Collaborative Spectrum Sensing under Spatially Correlated Shadowing Fading

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***Abstract*—Cognitive Radio is an innovative technology that allows unlicensed (secondary users) users to opportunistically access channels licensed to other users (primary users). A key procedure in the context of opportunistic access is the spectrum sensing, performed by secondary user to determine whether the channel is idle or busy. However, decisions regarding the channel state can be corrupted by fading conditions, leading to wrong decisions regarding the channel state. Collaborative spectrum sensing schemes have been proposed in the literature as a possible way to mitigate the effects of fading. In these schemes, local decisions or observations about the channel state are combined to reach a global decision. Even though collaborative spectrum sensing in general leads to a higher performance, correlated shadowing may reduce the benefits of collaboration. In this paper we investigate the performance of different combining rules in collaborative spectrum sensing in correlated shadowing environment. Our results show that the incremental performance gain achieved by adding more users in the collaboration scheme tends to reduce when the number of users in the collaboration grows, indication that there is a limit in the performance of collaborative spectrum sensing.**

***Index Terms*—Spectrum sensing, cognitive radio, correlated shadowing fading.**

I. INTRODUCTION

RECENT measurements of spectrum utilization shows that most of the spectrum is unused for some period of time, representing a low efficiency in the spectrum usage. A possible solution to this problem is based on the opportunistic use of spectrum, when unlicensed users (also known as **secondary users**), can transmit over a given channel as long as that band is unused by the users that hold the license to use that band (known as **primary users**). Clearly, secondary users cannot disturb primary users [1].

Cognitive radio is an innovative technology that can be used in the implementation of opportunistic channel access, when secondary users has the ability to learn about the transmission environment surrounding them (*i.e.*, unused spectrum bands, primary users behavior, etc,) and change their transmission characteristics in order to access a vacant spectrum band [2].

A key procedure in opportunistic channel access is related to the decision on whether the intended channel is vacant or not. This procedure, known as **spectrum sensing**, is based on the observation of some feature of the intended spectrum band, and must be performed as accurately as possible. First of all, the secondary user must be able to detect the presence of a primary user in the intended channel, in order to avoid interference to primary users. On the other hand, a transmission opportunity due to a vacant channel must not be missed, so that to increase secondary users capacity.

There are number of challenges associated with spectrum sensing. For instance, propagation channel conditions may degrade the performance of spectrum sensing, due to high noise level (i.e., low signal-to-ratio - SNR) and fading disturbance. Particularly harmful is the shadowing fading, since this kind of fading is typically non-ergodic and its effect cannot be removed by averaging samples of the received signal. A possible way to mitigate the effects of shadowing fading in the performance of spectrum sensing is by exploiting the spatial diversity among the observations made about the channel status by different secondary users. In light of the benefits achieved from diversity, *cooperative spectrum sensing* techniques have been proposed in the literature [3]. Several combining strategies have been proposed, but all of them are based on the same idea: in a network of secondary users, local decisions or observations about the channel, made by each secondary user, are combined at a fusion center according to a pre-defined rule, in order to achieve a global decision. This decision is then made available to all secondary users in the network.

Even though cooperative spectrum sensing is shown to be a very efficient way to overcome the problem due to fading, the gain achieve by cooperative spectrum sensing may be reduced when shadowing fading is spatially correlated. In fact, this is a well known result in the diversity techniques field [4]: diversity gain is reduced when the combined signals are correlated.

In this paper we investigate the performance of cooperative spectrum sensing techniques under correlated shadowing fading. We consider three different hard-decision combining techniques, under different levels of spatial correlation. Our results show that the performance improvement tends to reach a limit as the number of collaborating secondary users increases, reducing benefits of collaboration.

This paper is organized as follows. Section II reviews the key aspects of spectrum sensing based on energy detection. In Section III, we discuss cooperative strategies for spectrum sensing, with emphasis in hard decision rules. Section IV describes the simulation model used in the numerical analysis, with special attention given to the procedure for correlated shadowing generation. Finally, Section VI concludes the paper with the main findings.

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II. SPECTRUM SENSING

With the increasing interest in opportunistic channel access, several techniques for spectrum sensing have been proposed in

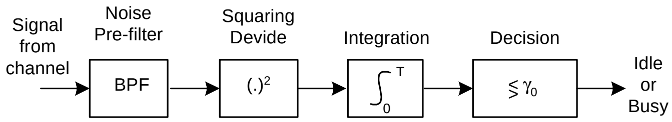

Fig. 1. Energy detection spectrum sensing.

the literature. All these techniques can be classified into three groups [5]: (*i*) energy detection, (*ii*) matched filter and (*iii*) feature detection. The energy detection technique is a good choice when the signal to be detected is unknown, or when low complexity is a key requirement. Spectrum sensing based on matched filter requires knowledge on the transmitted filter, what can be prohibited requirement in some scenarios. Finally, the detection feature technique has an improved performance, but at the expenses of a higher complexity. In this work we consider the energy detection technique, which, due to its simplicity, has receive a great deal of attention in the last years.

A. Energy Detection Spectrum Sensing

The key idea behind the energy detection spectrum sensing is the measurement of the energy in the channel under observation, and based on the measured energy, decide whether the channel is idle (low energy) or busy (high energy). Figure 1 shows the basic block diagram of such spectrum sensing technique. After filtering out the signal outside the band of interest, the energy E of the signal observed in the channel is computed, by squaring and integrating the signal over an interval T. The resulting energy E is then compared to a pre-defined threshold γ_0 to decide whether the channel is idle or busy.

In order to present a more formal description of the performance of the energy detector, we will define some variables of interest. Following [6], we consider a channel model that includes the deterministic path loss and shadowing fading. Therefore, the propagation channel gain (in terms of amplitude) between the primary transmitter and the l-th secondary user is given by

$$h_l = (d_l/d_0)^{-\eta/2} 10^{\zeta_l/20}, \tag{1}$$

where d_0 is a close-in reference distance, d_l is distance between the l-th secondary user and the primary user, η is the path-loss exponent and ζ_l is a normal distributed random variable modeling the shadowing fading.

As the spectrum sensing procedure can be viewed as a decision problem, we will define two hypotheses:

$$\begin{array}{ll} H_0: & \text{channel is idle,} \\ H_1: & \text{channel is busy.} \end{array} \tag{2}$$

Therefore, the n-th sample of the signal observed by the l-th secondary user in the channel of interest is given by

$$r_l[n] = \begin{cases} \nu[n] & \text{if } H_0 \text{ is true} \\ h_l[n]\; x[n] + \nu[n] & \text{if } H_1 \text{ is true,} \end{cases} \tag{3}$$

where $x[n]$ are samples of the signal transmitted by the primary user and $\nu[n]$ are samples of the additive gaussian noise.

The energy of the signal observed by the l-th secondary user in the channel is computed as

$$E_l = \frac{1}{L} \sum_{n=1}^{L} |r_l[n]|^2, \tag{4}$$

where L is the number of samples considered. Finally, the decision process is performed, by comparing the energy E_l to a pre-defined threshold γ_0:

$$\begin{array}{ll} \text{If } E_l < \gamma_0: & \text{decide that the channel is idle} \\ \text{If } E_l \geq \gamma_0: & \text{decide that the channel is busy.} \end{array} \tag{5}$$

The performance of the spectrum sensing procedure is measured in terms of the *missed detection probability* P_{md} and the false alarm probability P_{fa}. The probability P_{md} is defined as the probability of deciding in favor of channel idle when the channel is in use by the primary user, *i.e.*,

$$P_{md} = \Pr\{E_l < \gamma_0 | H_1\}. \tag{6}$$

On the other hand, P_{fa} is defined as the probability of deciding in favour of channel occupied when the channel is idle, *i.e.*,

$$P_{fa} = \Pr\{E_l > \gamma_0 | H_0\}. \tag{7}$$

Note that P_{fa} and P_{md} are the probabilities of wrong decisions in the hypotheses H_0 and H_1, respectively, and therefore we would like to have both of them as low as possible. However, if all the other parameters are kept fixed, it is not possible to reduce both probabilities at the same time. In fact, in order to have a small missed detection probability, we could use a small threshold value γ_0. However, by doing so, we also increase the false alarm probability.

It should be pointed out that the false alarm probability can be reduced by using a larger integration period T in the energy calculation (which corresponds to a larger number of samples L in (4)). If the integration period is large enough, we could also reduce the threshold value, what would additionally reduce P_{md}, as desired, improving the overall performance.

III. Collaborative Spectrum Sensing

The performance of spectrum sensing can be greatly degraded by fading conditions, as the energy measure can be affected by a strong attenuation. Recent works have shown that *cooperative spectrum sensing* can be used to mitigate the effects of fading [3], [7]. The key concept of cooperative spectrum sensing is to combine local decisions or observations made by each secondary user, using some pre-define rule, in order to reach a global decision. As it is unlikely that most of the secondary users will suffer from a severe fading condition at the same time, we can expect a performance improvement when cooperative spectrum sensing is used.

Two forms of combinations have been investigated in the literature: soft decision and hard decision. In the **soft decision strategy** [8], each secondary reports its observation about the channel (*e.g.*, the energy of the signal in the channel under consideration). The fusion center then combines somehow these values of energy in order to compute a final metric, used to reach a global decision. In the **hard decision strategy** [9], the secondary users report their local decisions (either *channel* *busy* or *channel idle*). Then, the fusion center combines these local decisions using some hard decision rule, to reach the global decision. Usually, soft decision strategies lead to higher performance, when compared to hard decision strategies, as in the former the final metric used to reach the global decision conveys more information about the channel state [10]. In this paper, we concentrate our study on *hard decision strategies*, investigating three combining rules, as discussed in the following paragraphs.

Three hard-combining decision rule have been extensively investigated in the literature, namely the AND, OR and Majority rules. All these rules are based on local decisions, which can be represented by bit 0 (channel idle) or 1 (channel busy). According to the **AND rule**, the global decision will be in favor of busy channel only if all local decisions are in favor of busy channel. Now, if the **OR rule** is used, the global decision will be in favor of busy channel if at least one local decision is in favor of busy channel. Finally, in the **Majority rule**, busy channel will be the global decision if the majority of local decisions are in favor of busy channel. All these three rules can be represented by the K-out-of-N decision rule, where N is the number of secondary users in the cooperative technique: $K = N$ corresponds to the AND rule; if $K = 1$, we have the OR rule; if $K = N/2 + 1$, we have the Majority rule.

If the local decisions are independent to each other, and all secondary users have the same local false alarm probability P_{fa} and detection probability $P_d = 1 - P_{md}$, then the collaborative probabilities of detection and false alarm are given by [11]:

$$Q_d = \sum_{n=K}^{N} \binom{N}{n} P_d^n \, (1 - P_d)^{N-n} \quad (8)$$

$$Q_{fa} = \sum_{n=K}^{N} \binom{N}{n} P_{fa}^n \, (1 - P_{fa})^{N-n}, \quad (9)$$

where K is selected according to the desired combining rule. Clearly, $Q_{md} = 1 - Q_d$.

In this work, we are interested in the performance of energy detection spectrum sensing under spatially correlated shadowing fading. The spatial correlation in the shadowing fading makes the expressions (8) and (9) not so useful, as the local decisions are no longer independent to each other. In fact, the correlation in the shadowing fading tends to degrade the overall performance of collaborative spectrum sensing, due to the reduction of diversity gain caused by correlation [12].

In the next sections we describe results of simulation experiments to show the effects of correlation on the performance of collaborative spectrum sensing. We will consider a 2-dimension network of secondary users, with different degree of correlation of shadowing fading, and different hard-decision rules.

IV. Simulation Model

A. Network model

We consider a secondary network of N users, that collaboratively sense the spectrum licensed to a primary user. The secondary network region is a square of area 1 km^2, with N

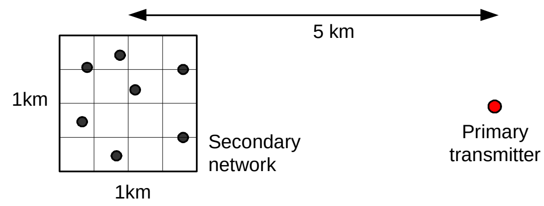

Fig. 2. Network model used in the simulation.

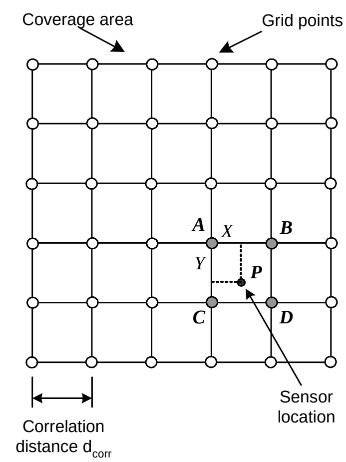

Fig. 3. Model for computing samples of spatially correlated shadowing fading.

secondary users randomly placed. Only one primary user is simulated, which is located 5 km^2 away from the center of secondary network, as shown in Figure 2. Therefore, we can assume that the deterministic path losses from the primary user and each of the secondary users are approximately the same. This arrangement helps to emphasize the effects of correlated shadowing in the results. The channel model is that described in expression (1), with $d_0 = 1$ m, $\eta = 3.5$ and the standard deviation of the shadowing fading is set to $\sigma_{\mathrm{dB}} = 4$ dB. The additive noise power and the primary transmit power are adjusted based on the desired SNR at the secondary terminals.

B. Spatially correlated shadowing fading

A key component in the simulation model used in the experiments is the generation of samples of spatially correlated shadowing fading. In this work we used the technique introduced in [13], which is briefly described in the next paragraphs.

The coverage area is divided according to a square grid, defining grid points with separation distance denoted *correlation distance* d_{corr}, as shown in Figure 3. The grid points are associated with samples of uncorrelated shadowing fading with standard deviation σ_{dB}. The shadowing fading at a generic point P (i.e., not a grid point) is correlated with the shadowing fading values of the grid points of the square where the point P is located (points A, B, C and D in Figure 3). Clearly, the shadowing value at point P, denoted by S_P, depends on the shadowing fading at those four points surrounding P, denoted as S_A, S_B, S_C and S_D, and on the distances X and Y from one these four points (selected as the reference point). Using

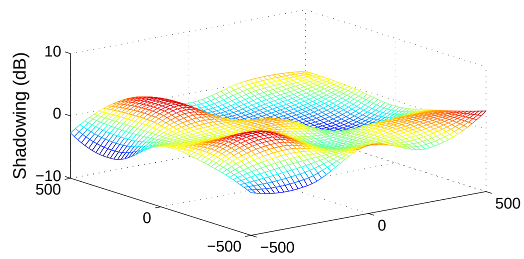

Fig. 4. Example of spatial samples of correlated shadowing fading.

the bi-linear regression, S_P is given by

$$S_P = G^{-1}\{[S_A\,X + S_B\,(1-X)]\,Y + \\ + [S_C\,X + S_D\,(1-X)]\,(1-Y)\}, \quad (10)$$

where X and Y are the distances of point P from point A (reference point, see Figure 3), normalized with respect to the correlation distance d_{corr}, and G is given by

$$G = \sqrt{(1-2X+2X^2)+(1-2Y+2Y^2)}. \quad (11)$$

The factor G in (10) guarantees that the shadowing variance at point P is equal to σ_{dB}. It should be noted that the distance d_{corr} controls the level of spatial correlation in the network area: larger d_{corr} means higher level of spatial correlation.

Figure 4 shows an example of the shadowing fading over the network area, generated by the above procedure, where it is evident the spatial correlation.

V. Performance Analysis

In this section we present a performance analysis of collaborative spectrum sensing under correlated shadowing fading. Combining strategies based on the AND, OR and Majority rules are tested, under different levels of spatial shadowing correlation.

We begin by analyzing the benefits of collaboration in spectrum sensing. Figure 5 shows the curves Q_{fa} vs. Q_{md} (also known as Receiver Operating Characteristic - ROC) of collaborative spectrum sensing under OR rule, for different number N of secondary users participating in the collaborative scheme. We can see the clear improvement achieved by combining local decisions (the ROC curves move toward the lower left portion of the plot as N increases).

Figure 5 also shows that the incremental gain achieved by adding more secondary users in the collaboration scheme decreases as the total number of collaborating users increases. This behaviour can be better observed in Figure 6, where we show the probability of missed detection Q_{md}, as a function of the number of secondary users N in the collaborative scheme, for the OR rule, for different levels of correlation (*i.e.*, different correlation distances d_{corr}). This reduction in the incremental gain as N increases is a well known result in the diversity theory field. The amount of new information brought by a secondary user just added to the collaboration scheme depends on the amount of information already provided by the secondary users in the scheme. Therefore, there is a lower bound on the probability of missed detection Q_{md} (as well

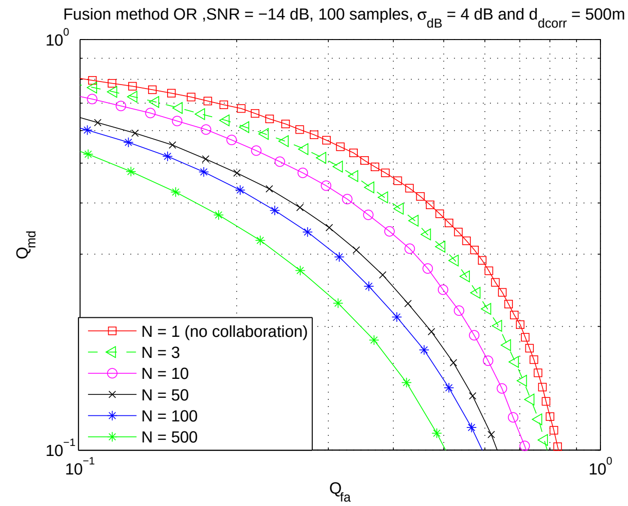

Fig. 5. Probability of missed detection Q_{md} vs. probability of false alarm Q_{fa}, for OR rule, $SNR = -14$ dB, $L = 100$ samples, $d_{corr} = 500$ m, σ_{dB} = 4 dB, and different number of secondary users N in the collaborative scheme.

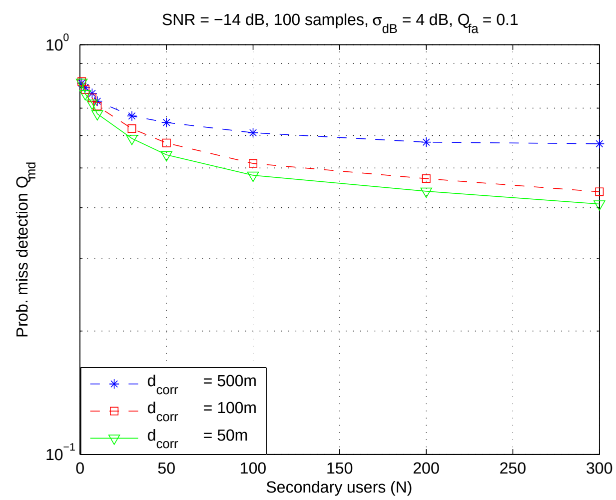

Fig. 6. Probability of missed detection Q_{md} vs. number of secondary users in the collaborative spectrum sensing N, for OR rule, $SNR = -14$ dB, $K = 100$ samples, $\sigma_{dB} = 4$ dB, $d_{corr} = 50, 100$ and 500 m.

as on the false alarm probability). In fact, the authors in [12] shows the existence of this lower bound in a network with one-dimensional distribution of secondary users.

Figure 6 also shows the effects of the severity of spatial correlation on the performance of collaborative spectrum sensing. As the correlation distance increases (i.e., higher correlation), the performance degrades. From this figure, one can infer that the mentioned above lower bound on Q_{md} increases with the correlation severity[1]. In fact, in a strongly correlated shadowing environment there is a small room for an improvement by using diversity, since local decisions tend to follow the same trend, representing a small the diversity gain.

[1]In order to observe these lower bounds on Q_{md} in Figure 6 a much larger number N of secondary users should be simulated, what proved to be prohibited due to the simulation time required.

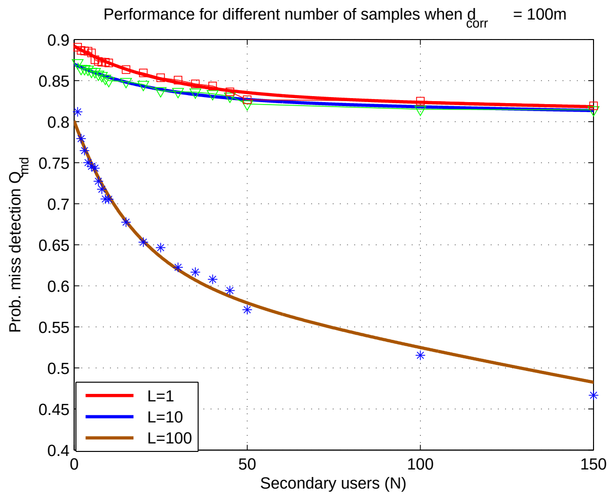

Fig. 7. Probability of missed detection Q_{md} vs. number of secondary users in the collaborative spectrum sensing N, for OR rule, $SNR = -14$ dB, σ_{dB} = 4 dB, d_{corr} = 100 m, for different number of samples L in the integration.

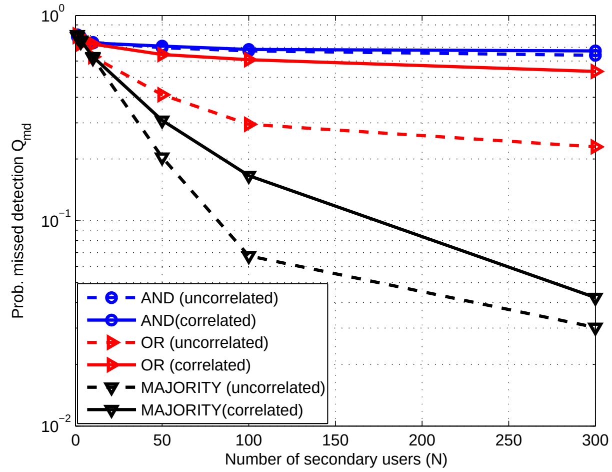

Fig. 8. Probability of missed detection Q_{md} vs. number N of secondary users in the collaborative schemes, for both uncorrelated and correlated shadowing fading (d_{corr} = 500 m). Other paramenter: Q_{fa} = 0.1, $SNR = -14$ dB, $L = 100$ samples, σ_{dB} = 4 dB.

In Figure 7 we show the effect of the number of samples L in the energy computation. In this figure, the missed detection probability Q_{md} is plotted versus the number N of secondary users participating in the collaborative spectrum sensing, for different L. It is evident in this figure the performance improvement as the number of samples increases, which is, in fact, an expected result. The use of more samples of the received (i.e., larger integration period) in the energy computation helps to reduce the effects of additive noise. In this figure, it is more evident the existence of the above mentioned lower bound on the missed detection probability, particularly for small number of samples.

In Figure 8 we compare all three combining rules discussed in Section III, in both correlated and uncorrelated environments. This figure shows the missed detection probability Q_{md} versus the number of secondary users N, for combining rules AND, OR and Majority. First of all, we can see that, regardless of the presence of correlation in the shadowing process, the majority rule provides the best performance, in terms of detection probability, followed by the OR and AND rules, in this order. This figure also evidences the degradation due to correlation, as already discussed.

VI. Conclusion

In this paper we investigated collaborative spectrum sensing in spatially correlated shadowing fading environment. Hard decision combining rules AND, OR and Majority were investigated by means of simulation. Our results show the existence of a bound in the performance improvement achieved by collaboration, when shadowing is correlated. In fact, the incremental gain achieved when more users are added to the collaboration scheme reduces as the number of users collaborating increases, indicating that no new information about channel state is been added. Moreover, our results show that the Majority rule is more robust than the other two combining rules, even in spatially correlated environment.

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