(\frac{\mathbb{Q}(z)}{t_s}\right)}{\partial t_s} = 0 \quad \Leftrightarrow \quad \frac{\frac{\partial(\mathbb{Q}(z))}{\partial z}.\frac{\partial z}{\partial t_s}.t_s - \mathbb{Q}(z)}{t_s^2} = 0$$
$$\Leftrightarrow \quad \frac{\partial(\mathbb{Q}(z))}{\partial z}.\frac{\partial z}{\partial t_s}.t_s = \mathbb{Q}(z) \quad (17)$$

It can be shown that solving (16) analytically is extremely difficult due to the exponential characteristic of the $\mathbb{Q}$-function. Therefore, an approximation approach to solve (16) is proposed, using the well-known approximation for $\mathbb{Q}(z)$:

$$\mathbb{Q}(z) \approx \begin{cases} \frac{1}{2}e^{-z^2/2} & \text{if } z \geq 0 \quad (18) \\ 1 - \frac{1}{2}e^{-z^2/2} & \text{if } z < 0 \quad (19) \end{cases}$$

When $z \geq 0$, the approximated optimal sensing interval can be found by substituting (18) into (17) as follows:

$$\frac{\partial(\frac{1}{2}e^{-\frac{z^2}{2}})}{\partial z}.\frac{\partial z}{\partial t_s}.t_s = \frac{1}{2}e^{-\frac{z^2}{2}} \Leftrightarrow (-z).\frac{\partial z}{\partial t_s}.t_s = 1 \quad (20)$$

Then $\frac{\partial z}{\partial t_s}.t_s$ is found as:

$$\frac{\partial z}{\partial t_s}.t_s = \frac{\partial\left(\frac{\lambda - 2t_sW(\gamma^{min}+1)\sigma_n^2}{\sqrt{4t_sW(\gamma^{min}+1)\sigma_n^2}}\right)}{\partial t_s}.t_s$$
$$= -\frac{\lambda + 2t_sW(\gamma^{min}+1)\sigma_n^2}{4\sqrt{t_sW}.(\gamma^{min}+1)\sigma_n^2} \quad (21)$$

Substituting (21) into (20) yields:

$$z.\frac{\lambda + 2t_sW(\gamma^{min}+1)\sigma_n^2}{4\sqrt{t_sW}.(\gamma^{min}+1)\sigma_n^2} = 1$$
$$\Leftrightarrow \quad \left(x + 2(\gamma^{min}+1)\sigma_n^2\right)^2 = \lambda^2 + 4(\gamma^{min}+1)^2\sigma_n^4$$
$$\text{where } x \text{ is given by: } x = 2t_sW(\gamma^{min}+1)\sigma_n^2$$

The approximated optimal sensing interval (i.e. the approximated root of (17)) can now be found as:

$$t_s^* = \frac{\sqrt{\lambda^2 + 4(\gamma^{min}+1)^2\sigma_n^4} - 2(\gamma^{min}+1)\sigma_n^2}{2W(\gamma^{min}+1)\sigma_n^2} \quad (22)$$

On the other hand, when z is negative the approximate optimal sensing interval is found using (19) instead of (18) as the approximation. However, solving the root of (17) analytically by this approximation is still extremely difficult. In this case, we solve the proposed optimization problem numerically to validate the accuracy of that approximation. The benefit here is that the complexity of finding the optimality will be significantly reduced compared to the complexity of solving (16) directly. Providing accurate analytical solutions for this is considered as the future work. With the solved optimal sensing interval t_s^* above, the optimal number of cooperative cognitive sensors can be found as:

$$n^* = \left\lceil \frac{\log(1 - \bar{Q}_d)}{\log(1 - \hat{P}_d^{*min})} \right\rceil \quad (23)$$
$$\text{where: } \hat{P}_d^{*min} = P_{on}.\mathbb{Q}\left(\frac{\lambda - 2t_s^*W(\gamma^{min}+1)\sigma_n^2}{\sqrt{4t_s^*W(\gamma^{min}+1)\sigma_n^2}}\right)$$

5. NUMERICAL RESULTS

In this section, numerical calculations are presented to validate the approximated optimal sensing interval and the approximated optimal number of collaborating sensors that minimize the total energy consumption of the cooperative spectrum sensing. Mean absolute error is calculated as the accuracy metric for the approximated results. In all the numerical calculations, we use the following settings: $\delta E^{ss} = 0.05$ J, $T_{on} = 1$ sec, $T_{off} = 2$ sec, $\bar{Q}_d = 0.9$, $\bar{Q}_f = 0.1$, and bandwidth $W = 1$ MHz. The minimum SNR threshold (γ^{min}) varies from 1 to 20 dB for comparison.

First of all, the validation of the accuracy and performance of the proposed approach is presented in Fig. 1 - Fig. 3 with the chosen parameters for the energy threshold and signal noise as $\lambda = 15$ dB, $\sigma_n = -5$ dB, respectively. Fig. 1 illustrates the minimum total energy consumption for cooperative spectrum sensing. The solid curve illustrates the minimum value of the energy consumption found by solving the original optimization (16) numerically. The dash-dot-asterisk curve, on the other hand, shows the corresponding minimum value found by our proposed analytical approximate solution. The results indicate that our approximation gives a rather good solution to the original optimization problem, as the error is around 8.6% on average. It is also observed that when the minimum SNR increases, less energy is needed for the cooperative spectrum sensing while still satisfying the required spectrum sensing accuracy.

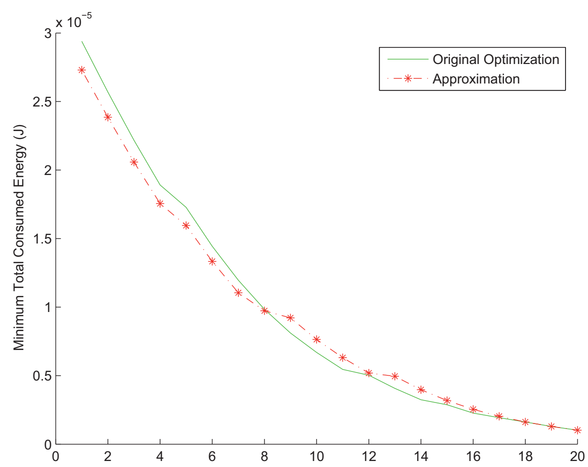

Figure 1: The minimum total energy consumption.

A similar trend can also be observed from Fig. 2. The figure reconfirms that the optimal sensing interval solved by our proposed approximation (the dash-dot-asterisk curve) follows closely to that of the original optimization (the solid curve). Again it is seen that the higher the minimum SNR

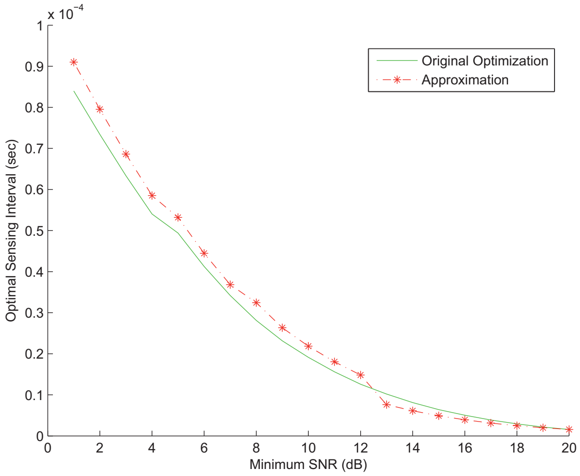

Figure 2: The optimal sensing interval.

threshold, the shorter time the cooperative cognitive sensors will need to complete the spectrum sensing while still satisfying the required accuracy of the sensing. However, the optimal sensing interval solved by our approach is a bit longer (about 13.6% on average) than that of the original optimization. This inaccuracy occurs as a consequence of approximating the $\mathbb{Q}$-function.

Fig. 3 presents the optimal number of cognitive sensors found by our approach (the dashed bar) and that of the original optimization (the solid bar). The results show that

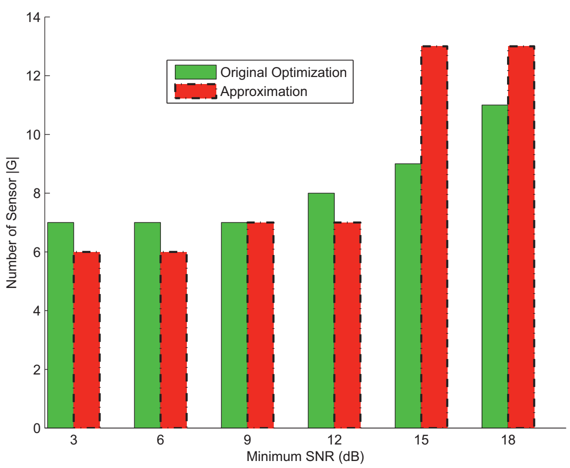

Figure 3: The optimal number of sensor.

the error between our approach and the original one is between 1 and 2 sensors on average. When the SNR condition is better, the optimal number of sensors is higher, which is due to the reason that the energy minimization produces shorter optimal sensing interval under the good SNR condition. However, it needs to satisfy the requirement for detection accuracy, hence the sufficient number of sensors will need to be included during the optimization. It is also observed here that a higher error is caused when the minimum SNR is higher than 12 dB, which is due to the inaccuracy of the proposed approximation. Improving this high inaccuracy is considered as the future work of the present paper.

The performance metric for the spectrum detection accuracy is evaluated in terms of the summation (*the maximum total detection error probability*: err^{max}) of the miss-detection and false alarm probabilities as: $err^{max} = (1 - Q_d^{*min}) + Q_f^{*max} = (1 - \hat{P}_d^{*min})^{n^*} + 1 - (1 - \hat{P}_f^{*max})^{n^*}$. Fig. 4 presents this maximum total detection error probability with regard to the noise uncertainty. It can be seen the

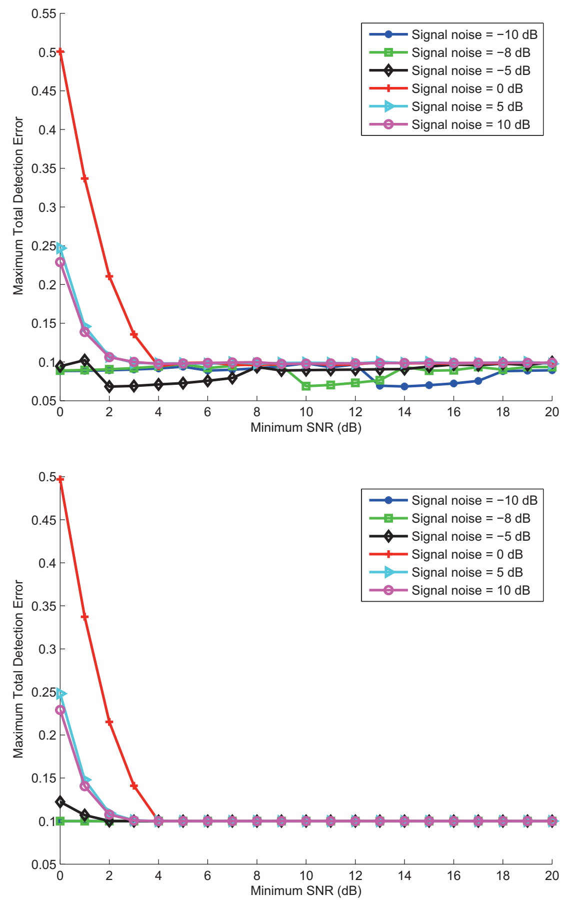

Figure 4: Two graphs of the maximum total detection error probability when the ceiling function is used and not used for n^* in (23). $\lambda = 10$ dB

slightly difference between the upper and lower graphs in Fig. 4. It is caused by using the ceiling function in (23) to round the optimal number of sensors up to an integer. Since the number of sensors must be an integer, so it can be also observed from all the graphs in this section that they are not as smooth as the graphs resulted by not using the ceiling function in (23). The results in Fig. 4 show that the signal noise uncertainty has strong effect on the detection accuracy of the cooperative spectrum sensing using the energy detector, especially when the minimum SNR condition is bad. The main reason is due to the fact that the energy detection scheme is not robust in the low SNR conditions and is sensitive to the signal noise [13]. It also confirms that our approach produces good detection accuracy when the signal noise uncertainty is not very high and the SNR condition is not very low. Tackling the detection inaccuracy under very low minimum SNR conditions and strong noise uncertainty is the future work of the present paper.

Second of all, the impact of the noise uncertainty σ_n, the choice of the energy threshold λ, and the spectrum bandwidth W on the detection accuracy and the minimum total

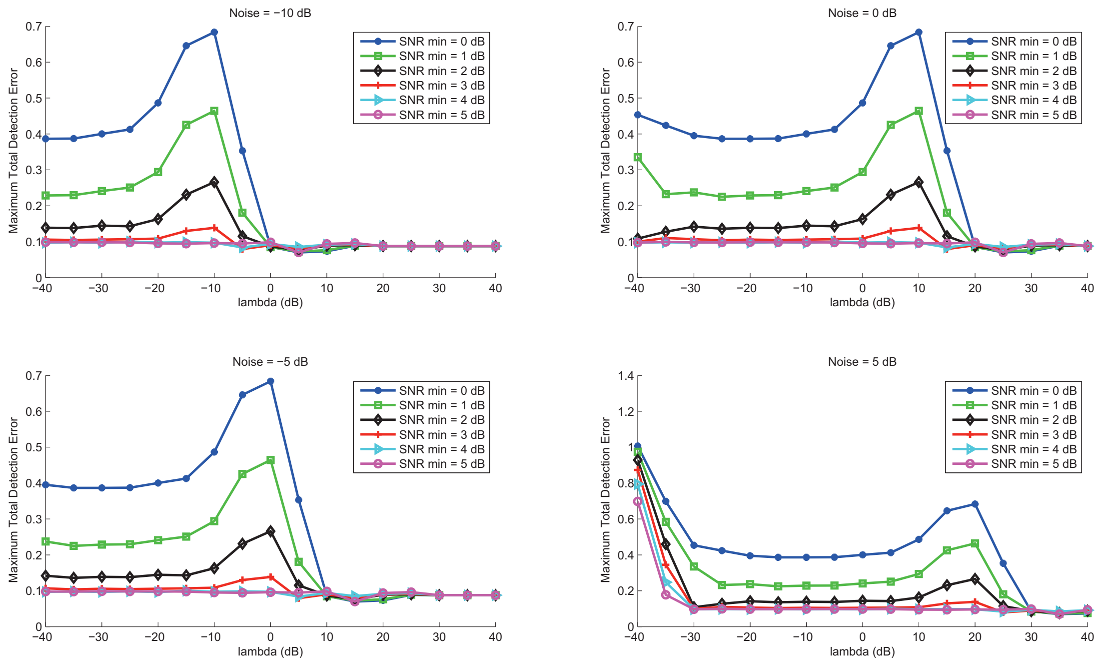

Figure 5: The maximum total detection error probability vs. energy threshold and noise uncertainty.

energy consumption for the cooperative spectrum sensing scheme, especially under the low minimum SNR conditions, is studied in Fig. 5 - Fig. 7. The results in Fig. 5 show how the energy threshold and the noise uncertainty affect the maximum total detection error probability err^{max} under different minimum SNR conditions. It can be observed that under noise uncertainty, the energy detector can only perform well under the low minimum SNR conditions if the energy threshold is set high enough. For example, when $\sigma_n = -5$ dB, it is better to choose $\lambda = 15$ dB, as we use in the calculations for Fig. 1 - Fig. 3, in order to keep $err^{max} \leq 0.1$ when the minimum SNR $\gamma^{min} \leq 3$ dB .

In addition, the four graphs in Fig. 5 illustrate that when the noise uncertainties are -10 dB, -5 dB, 0 dB, and 5 dB, the corresponding energy thresholds should be selected as about 5 dB, 15 dB, 25 dB, and 35 dB, respectively in order to keep the energy detector detecting the spectrum accurately under the low minimum SNR conditions. This can be implied generally that when the noise uncertainty increases by 5 dB, the energy threshold should have to be increased by around 10 dB, which requires much more energy consumption in order to produce high detection accuracy under the low minimum SNR conditions. It indicates again that the cooperative spectrum sensing using energy detector is highly sensitive to the noise uncertainty and the choice of the energy threshold. Thus, the important issue of finding an analytical form of the optimal energy threshold under a specific range of the noise uncertainty while satisfying a given spectrum detection accuracy is considered as the future work of the present paper.

Furthermore, we observe how the choice of the energy threshold λ for the energy detector affects the minimum total energy consumption when the noise uncertainty is fixed as $\sigma_n = -5$ dB in Fig. 6. Obviously, the higher energy threshold, the more sensing energy will need to be consumed by the group of collaborating sensors. However, under the noise $\sigma_n = -5$ dB, the results in Fig. 5 show that the energy threshold should be selected as $\lambda = 15$ dB in order to yield $err^{max} \leq 0.1$ under the low minimum SNR conditions. Hence there is a tradeoff in selecting the energy threshold to keep the minimum total energy consumption and the maximum total detection error probability as low as possible at the same time, especially when the minimum SNR condition is bad. On the other hand, under the good minimum SNR conditions, for example when $\gamma^{min} \geq 5$ dB, a wide range of λ could be selected to yield $err^{max} \leq 0.1$, hence the lower the selected λ, the lower the minimum total energy consumption. It again indicates that the cooperative

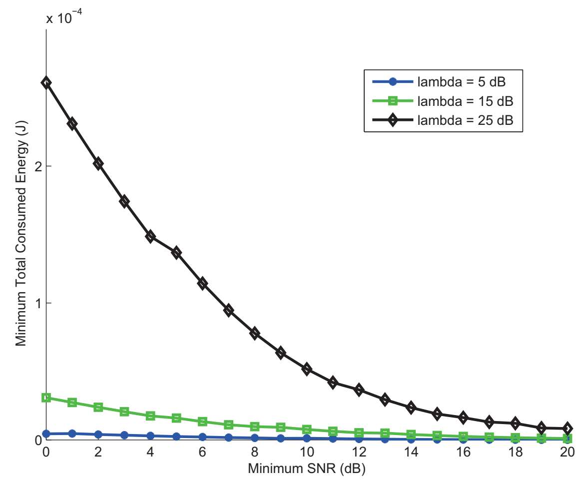

Figure 6: Minimum total energy consumption vs. energy threshold λ for the energy detector.

spectrum sensing scheme using energy detector is highly sensitive to the energy threshold under the low minimum SNR conditions. Thus, making this scheme be less sensitive to the noise uncertainty and/or the energy threshold in a wide range of the minimum SNR conditions is seen to be an important issue. We consider this observation as the future work of the present paper.

Finally, the impact of the spectrum bandwidth on the minimum total energy consumption for cooperative spectrum sensing is presented in Fig. 7. In this figure, the energy threshold and the signal noise are set as $\lambda = 15$ dB, $\sigma_n = -5$ dB, respectively. The similar observation can also be seen here that the higher the minimum SNR, the lower the total energy consumption. However, the larger the spectrum bandwidth to be sensed, the lower the total energy consumption, which is caused by performing shorter sensing interval in cooperative spectrum sensing.

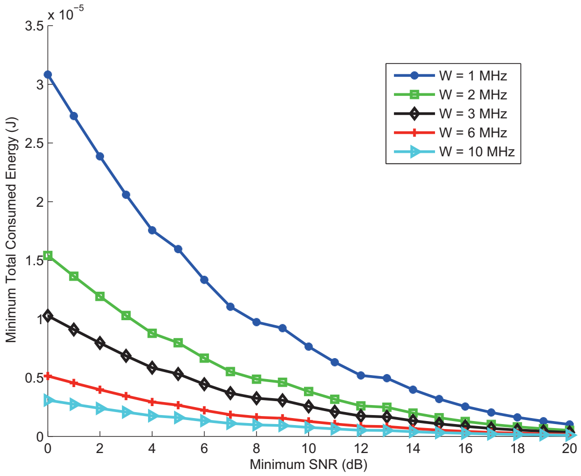

Figure 7: Minimum total energy consumption vs. bandwidth W.

6. CONCLUSION AND FUTURE WORK

This paper explores the problem of optimal cooperative spectrum sensing in cognitive-enabled sensor networks. The cognitive-enabled sensors are assumed to be battery powered and constrained by limited power resources. Thus, the key problem is how to minimize the total energy consumption for cooperative spectrum sensing by a group of cognitive sensors while still satisfying the given threshold for the spectrum detection accuracy. First, an expression for the lower and upper bound for the number of cognitive sensors participating in the spectrum sensing is found. The optimization problem for minimizing the total energy consumed by that group for cooperative spectrum sensing is also proposed. Furthermore, an approximation approach to solve the proposed energy consumption minimization is presented. Finally the accuracy of the approximation is validated using numerical calculation to compare the approximated optimization with the original proposed optimization. The impact of the noise uncertainty, the choice of the energy threshold for the energy detector, and the spectrum bandwidth on the spectrum detection accuracy and the minimum total energy consumption for the cooperative spectrum sensing scheme is also discussed.

In the future, improving the detection accuracy under extremely low minimum SNR conditions and high noise uncertainty as well as finding more accurate approximations for analytically solving the optimal results are necessary. Furthermore, finding an analytical form of the optimal energy threshold under a specific range of the noise uncertainty while satisfying a given spectrum detection accuracy is addressed as an important issued for the future work. Finally, making the cooperative spectrum sensing scheme using energy detector be less sensitive to the noise uncertainty and/or the energy threshold in a wide range of the minimum SNR conditions is the future work as well.

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