Effects of Correlated Shadowing on Cooperative Spectrum Sensing

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***Abstract*— Cognitive radio networks have been extensively study in the last decade as a way to overcome the scarcity of radio-frequency spectrum, by allowing unlicensed users (secondary users) to access a channel when the license holders (primary users) are not accessing the channel. In this context, spectrum sensing is a key procedure, performed by the secondary users to determine whether the channel is idle or busy. However, decisions regarding the channel state can be corrupted by fading conditions, leading to interference to primary users, or missed transmission opportunities to secondary users. Cooperative spectrum sensing schemes have been proposed as a way to mitigate the effects of fading. Even though Cooperative spectrum sensing in general leads to a higher performance, correlated shadowing may reduce the benefits of cooperation. In this paper we present a survey of techniques designed to mitigate the effects of correlated fading on the performance of cooperative spectrum sensing.**

***Index Terms*— Cognitive radio networks, correlated fading, spectrum sensing.**

I. Introduction

A key procedure in the context of cognitive radio 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 (*i.e.*, users that want to opportunistically access the channel) must be able to detect the presence of primary users (*i.e.*, users that hold the license to use the channel) 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.

Several techniques for spectrum sensing have been proposed [1], [2], but all of them are based on observing the signal present in the intended channel, and deciding the state of the channel (either idle or busy) based on the observation made. Therefore, the performance of spectrum sensing is strongly affected by the propagation effects, such as deterministic path loss, short-term fading and shadowing.

Cooperative spectrum sensing has been proposed to mitigate the effects of fading on the performance of spectrum sensing. The rationale behind the use of cooperation in spectrum sensing is the exploitation of the spatial diversity among the observations made about the channel status by different secondary users [3]. However, the effectiveness of cooperative spectrum sensing in counteracting the effects of fading is reduced when fading is spatially correlated. In fact, this is a well known result in the diversity techniques field: diversity gain is reduced when the combined signals are correlated. This performance degradation due to correlated fading has been investigated by many authors, resulting in several techniques to circumvent this degradation effects.

In this paper we present a survey of techniques designed to mitigate the effects of correlated shadowing fading on the performance of cooperative spectrum sensing. We begin with a brief overview of spectrum sensing in Section II, including a review of typical correlated fading models. Next, in Section III we review the key aspects of cooperative spectrum sensing. In Section IV we discuss the effects of correlated shadowing on the performance of cooperative spectrum sensing, and some techniques for mitigating these effects are discussed in Section V. Section VI reviews a technique that takes advantage of correlated shadowing to increase the capacity of the secondary network, and in Section VII we discuss an adaptive fusion rule designed to mitigate the effects of correlated fading. Finally, Section VIII concludes the paper.

II. Spectrum Sensing

Spectrum sensing techniques can be roughly classified into three groups: (*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 signal, what can be a prohibited requirement in some scenarios. Finally, the detection feature technique has an improved performance, but at the expenses of a higher complexity. These techniques can be used to implement local spectrum sensing, *i.e.*, a secondary user makes a decision regarding the state of the channel based on the local observations. Any of these techniques can be used in a cooperative spectrum sensing scheme, *i.e.*, local decisions or local observations are combined to reach a global decision.

A. Signal Model and Channel Model

In order to present a more formal description of the performance of cooperative spectrum sensing in correlated fading environments, we will briefly present some models for

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signals and channels. We begin with the channel model, that includes the deterministic path loss and shadowing fading. The propagation channel gain (in terms of amplitude) between the primary transmitter and the l-th secondary user is given by [4]

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

where d_0 is a close-in reference distance, η is the path-loss exponent and ζ_l is a zero-mean normal random variable that models the shadowing fading.

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

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

Therefore, the base-band signal observed by the l-th secondary user in the channel of interest can be written as

$$r(t) = \begin{cases} \nu(t) & \text{if } H_0 \text{ is true} \\ h_l(t)\, x(t) + \nu(t) & \text{if } H_1 \text{ is true,} \end{cases} \quad (3)$$

where $x(t)$ is the signal transmitted by the primary user and $\nu(t)$ is the additive Gaussian noise.

Based on the observation of $r(t)$, a decision metric is computed, according to the spectrum sensing technique adopted, and compared to a given threshold to reach a local decision. For instance, if energy detection is used, the energy E_l of the signal observed by the l-th secondary user in the channel is computed as

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

where $r_l[n]$ are samples of the received signal and L is the number of samples considered. A decision is made by comparing the energy E_l to a pre-defined threshold γ_0:

$$\begin{array}{ll} \text{If } E_l < \gamma_0: & \text{the channel is idle} \\ \text{If } E_l \geq \gamma_0: & \text{the channel is busy.} \end{array} \quad (5)$$

The propagation environment may cause the shadowing fading to be spatially correlated, due to large obstacles. In other words, if a receiver is suffering from a strong fading, there is a high probability that another receiver close to the first one will also suffer from a strong fading. Therefore, the random variables ζ_l in (1) observed at different locations will be correlated. A spatial correlation model commonly used in the literature is the one proposed by Gudmundson [5]. According to this model, the spatial correlation coefficient between the channels $h_l(t)$ and $h_k(t)$ is given by

$$\begin{aligned} \rho_{lk}(t) &= \frac{\text{COV}\left[h_l(t), h_k(t)\right]}{\sigma_{h_l}\sigma_{h_k}} \\ &= \exp\left(-\frac{d_{lk}(t)}{D}\right), \end{aligned} \quad (6)$$

where d_{lk} is the distance between the l-th and the k-th secondary users, and D is the correlation distance. Measurements have shown that $D \approx 8$ m for urban areas at 1,7 GHz, and $D \approx 500$ m for suburban areas at 900 MHz [5].

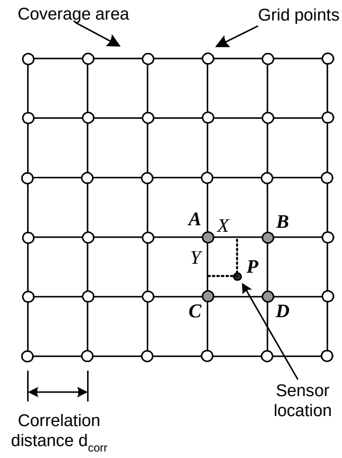

Fig. 1. Model for computing samples of spatially correlated shadowing fading.

Another spatial correlation model found in the literature is the one proposed by Chuang in [6], which is appropriate for simulation studies. According to this model, the coverage area is divided according to a square grid, defining grid points with separation distance denoted *correlation distance* $d_{\texttt{corr}}$, as shown in Figure 1. 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 1). 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 the bi-linear regression, S_P is given by

$$\begin{aligned} S_P &= G^{-1}\left\{\left[S_A\, X + S_B\, (1-X)\right] Y + \right. \\ &+ \left. \left[S_C\, X + S_D\, (1-X)\right] (1-Y)\right\}, \end{aligned} \quad (7)$$

where X and Y are the distances of point P from point A (reference point, see Figure 1), normalized with respect to the correlation distance $d_{\texttt{corr}}$, and G is given by

$$G = \sqrt{(1 - 2X + 2X^2) + (1 - 2Y + 2Y^2)}. \quad (8)$$

The factor G in (7) guarantees that the shadowing variance at point P is equal to σ_{dB}.

Figure 2 shows an example of the shadowing fading over a network area, generated by the procedure described above, where it is evident the spatial correlation.

It should be noted that, in both models, the correlation distance ($d_{\texttt{corr}}$ or D) controls the level of spatial correlation in the network area: larger correlation distance means higher level of spatial correlation.

B. Performance Metrics

The performance of the spectrum sensing procedure is measured in terms of the *detection probability* P_d and the false

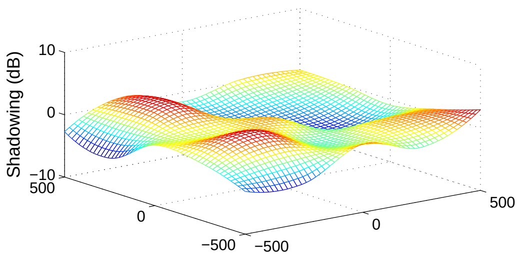

Fig. 2. Example of spatial samples of correlated shadowing fading.

alarm probability P_{fa}. The detection probability P_d is defined as the probability of deciding for channel occupied when the channel is in fact in use by the primary user, *i.e.*,

$$P_d = \Pr\{\text{decided that the channel is busy}|H_1\}. \tag{9}$$

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

$$P_{fa} = \Pr\{\text{decided that the channel is busy}|H_0\}. \tag{10}$$

The performance analysis of spectrum sensing techniques is typically based on the *Receiver Operating Characteristic* (ROC) curve, that relates the false alarm probability with the missed detection probability P_{md}, which is the complement of the detection probability, i.e., $P_{md} = 1 - P_d$.

Clearly, we would like to have large P_d, in order to avoid interference at the primary receiver caused by secondary transmissions. On the other hand, we also would like to have small P_{fa}, that is, we do not want to miss any transmission opportunity. However, this two objectives are conflicting. In fact, in order to have a high detection probability, we should use a small threshold value γ_0. However, by doing so, we also increase the false alarm probability.

In addition to the probabilities P_{md} and P_{fa}, we can define the *average error probability* P_e as

$$P_e = \alpha P_{fa} + (1-\alpha)P_{md} \tag{11}$$

where α is the probability that the primary user is absent [7].

III. Cooperative Spectrum Sensing

As already mentioned, there are a number of challenges associated with the spectrum sensing procedure. Low *SNR* and fading environment are two important conditions usually found the in wireless communications that strongly degrade the performance of spectrum sensing. The degradation due to low *SNR* condition can be minimized by increasing the observation length. For instance, we can use a large number L of samples when computing the energy level in (4). However, this strategy is not so efficient to mitigate the effects of fading. This is particularly true in the case of shadowing fading, due to its non-ergodicity.

Cooperative spectrum sensing has been proposed by several authors to mitigate the effects of fading. (see [1], [2], [8], [3]). The key concept of cooperative spectrum sensing is to combine the local decisions or local observations made by each secondary user, using some pre-define fusion 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.

Cooperation can be performed in centralized or decentralized ways. In a **decentralized** way, the secondary users form an ad-hoc network to exchanging their sensing information (local decision or observation) to each other. Each secondary user then combine all the information received to reach a final decision on the channel state. On the other hand, in a **centralized** way, secondary users report their local observations or decisions to a **fusion center**, that is responsible for combining all local decisions.

Two forms of combinations have been investigated in the literature: soft combination and hard combination. In the **soft decision strategy**, each secondary reports its observation about the channel. The fusion center then combines somehow these observations in order to compute a final metric, used to reach a global decision. In the **hard decision strategy**, the secondary users report their local decisions (either *channel busy* or *channel idle*) and then the fusion center combines these local decisions using some hard decision rule, to reach the global decision. When soft decision strategy is employed, the global decision is based on local observations conveying more information about the channel state, and we can expect a better performance of this combination strategy. However, the transmission of local observations to the fusion center requires a larger bandwidth than that required to transmit the local decision (one bit only).

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 for channel busy only if all local decisions are for busy channel. Now, if the **OR rule** is used, the global decision will be for busy channel if at least one local decision is for busy channel. Finally, in the **Majority rule**, busy channel will be the global decision if the majority of local decisions are for 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.

A. Performance Metrics

As in the local spectrum sensing, the main performance metrics in cooperative spectrum sensing are the probability of detection and the probability of false alarm. These probabilities will, of course, depend on both their local versions and the combining rule adopted. For instance, 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, then the *cooperative probability of detection* Q_d and *cooperative probability of false alarm* Q_{fa} for the

K-out-of-N decision rule are given by [9]

$$Q_d = \sum_{n=K}^{N} \binom{N}{n} P_d^n \, (1 - P_d)^{N-n} \tag{12}$$

$$Q_{fa} = \sum_{n=K}^{N} \binom{N}{n} P_{fa}^n \, (1 - P_{fa})^{N-n}, \tag{13}$$

where K is selected according to the desired combining rule. It should be emphasized that expressions (12) and (13) are no longer valid if the local observations, and therefore the local decisions, are not independent, which is the case when fading is correlated.

We can also define the *cooperative average error probability* as

$$Q_e = \alpha \, Q_{fa} + (1 - \alpha) Q_{md}, \tag{14}$$

where $Q_{md} = 1 - Q_d$.

The benefits of cooperative spectrum sensing relies on the diversity, *i.e.*, different views, about the channel state available at the fusion center. Therefore, this benefit can be quantified by means of the metric *diversity order*, which is a concept commonly used to evaluate the performance of the diversity schemes employed in wireless communications. In the context of spectrum sensing, the diversity order d is defined as [7]

$$d_* = - \lim_{\mathrm{SNR} \to \infty} \frac{\log Q_*}{\log \mathrm{SNR}}, \tag{15}$$

where SNR is the average signal-to-noise ratio at the secondary users, and $*$ can be *d*, *fa* or *e*. The diversity order can be seen as the slope of the curve $\log Q_*$ as $\mathrm{SNR} \to \infty$ [10].

Duan *et al.* showed that, for a cooperative spectrum sensing using N statistically independent measurements of the channel, and soft decision strategy, $d_f = d_{fa} = d_e = N$, as expected, since the decision is based on N independent views of the channel. To the best knowledge of the authors, no closed form for diversity order for correlated fading condition is found in the literature. However, intuitively we can infer that correlated fading degrades the diversity order.

IV. Spectrum Sensing in Correlated Shadowing

As discussed in the previous section, cooperative spectrum sensing is an appropriate way to deal with fading and other propagation effects. In fact, Visotsky *et al.* [11] show that, when local decisions are independent, *i.e.*, when the fading realizations observed at different locations are not correlated, and all cooperating users have the same individual performance, the missed detection probability and the false alarm probability can be made as small as desired, by increasing the number of cooperating nodes, thanks to the diversity gain. It should be noted that this desired behavior, i.e., $Q_{fa} \to 0$ as $N \to \infty$, requires that all secondary users have the same the signal-to-noise ratio. Peh and Liang [12] showed that users with poor performance may degrade the overall performance of cooperative spectrum sensing, what can be explained by the fact that users with poor performance contribute with unreliable information about the channel state.

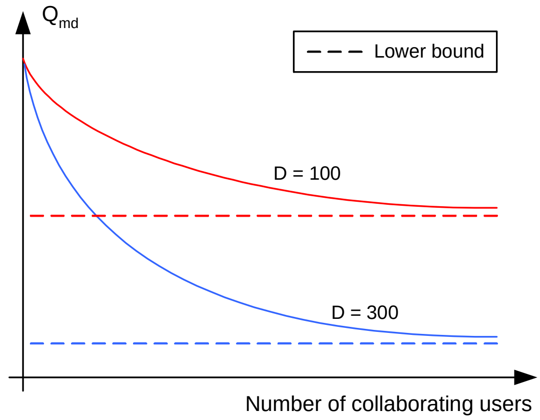

Fig. 3. Cooperative missed detection Q_{md} vs. number of cooperating users N for correlated shadowing, where D is the inter-distance between secondary users. In both curves, the correlated fading environment is the same, and therefore the level of correlation is quantified by the distance D between users: smaller D corresponds to higher correlation.

However, when fading observed at different locations are correlated, the diversity gain reduces, as users located close to each other will suffer from similar levels of fading, i.e., their observations about the channel will be similar. Consequently, the performance of cooperative spectrum sensing is expected to degrade. Ghasemi and Sousa [13] showed, by means of simulation, that high correlation levels result in strong performance degradation. More importantly, the same authors showed in [14] that the performance of cooperative spectrum sensing is upper bounded when shadowing fading is correlated. More specifically, they showed that the cooperative missed detection probability can not be reduced as much as we desire by adding more cooperating users, as illustrated in Figure 3. In fact, Ghasemi and Sousa derived the asymptotic missed probability, i.e., for $N \to \infty$, also show in Figure 3. This result shows that, when fading is correlated it might not be a good strategy to increase the number N of cooperating users in the cooperative spectrum sensing, as discussed later.

The degradation of correlated shadowing was also investigated in [15], where the performance of different hard decision fusion rules were compared. Simulation results showed that the effect of correlated local decisions on the performance depends on the decision rule (see Figure 4).

On the other hand, Headley *et al.* [16] showed that when some information about the correlation in the fading process is considered in the decision process, the negative effects of correlation can be reduced. In their study, the authors of [16] formulated the likelihood ratio test for the soft decision case, taking into account information about correlation among the observations made by different secondary users, as well as information about the reliability of local observations. Simulation results showed that the use of these two types of information (correlation and reliability) can improve the performance of cooperative spectrum sensing.

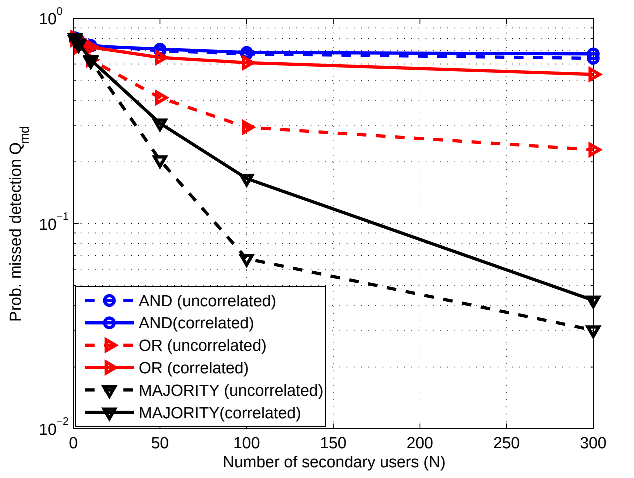

Fig. 4. Probability of missed detection Q_{md} vs. number N of secondary users in the collaborative schemes, for both uncorrelated and correlated shadowing fading (d_{corr} = 500 m). Other paramenter: Q_{fa} = 0,1, $SNR = -14$ dB, $L = 100$ samples, σ_{dB} = 4 dB.

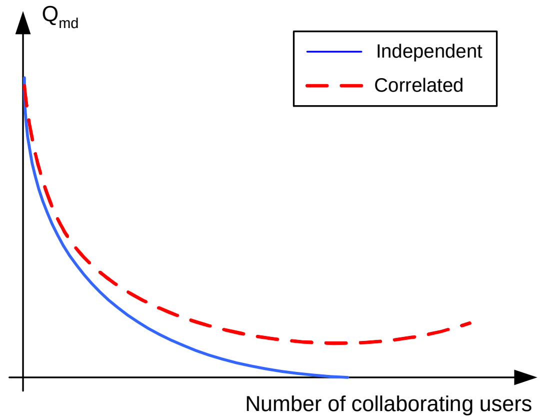

Fig. 5. Cooperative missed detection Q_{md} vs. number of cooperating users N for correlated shadowing, when the quality of observations are different: adding more users in the cooperative scheme may cause degradation.

V. When Less is More

As discussed above, the performance of cooperative spectrum sensing can be enhanced as much as we like by adding more cooperating users only when the observations made by cooperating users are identically and independent distributed (i.e., the local decisions are independent and local spectrum sensing procedures have the same performance). However, even though increasing the number N of cooperating users may seem to be a good strategy in the ideal situation, we should note that N also affects other performance metrics. For instance, in a cooperative spectrum sensing, all users have to report their local observations or decisions to a data fusion using control messages, adding overhead to the secondary network. Also, user terminals may have limited energy supply, and the amount of energy used in the whole spectrum sensing procedure (observation and transmission) may reduce their lifetime. Therefore, there is a cost (higher overhead, higher congestion level, shorter battery lifetime) associated with a larger number of cooperating users.

When propagation environment is spatially correlated, the observations made by the sensors are no longer independent and identically distributed, and the quality of the observations made by a subset of users (for instance, close to each other) may be poor, due to a strong fading caused by a large obstacle. In this case, the performance of cooperative spectrum sensing may degrade when we add more cooperating users, as shown by Kasiri and Cai [17] and Mai *et al.* [18], and illustrated in Figure 5.

Based on the facts that (*i*) correlated observations do not add much information about the channel state to the decision process, and (*ii*) poor quality observations may, in indeed, degrade the performance of cooperative spectrum sensing, several schemes for selecting a subset of cooperating users were proposed. In fact, Figure 3 shows that, under correlated fading, having few cooperating users spread over a larger area may lead to a higher performance than having a larger number of users.

Kasiri and Cai [17] proposed a user selection scheme that removes from the set of cooperating users those users that suffer from the worst shadowing fading (lowest observation quality), and those with the highest correlation with the former.

Cacciapouti *et al.* [19] proposed a scheme to select users with uncorrelated observations in a correlated fading environment. Their scheme is based on estimating the correlation among the signals received by users, and selecting those users with correlation below a given threshold. They compared the proposed scheme against a distance-based selection scheme (*i.e.*, users with the largest distances between any two of them are selected) and a random selection scheme, to show that their scheme requires a smaller number of cooperating users to achieve the same performance.

VI. Taking Advantage of Correlated Shadowing

In the previous section, we have discussed strategies to mitigate the negative effects of correlated shadowing. In fact, in the works reviewed in the previous section correlated shadowing was treated as a source of degradation of the performance of cognitive radio networks .

Pratas *et al.* [20] took a different look at the effects of correlated shadowing. When a secondary user is under a strong shadowing fading, *i.e.*, the power of the primary signal received at the secondary user is very low, we may assume that there is a large obstacle in the path between the primary user and that secondary user. Therefore, a transmission form that the secondary user will probably not cause harmful interference to the primary user, as this strong fading condition will protect the primary user. In other words, strong fading may represent transmission opportunities for secondary users. However, if local observations made by all secondary users are combined in order to reach a global decision regarding the channel status (idle or busy), then these transmission opportunities are missed.

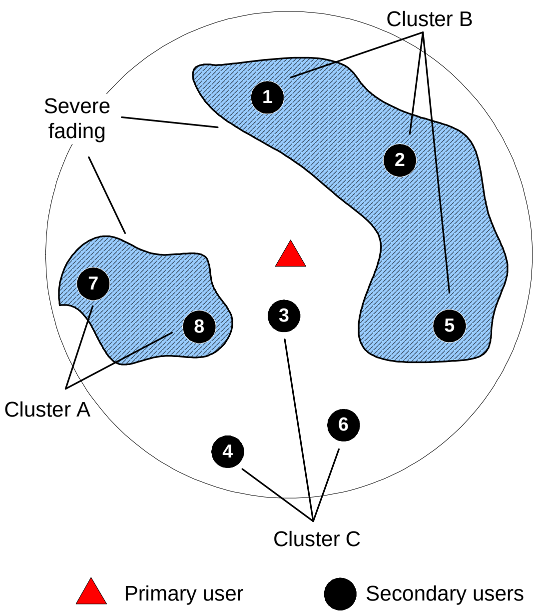

Fig. 6. Secondary users may suffer correlated shadowing conditions.

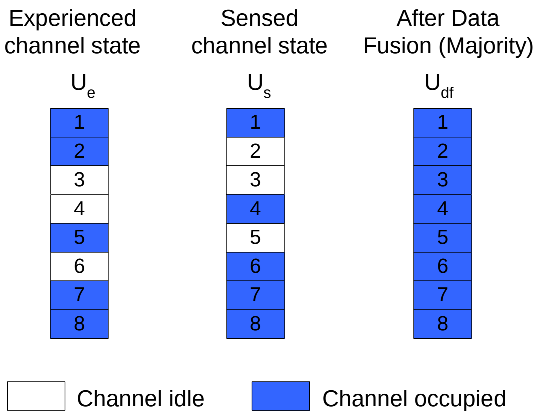

Fig. 7. Illustration of the concepts of experienced channel state and sensed channel state: local decisions are combined to reach a global decision (in this example, majority decision rule was used).

Based on this idea of relating strong shadowing conditions to transmission opportunities, Pratas *et al.* [20] proposed a clustering scheme where secondary users experiencing similar channel fading conditions (i.e., correlated fading) are grouped together in clusters, and spectrum sensing are performed separately within each cluster (see Figure 6).

Figures 7 and 8 illustrate the rationale behind the scheme proposed by Pratas *et al.*. Two binary variables related to the channel states are defined: the *experienced channel state* U_e refers to the actual state of the channel, before spectrum sensing is performed; and the *sensed channel state* U_s, which is the result of local spectrum sensing. If the sensed channel states are combined, all secondary users will have to follow the global decision reached by the data fusion, as illustrated in Figures 7. If, instead, users experiencing correlated fading conditions (*i.e.*, suffering from similar fading conditions) are grouped together, transmission opportunities can be identified, as exemplified in Figure 8. Pratas *et al.* also proposed a clustering scheme based on the correlation among local decisions.

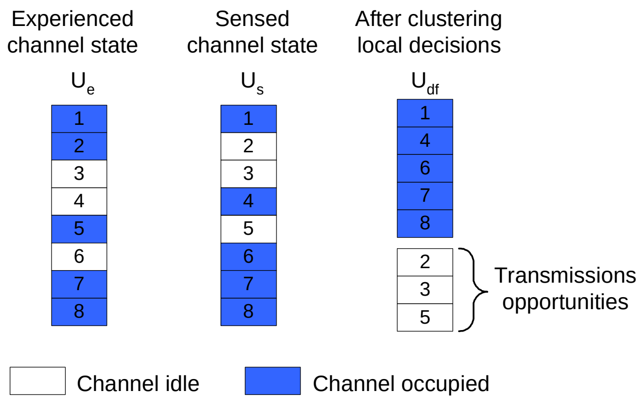

Fig. 8. Illustration of the concepts of experienced channel state and sensed channel state: similar local decisions are clustered together.

VII. Adaptive Counting Rule

In Section III, typical hard-decision fusion rules were presented, which can be summarized by the K-out-of-N rule. Pratas *et al.* [21] showed that the optimal value of K depends on the level of correlation between local decisions, which is related to the correlated shadowing fading. Additionally, they showed that when K is increased, both the probability of detection and the probability of false alarm increase. Based on this observation, the authors of [21] proposed an *adaptive counting rule scheme* that adjusts the value of K according to the level of correlation experienced by secondary users. More specifically, the proposed scheme decrements K whenever the channel is assumed to be idle (by the spectrum sensing procedure), but it is found to be not idle. This means that, to avoid further erroneous decisions, a smaller number K of local decisions must be positive to result in a positive global decision. On the other hand, whenever the channel is assumed to be busy, but it is indeed idle, the value of K must be increased. To find out the true state of the channel, the authors proposed the use of any *a priori* procedure. For instance, the success (or not) of a secondary transmission can be used as an indication of the true state of the channel.

VIII. Conclusion

Even though cooperative spectrum sensing is shown to be a very efficient way to overcome the degradation due to fading, the gain achieved by cooperative spectrum sensing may be reduced when shadowing fading is spatially correlated. In this paper we presented a survey of techniques designed to mitigate the effects of correlated fading on the performance of cooperative spectrum sensing.

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