A Practical Method for Performance Estimation for Collaborative Sensing in Cognitive Radio Networks

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Abstract. *This paper presents a novel practical method for evaluating the local sensing performance of the participating users in collaborative spectrum sensing in cognitive radio networks. The proposed method considers data delivery as a base to evaluate the local sensing performance of each user. Moreover, the proposed method does not rely on any prior information about users. The estimated local sensing performance of all users is used further to evaluate the global performance of the whole network. Mathematical analysis and simulation results demonstrate the high accuracy of the proposed method.*

Keywords

Cognitive radio, cognitive radio networks, collaborative spectrum sensing, performance estimation

1. Introduction

Cognitive Radio (CR) has been widely presented as a promising solution for the spectrum scarcity problem [1]. CR allows unlicensed users, aka cognitive users (CU), to share the spectrum with the licensed users, aka primary users (PUs) [2]. There are three different models that describe the spectrum sharing between CUs and PUs, namely, underlay, overlay and interweave [3]. In overlay and underlay models, both PUs and CUs can simultaneously use the spectrum. In underlay model, the interference generated by CUs must be within an acceptable range for PUs, while, in overlay model, a CU acts as relay for the PU signal and divides its resources between its own transmission and the PU transmission. On the other hand, interweave model allows CUs to access unused portions of the licensed spectrum. Thus, concurrent transmission from the CU and the PU is forbidden. Interweave model is the most popular in the literature and the is adopted in this work.

A cognitive transmission should avoid any interference with PUs in order to guarantee their quality of service. Thus, spectrum should be priorly sensed to detect the activity of licensed users and identify the unused portions. Such a process is mostly accomplished through what is called Spectrum Sensing (SS) [4], [5]. However, SS cannot provide reliable results about the activity of the PU, which may cause a harmful interference at the PUs. To this end, Collaborative Spectrum Sensing (CSS) has been proposed a solution aiming at improving the reliability of the sensing results [6], [7]. In CSS, each CU individually senses the spectrum and makes a local decision regarding the spectrum status, either idle or busy. Local decisions are then transmitted to a central entity, called Fusion Center (FC), that is responsible for fusing the received local decisions and making a global decision [8].

CCS has been widely investigated in the literature from its different aspects. In [9], the different involved parameters in CSS are optimized in order to improve the achievable reliability. Enhancing the energy efficiency of CCS is addressed in [10] by selecting a partial set of the CUs to participate in the sensing process. In [11], the performance of CSS in presence of CUs equipped by multiple antennas is considered. Other works have been dedicated for the security aspects in CSS such as malicious detection [12], and authentication protocols [13].

The reliability of the global decision can be highly improved if the FC uses prior information about individual sensing performance of the CUs [5]. Local performance for a specific CU can be used as weight for its transmitted local decision, where CUs with high local performance should have higher weight and via versa [14]. Moreover, information about local performance can be further exploited to identify malicious CUs in order to ignore their local decisions at the FC [15].

To the best of our knowledge, most of the literature assumes that local performance of each CU is available at the FC [16]. However, there are no previous works that discuss the mechanism of making them available. In practical applications, even the CU itself is unaware of its actual sensing performance. This is due to the fact that the actual spectrum status is unknown.

This paper proposes a practical method to estimate the local sensing performance of each CU. The proposed method does not require any extra information except than that of the transmitted local decisions. Thus, it does not induce any overhead or time-energy expenditure [17]. Moreover, the proposed method does not introduce any transmission delay, as the local performance of each CU is estimated seamlessly while CSS is run. Simulation results demonstrate the accuracy of the estimated local performance obtained by the proposed method.

Section 2 deals with the system model and the necessary mathematical formulations. Section 3 presents the novel estimation method of the local and global performance of the participating CUs. In Sec. 4, the accuracy of the proposed method is analyzed mathematically, while simulation results are shown in Sec. 5 in order to demonstrate the accuracy of the proposed method. Section 6 concludes the paper.

2. System Model

The considered model consists of N CUs. All CUs concurrently sense the spectrum and each CU issues a local decision, denoted by d_n. The local decision is a binary value, i.e. either 0 or 1. A local decision of 1 means that the corresponding CU decides that the spectrum is busy, while a local decision of 0 refers to the case when the spectrum is decided to be idle [18]

The local sensing performance of the n^{th} CU is described by the detection rate ($P_{\text{d}n}$) and the false alarm rate ($P_{\text{f}n}$). The detection rate is defined as the ratio between the number of times in which the corresponding CU correctly identifies the busy spectrum to the number of times in which the spectrum is actually busy. The false-alarm rate is defined as the ratio between the number of times in which the corresponding CU incorrectly identifies the idle spectrum to the number of times in which the spectrum is actually idle. It is worth noting that better local performance can be achieved at high values of $P_{\text{d}n}$ and low values of $P_{\text{f}n}$.

Local decisions will be transmitted to the FC which applies a specific rule in order to obtain a global decision regarding spectrum occupancy, denoted by D. Generally, the FC counts the number of received 1's and compares it to the detection threshold K. If it exceeds K, the spectrum is globally declared as busy. Otherwise, the spectrum is globally declared as an idle [9]. The global decision is expressed as follows

$$\mathrm{D} = \begin{cases} busy\,(1), & \text{if } \sum_{n=1}^{N} u_{\text{n}} \geq K, \\ idle\,(0), & \text{if } \sum_{n=1}^{N} u_{\text{n}} < K. \end{cases} \quad (1)$$

where u_{n} is the local decision received by the n^{th} CU.

The reliability of the global decision is evaluated by the global detection rate (P_{D}) and the global false-alarm rate (P_{F}). Both rates (P_{D} and P_{F}) are defined by a similar way to $P_{\text{d}n}$ and $P_{\text{f}n}$, respectively. Mathematically, the global detection and false-alarm rates are given as follows:

$$P_{\text{D}} = \sum_{k=K}^{N} \sum_{j=1}^{\binom{N}{k}} \prod_{n \in A_j^{(N,k)}} P_{\text{d}n} \prod_{i \notin A_j^{(N,k)}} (1 - P_{\text{d}n}), \quad (2)$$

$$P_{\text{F}} = \sum_{k=K}^{N} \sum_{j=1}^{\binom{N}{k}} \prod_{n \in A_j^{(N,k)}} P_{\text{f}n} \prod_{i \notin A_j^{(N,k)}} (1 - P_{\text{f}n}) \quad (3)$$

where $A_1^{(N,k)}, A_2^{(N,k)}, ..., A_{\binom{N}{k}}^{(N,k)}$ represent all the possible combinations of k integers drawn from the interval $[1, N]$, and the number of these combinations is $\binom{N}{k}$.

There are two popular special cases of the general fusion rule, namely AND rule and OR rule. In AND rule, the value of the detection threshold K is equal to N, while, the value of K is equal to 1 for OR rule. Accordingly, P_{D} and P_{F} can be simplified for AND rule as follows [19]:

$$P_{\text{D|AND}} = \prod_{n=1}^{N} P_{\text{d}n}, \quad (4)$$

$$P_{\text{F|AND}} = \prod_{n=1}^{N} P_{\text{f}n}. \quad (5)$$

Similarly, considering OR rule, the two rates can be expressed as follows [20]:

$$P_{\text{D|OR}} = 1 - \prod_{n=1}^{N} 1 - P_{\text{d}n}, \quad (6)$$

$$P_{\text{F|OR}} = 1 - \prod_{n=1}^{N} 1 - P_{\text{f}n}. \quad (7)$$

According to the global decision made by the FC, data transmission can be commenced or not. In detail, if the spectrum has been decided as idle, the FC will schedule a CU to use the spectrum for its own data transmission. Otherwise, none of the CUs will use the spectrum and another sensing round is initiated [21].

3. The Proposed Method

As the actual spectrum status is unknown, the FC cannot distinguish if a local decision or the global decision is correct or not. However, our proposed method exploits the delivery of the transmitted data as an indicator of the actual spectrum status. In detail, if the spectrum is declared as idle, one of the CUs will start data transmission. Notice that if the spectrum is actually idle, the data will be successfully delivered. On the other hand, if the data have not been successfully delivered, the FC can realize that the spectrum is actually busy. As a result, the FC can realize the actual spectrum status, and hence, global and local decision can be assessed.

The proposed method implies defining four different counters at the FC. Specifically, the counters are denoted by α_i, β_i, $\gamma_{n,i}$ and $\zeta_{n,i}$ and are zero-initialized and updated each sensing round as follows:

$$\begin{cases} \alpha_i = \alpha_{i-1} + 1, \text{if } \mathrm{D}_i = 0 \,\&\, \mathrm{S}_i = 1, \\ \beta_i = \beta_{i-1} + 1, \text{if } \mathrm{D}_i = 0 \,\&\, \mathrm{S}_i = 0, \\ \gamma_{n,i} = \gamma_{n,i-1} + 1, \text{if } \mathrm{D}_i = 0 \,\&\, \mathrm{S}_i = 0 \,\&\, d_{n,i} = 0, \\ \zeta_{n,i} = \zeta_{n,i-1} + 1, \text{if } \mathrm{D}_i = 0 \,\&\, \mathrm{S}_i = 1 \,\&\, d_{n,i} = 0 \end{cases} \quad (8)$$

where S_i is the actual spectrum status of the i^{th} sensing round.

At the i^{th} sensing round, the counter α_i is incremented by one if the global decision is idle ($\mathrm{D}_i = 0$) and the actual spectrum status is busy ($\mathrm{S}_i = 1$), and the counter β_i is incremented by one if the global decision is idle ($\mathrm{D}_i = 0$) and the actual spectrum status is idle $\mathrm{S}_i = 0$. On the other hand, for each CU, other two counters $\gamma_{n,i}$ and $\zeta_{n,i}$ are incremented as follows. If $\mathrm{D}_i = 0$, $\mathrm{S}_i = 0$ and the local decision of the n^{th} CU is idle (i.e. $d_{n,i} = 0$), its corresponding counter $\gamma_{n,i}$ will be incremented by one. Similarly, if $\mathrm{D}_i = 0$, $\mathrm{S}_i = 1$ and the local decision of the n^{th} CU is idle (i.e. $d_{n,i} = 0$), its corresponding counter $\zeta_{n,i}$ will be incremented by one.

Notice that all counters are updated only if the global decision is idle ($\mathrm{D}_i = 0$). This is because the proposed method depends upon the delivery of the transmitted data, which only occurs if the the global decision is idle.

Consequently, based on the definition of the local detection rate mentioned earlier, the local detection rate of the n^{th} CU can be estimated as follows

$$\hat{P}_{\mathrm{d}n} = 1 - \frac{\zeta_{n,i}}{\alpha_i}. \tag{9}$$

Similarly, the local false-alarm rate of the n^{th} CU can be estimated as follows

$$\hat{P}_{\mathrm{f}n} = 1 - \frac{\gamma_{n,i}}{\beta_i}. \tag{10}$$

Notice that the estimated values $\hat{P}_{\mathrm{d}n}$ and $\hat{P}_{\mathrm{f}n}$ mainly depend on the index of the sensing round i. Specifically, i should be large enough to provide accurate estimated values of the local sensing performance. Also, it is worth highlighting that the counter $\zeta_{n,i}$ cannot exceed the value of the counter α_i (i.e, $\zeta_{n,i} \le \alpha_i$), and the counter $\gamma_{n,i}$ cannot exceed the value of the counter β_i (i.e, $\gamma_{n,i} \le \beta_i$).

As the local performance of each CU is available at the FC, the global performance in terms of P_{D} and P_{F} can be seamlessly estimated using (2) and (3), respectively.

4. Mathematical Analysis

The performance of the proposed estimation method is mathematically analyzed in this section. Moreover, the effect of the number of available CUs N and the detection threshold K on the accuracy of the estimated values are investigated.

The probability that the counters α, β, γ and ζ are incremented at a specific sensing round can be modeled as a Bernoulli random variable with probabilities P_α, P_β, P_γ and P_ζ, respectively. Based on (8), these values can be expressed as follows:

$$\begin{cases} P_\alpha = \mathrm{Prob.}\{\mathrm{D}_i = 0 \cap \mathrm{S}_i = 1\}, \\ P_\beta = \mathrm{Prob.}\{\mathrm{D}_i = 0 \cap \mathrm{S}_i = 0\}, \\ P_{\gamma_n} = \mathrm{Prob.}\{\mathrm{D}_i = 0 \cap \mathrm{S}_i = 0 \cap d_{n,i} = 0\}, \\ P_{\zeta_n} = \mathrm{Prob.}\{\mathrm{D}_i = 0 \cap \mathrm{S}_i = 1 \cap d_{n,i} = 0\}. \end{cases} \tag{11}$$

Likewise, the actual value of any of the counters at the i^{th} sensing round can be modeled as a binomial random variables, where their averages can be computed as follows

$$\begin{cases} \overline{\alpha_i} = i \cdot P_\alpha, \\ \overline{\beta_i} = i \cdot P_\beta, \\ \overline{\gamma_{n,i}} = i \cdot P_{\gamma_n}, \\ \overline{\zeta_{n,i}} = i \cdot P_{\zeta_n}. \end{cases} \tag{12}$$

Accordingly, the average value of the estimated value $\hat{P}_{\mathrm{d}n}$ can be expressed using (12) as follows

$$\hat{P}_{\mathrm{d}n} = 1 - \frac{\overline{\zeta_{n,i}}}{\overline{\alpha_i}} = 1 - \frac{P_{\zeta_n}}{P_\alpha}. \tag{13}$$

Now, by substituting the values of P_α and P_{ζ_n} from (11):

$$\hat{P}_{\mathrm{d}n} = 1 - \frac{\mathrm{Prob.}\{\mathrm{D}_i = 0 \cap \mathrm{S}_i = 1 \cap d_{n,i} = 0\}}{\mathrm{Prob.}\{\mathrm{D}_i = 0 \cap \mathrm{S}_i = 1\}}, \tag{14}$$

which can be rewritten using probability theory as follows

$$\hat{P}_{\mathrm{d}n} = 1 - \frac{P_1(1 - P_{\mathrm{d}n})\mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 1 \cap d_{n,i} = 0\}}{P_1 \mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 1\}} \tag{15}$$

where $P_1 = \mathrm{Prob.}\{\mathrm{S}_i = 1\}$ and is canceled to simplify (15) as follows

$$\hat{P}_{\mathrm{d}n} = 1 - \frac{(1 - P_{\mathrm{d}n})\mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 1 \cap d_{n,i} = 0\}}{\mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 1\}}. \tag{16}$$

Following the same procedure in (13)-(16), the average value of the estimated false-alarm probability $\hat{P}_{\mathrm{f}n}$ can be expressed as follows

$$\hat{P}_{\mathrm{f}n} = 1 - \frac{(1 - P_{\mathrm{f}n})\mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 0 \cap d_{n,i} = 0\}}{\mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 0\}}. \tag{17}$$

Regarding the influence of the number of available CUs N, it is clear that as N increases the accuracy of the estimation method increases as well and the estimated values of $\hat{P}_{\mathrm{d}n}$ and $\hat{P}_{\mathrm{f}n}$ approach the actual values $P_{\mathrm{d}n}$ and $P_{\mathrm{f}n}$, respectively. This is because for a large number of CUs the following approximations can be hold:

$$\mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 1 \cap d_{n,i} = 0\} \approx \mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 1\}, \tag{18}$$

$$\mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 0 \cap d_{n,i} = 0\} \approx \mathrm{Prob.}\{\mathrm{D}_i = 0/\mathrm{S}_i = 0\}, \tag{19}$$

which can be justified because the effect of a single CU is small when the number of CUs is large. Therefore, substituting these approximations in (16) and (17), the estimated values $\hat{P}_{\mathrm{d}n}$ and $\hat{P}_{\mathrm{f}n}$ for a large number of CUs can be approximated as follows

$$\hat{P}_{\mathrm{d}n} \approx P_{\mathrm{d}n}, \quad \hat{P}_{\mathrm{f}n} \approx P_{\mathrm{f}n}. \tag{20}$$

The same effect can be noticed as the detection threshold K increases, where the effect of a single CU on the final decision is small if the value of K is high. Thus, the estimated values will approach the actual values as K increases. Accordingly, applying the proposed estimation method on the AND rule is expected to have better performance than OR rule as K is higher in AND rule, as it will be demonstrated in the next section.

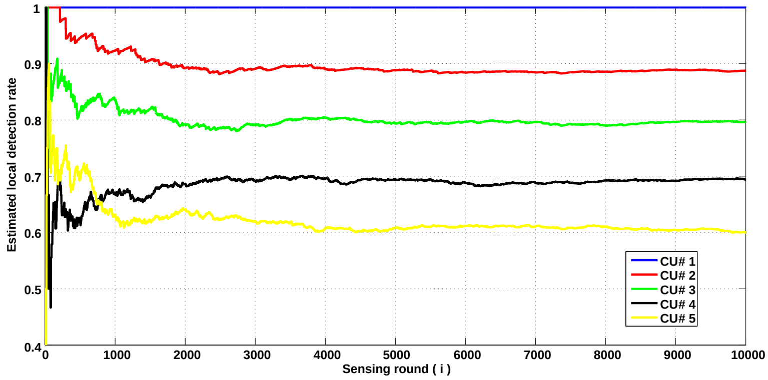

Fig. 1. The estimated local detection rate versus the sensing round for all CUs ($K = 5$).

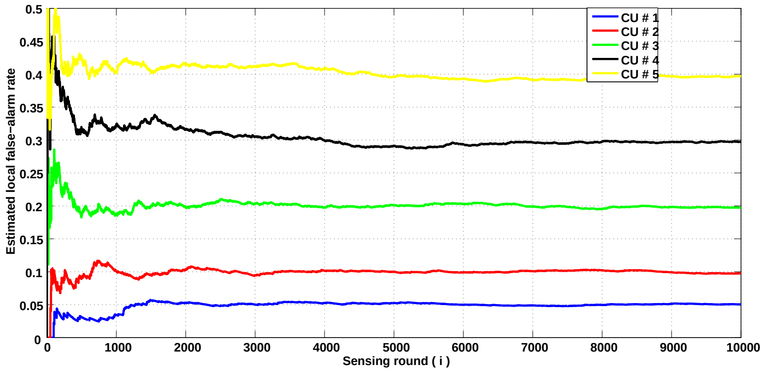

Fig. 2. The estimated local false-alarm rate versus the sensing round for all CUs ($K = 5$).

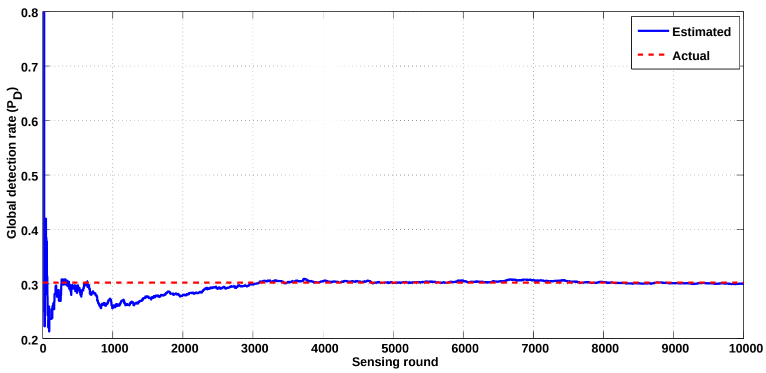

Fig. 3. The global detection rate versus the sensing round ($K = 5$).

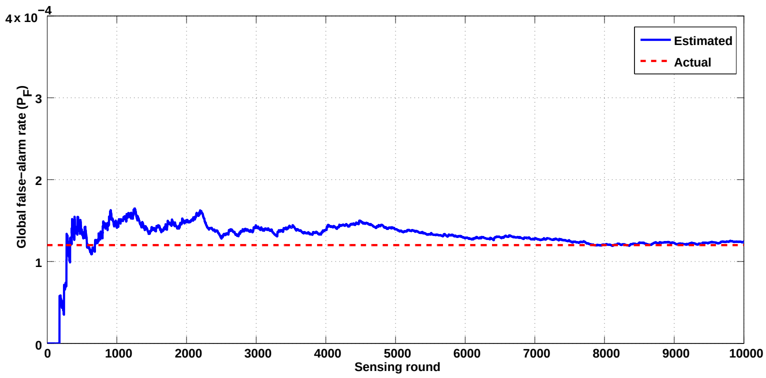

Fig. 4. The global false-alarm rate versus the sensing round ($K = 5$).

5. Simulation Results and Evaluation

In this section, we evaluate the accuracy of the proposed method using Monte Carlo simulations. A network of 5 CUs is considered. The local detection rates of the CUs are 1, 0.9, 0.8, 0.7 and 0.6, while the local false-alarm rates are 0.05, 0.1, 0.2, 0.3 and 0.4, respectively.

Figure 1 shows the estimated local detection rate for all CUs versus the index of the sensing round i. Clearly, the estimated values approach the actual values as i increases until they exactly match them for all CUs. This demonstrates the high accuracy of the proposed estimation method. Figure 2 plots the estimated false-alarm rate for all CUs versus the index of the sensing round i. similar to Fig. 1, the estimated values are almost equal to the actual values especially for $i > 1000$ where the difference can be neglected.

Regarding the global performance, the global detection and false-alarm rates are plotted in Fig. 3 and Fig. 4, respectively, versus the sensing round. The estimated values for the global performance are computed using the estimated local performance rates along with the usage of (2) and (3) for $K = 5$. The actual rates are added for comparison purpose. Results show a small gap between the estimated and the actual rates, which diminishes as i increases. Thus, the proposed method provide a high accuracy without a need for any further information to be reported by CUs.

6. Conclusions

A novel practical method, for estimating the local sensing performance of cognitive users that participate in a collaborative spectrum sensing is presented. The core idea of the method is to evaluate the local performance based on the data delivery once occurs. The proposed method shows a high accuracy for estimating the local and global performance in collaborative spectrum sensing as demonstrated by simulations.

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