Opportunistic Spectrum Access in Fading Channels Through Collaborative Sensing

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***Abstract*— Spectrum scarcity is becoming a major issue for service providers interested in either deploying new services or enhancing the capacity for existing applications. On the other hand, recent measurements suggest that many portions of the licensed (primary) spectrum remain unused for significant periods of time. This has led the regulatory bodies to consider opening up under-utilized licensed frequency bands for opportunistic access by unlicensed (secondary) users. Among different options, sensing-based access incurs a very low infrastructure cost and is backward-compatible with the legacy primary systems. In this paper, we investigate the effect of user collaboration on the performance of sensing-based secondary access in fading channels. In particular, we demonstrate that under independent fading or shadowing, a low-overhead collaboration scheme with a very simple detector as its building block, 1) improves the spectrum utilization significantly, 2) enables the individual users to employ less sensitive detectors, thereby allowing a wider range of devices to access the primary bands, 3) increases the robustness toward noise uncertainty, 4) reduces the time and bandwidth resources required for satisfactory sensing which translates into higher agility and efficiency of the secondary access.**

***Index Terms*— spectrum sensing, opportunistic access, cognitive radio, collaborative sensing**

I. Introduction

The frequency spectrum is currently managed in a very inflexible manner where bands are licensed to users by government agencies and the licensee has the exclusive right to access the allocated band regardless of its spatiotemporal usage characteristics. While this approach fully protects the licensee from inter-system interference, it results in spectrum being greatly under-utilized as evidenced by the recent measurements [1], [2].

With the increasing demand for the spectrum and the scarcity of vacant bands, a spectrum policy reform seems inevitable. The FCC's initiative to open up the TV bands for unlicensed access [3] along with several other projects including the Defense Advanced Research Projects Agency (DARPA)'s "Next Generation" (XG) program [4] and the national science foundation's "NeTS-ProWiN" project [5] signal a paradigm shift in the spectrum access policy. Meanwhile, IEEE has formed a working group on wireless regional area networks (IEEE 802.22) whose goal is to develop a standard for unlicensed access to the TV spectrum on a non-interfering basis [6]. This raises several new technical and regulatory issues to be addressed by academia as well as policy-makers. The interested reader is referred to [7]–[9] for a general overview of the issues associated with the spectrum access policy reform.

In order to alleviate the spectrum scarcity, *secondary* systems may be allowed to *opportunistically* access the temporarily unused licensed band of a *primary* system (a so-called white space). In the absence of cooperation or signalling between the primary licensee and the secondary user (e.g., when dealing with legacy primary systems), spectrum availability for the secondary access may be determined by direct spectrum sensing [10]. In this case, the licensed spectrum is deemed accessible if no primary activity is detected by the secondary user. Therefore, instead of guarding the licensed spectrum in a rigid command-and-control fashion, agile secondary users provide an *on-demand* interference-protection to the primary system by detecting and utilizing *only* the white spaces.

In this paper, simple energy detection (a.k.a. radiometry) [11] is chosen as the underlying spectrum sensing scheme since our goal is to characterize the gains achievable through collaboration without obscuring the analysis by employing more sophisticated detection methods. However, it is well-known that the energy detector's performance is susceptible to noise power estimation errors [12]. Indeed, to achieve a desired level of performance under uncertain noise power, the signal-to-noise ratio (SNR) has to be above a certain threshold. Moreover, this constraint can not be avoided by increasing the detection time, thereby calling for alternate detection schemes when operating at SNR levels below the threshold. In particular, when some information about the structure of the primary signal is available, ad hoc feature-detectors may be employed to address this issue [13].

In a heavily shadowed or fading environment, spectrum sensing is hampered by the uncertainty resulting from channel randomness. In such cases, a low received energy may be due to a faded primary signal rather than a white space. As such, a secondary user has to be more

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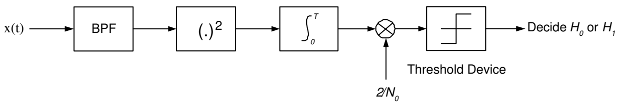


Figure 1. Block diagram of an energy detector

conservative so as not to confuse a deep fade with a white space, thereby resulting in poor spectrum utilization.

On the other hand, fading and shadowing effects may vary significantly depending on the receiver's location. Therefore, the uncertainty due to fading may be mitigated by allowing different users to share their sensing results and collaboratively decide on the occupancy status of the licensed band. Building upon this idea, collaborative spectrum sensing has been recently studied in [14]–[17]. The main focus of the present paper is to extend these works by analyzing the impact of user collaboration on the performance of opportunistic spectrum access. Particularly, we show that having a sufficient number of collaborating users with independently-fading channels, it is (theoretically) possible to detect a primary user at arbitrarily low SNR levels. Moreover, collaboration lowers the observation time and bandwidth required for the satisfactory detection of spectrum occupancy state, which in turn results in the higher agility and efficiency of the sensing process.

As we shall illustrate later, given a sufficient number of users, collaborative sensing is capable of delivering the desired performance under noise uncertainty even if the individual users do not meet the minimum SNR requirement. Thus, collaboration potentially obviates the need to employ more sophisticated detectors in such cases.

The remainder of this paper is organized as follows. Section II highlights the importance of collaboration by examining the performance degradation of local spectrum sensing due to channel uncertainty. Different options for collaboration are then considered and compared through simulations in Section III. We analyze the asymptotic performance for a large number of secondary users in terms of spectrum utilization, required SNR, detection time, and robustness to noise in Section IV. The impact of spatially-correlated shadowing on collaboration gain is characterized through simulation in Section V. Finally, this paper is concluded by providing some final remarks and further research directions in Section VI.

II. Local Spectrum Sensing in Fading Channels

Fig. 1 depicts the block-diagram of an energy detector. The input band-pass filter removes the out-of-band noise by selecting the center frequency, f_s, and the bandwidth of interest, W. This filter is followed by a squaring device to measure the received energy and an integrator which determines the observation interval, T. The output of the integrator is then normalized by $N_0/2$, where N_0 is the one-sided noise power spectral density. Finally, the normalized output, Y, is compared to a decision threshold, λ, to decide whether the signal is present.

The goal of spectrum sensing is to determine if a licensed band is not currently being used by its primary owner. This in turn may be formulated as a binary hypothesis testing problem[1],

$$x(t) = \begin{cases} n(t), & H_0 \ (\textit{white space}) \\ h\ s(t) + n(t), & H_1 \ (\textit{occupied}) \end{cases}$$

where $x(t)$ is the signal received by the secondary user, $s(t)$ is the primary users's transmitted signal, $n(t)$ is the additive white Gaussian noise (AWGN) and h is the amplitude gain of the channel. The SNR is defined as $\gamma = \frac{P}{N_0 W}$ with P being the power of the primary signal received at the secondary user.

Within the context of opportunistic spectrum access, the probability of detection determines the level of interference-protection provided to the primary licensee while the probability of false-alarm is the percentage of white spaces *falsely* declared occupied (i.e. the percentage of missed opportunities). Therefore, a sensible design criterion is to minimize P_f while guaranteeing that P_d remains above a certain threshold set by the regulator.

In order to properly set the stage for the discussion of collaborative sensing, we start with an analysis of local (individual) energy detection in fading channels. We denote the normalized output of the integrator in Fig. 1 by Y which serves as the decision statistic. For simplicity, we assume that the time-bandwidth product, TW, is an integer number which we denote by m. Urkowitz has shown Y to have central and non-central chi-square distributions under H_0 and H_1, respectively, each with $2m$ degrees of freedom and a non-centrality parameter of $\frac{PT}{N_0/2}$ for the latter distribution [11]. However, note that $\frac{PT}{N_0/2} = \frac{2PTW}{N_0 W} = 2m\gamma$. Therefore, the probability distribution function (pdf) of Y under the two hypotheses may be written as,

$$f_{Y|H_0}(y) = \frac{y^{m-1}e^{-y/2}}{\Gamma(m)2^m} \quad (1)$$

$$f_{Y|H_1}(y) = \frac{y^{m-1}e^{-(y+2m\gamma)/2}}{\Gamma(m)2^m}\, {}_0F_1\Big(m, \frac{m\gamma y}{2}\Big) \quad (2)$$

where $\Gamma(.)$ is the gamma function and ${}_0F_1(.,.)$ is the confluent hypergeometric limit function [18].

In a non-fading environment where h is deterministic, using the cumulative distribution functions of the central and non-central chi-square distributions, the probabilities of detection and false-alarm may be written as follows,

$$P_d = P\{Y > \lambda | H_1\} = Q_m(\sqrt{2m\gamma}, \sqrt{\lambda}) \quad (3)$$

$$P_f = P\{Y > \lambda | H_0\} = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)} \triangleq G_m(\lambda) \quad (4)$$

[1] It is assumed that during the sensing, all secondary users remain silent (e.g., through a MAC protocol). Thus, the received energy will be due to the primary transmission only.

where $\Gamma(a,b) = \int_b^{\infty} t^{a-1}e^{-t}dt$ is the incomplete gamma function [18] and $Q_m(.,.)$ is the generalized Marcum Q-function [19] as defined below,

$$Q_m(a,b) = \int_b^{\infty} \frac{x^m}{a^{m-1}} e^{-\frac{x^2+a^2}{2}} I_{m-1}(ax)\ dx$$

where $I_{m-1}(.)$ is the $(m-1)$th order modified Bessel function of the first kind.

Combining (3) and (4), the probability of detection is related to the probability of false-alarm through,

$$P_d = Q_m\left(\sqrt{2m\gamma}, \sqrt{G_m^{-1}(P_f)}\right) \quad (5)$$

The fundamental tradeoff between $P_m = 1 - P_d$ (the probability of missed detection) and P_f has different implications in the context of opportunistic spectrum access. A high P_m results in missing the presence of primary user with high probability, which in turn increases the interference inflicted on the primary licensee. On the other hand, a high P_f inevitably results in low spectrum utilization since the false-alarms increase the number of missed opportunities (white spaces).

As expected, P_f is independent of γ since under H_0 there is no primary signal present. On the other hand, when h is varying due to shadowing or fading, (3) gives the probability of detection *conditioned* on the instantaneous SNR, γ. In this case, the average probability of detection (which, with an abuse of notation, is also denoted by P_d) may be derived by averaging (3) over fading statistics,

$$\begin{aligned} P_d &= \int_{\gamma} Q_m(\sqrt{2mx}, \sqrt{\lambda}) f_{\gamma}(x)dx \\ &= \int_{\gamma} Q_m\left(\sqrt{2mx}, \sqrt{G_m^{-1}(P_f)}\right) f_{\gamma}(x)dx \quad (6) \end{aligned}$$

where $f_{\gamma}(x)$ is the pdf of SNR under fading.

Performance of energy detector for different values of the average SNR and m may be characterized through the complementary receiver operating characteristics (ROC) curves (the plot of P_m vs. P_f). In what follows, we study the performance under Rayleigh fading and log-normal shadowing.

A. Rayleigh Fading

Under Rayleigh fading, γ has an exponential distribution. In this case, a closed-form expression for P_d may be obtained (after some manipulation) by substituting $f_{\gamma}(x)$ in (6) [20],

$$\begin{aligned} P_d &= \frac{\Gamma(m-1, \frac{\lambda}{2})}{\Gamma(m-1)} + e^{-\frac{\lambda}{2(1+m\overline{\gamma})}} \left(1 + \frac{1}{m\overline{\gamma}}\right)^{m-1} \\ &\times \left[1 - \frac{\Gamma\left(m-1, \frac{\lambda m\overline{\gamma}}{2(1+m\overline{\gamma})}\right)}{\Gamma(m-1)}\right] \quad (7) \end{aligned}$$

where $\overline{\gamma}$ is the average SNR. Fig. 2 (a) provides plots of the complementary ROC curve under AWGN and Rayleigh fading scenarios. $\overline{\gamma}$ and m are assumed to be 5 dB and 5, respectively. We observe that Rayleigh fading

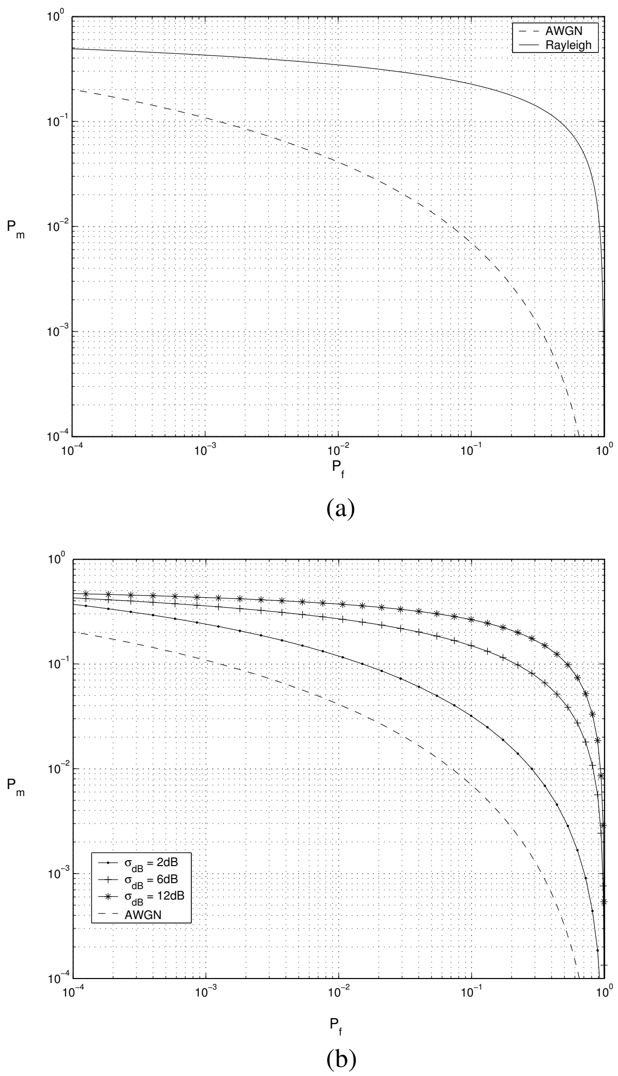


Figure 2. The complementary ROC (P_m vs. P_f) under i.i.d. (a) Rayleigh fading (b) log-normal shadowing with different dB-spreads. ($\overline{\gamma} = 5$ dB, $m = 5$). The AWGN curve is provided for comparison.

degrades the performance of energy detector significantly. Particularly, achieving $P_m < 10^{-2}$ entails a probability of false-alarm greater than 0.9, which in turn results in poor spectrum utilization.

B. Log-normal Shadowing

Empirical measurements suggest that the medium-scale variations of the received power, when represented in dB units, follow a normal distribution (see e.g., [21]). In other words, the linear (as opposed to dB) channel gain may be modeled by a log-normal random variable, e^X, where X is a zero-mean Gaussian random variable with variance σ^2. Log-normal shadowing is usually characterized in terms of its dB-spread, σ_{dB}, which is related to σ by $\sigma = 0.1\log_e(10)\sigma_{dB}$.

When γ is log-normally distributed due to shadowing, (6) may be evaluated numerically. Fig. 2 (b) shows the complementary ROC curves for three different dB-

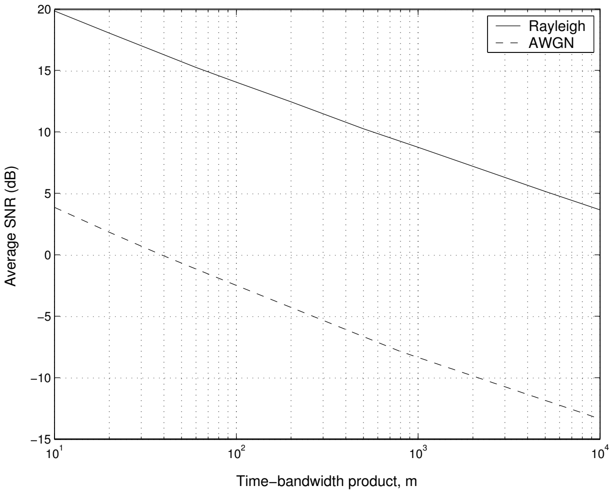


Figure 3. The required average SNR vs. the time-bandwidth product ($P_d = 0.99, P_f = 0.01$).

spreads. The average SNR, $\overline{\gamma}$, and m are assumed to be 5 dB and 5, respectively. A plot for the non-fading (pure AWGN) case is also provided for comparison.

Comparing the AWGN curve with those obtained under shadowing, we observe that for the regions of practical interest, spectrum sensing is more difficult in shadowed environments. Moreover, as the shadowing becomes more intense (higher dB-spread), the energy detector's performance degrades further.

As indicated by the results in Fig. 2, the energy detector suffers a significant performance loss in fading environments. While in theory it is possible to improve the detection performance by increasing the observation period, T, it turns out that this is not a viable solution in practice. In particular, Fig. 3 shows a plot of the average SNR, $\overline{\gamma}$, required to ensure $P_d = 0.99$ and $P_f = 0.01$ for different time-bandwidth products. It is evident that with the same average SNR and bandwidth, meeting the desired performance level in fading environments demands much higher integration times, thereby resulting in longer access delays. Moreover, in presence of noise uncertainty, even with an infinitely long observation period it may not be possible to reliably detect the primary signal [12].

III. Collaborative Spectrum Sensing in Fading Channels

Thus far, we have quantified the degrading effect of fading on the performance of opportunistic spectrum access in terms of increased P_f (hence reduced opportunities) given a certain P_d (i.e. a fixed interference-protection level for the primary user). In order to improve the spectrum sensing in presence of fading, we allow different secondary users to collaborate by sharing their information. This is achieved by having each user communicate either its measured energy, Y, or a function of it, to a central user or band manager. Based on the collected measurements, the band manager makes the final decision on the status of the band which is then broadcasted to all users.

Let n denote the number of collaborating users. For simplicity, we assume that the information is received at the band manager without any errors. We also assume that all n users experience independent and identically distributed (i.i.d.) fading or shadowing with the same average SNR. Spatially-correlated shadowing will be considered in Section V.

A fundamental result in distributed binary hypothesis testing states that when the observations of different sensors are conditionally independent (as in our case), the optimal decision rule for individual sensors is the likelihood ratio test (LRT) [22]. Moreover, the optimum individual thresholds are not necessarily equal and it is generally hard to derive them. However, performing LRT in a fading environment requires channel estimation, thereby giving rise to a more complex design. Thus, we assume that all users employ energy detection rather than LRT and use the same decision threshold, λ. While these assumptions render our scheme sub-optimum, they facilitate the analysis as well as the practical implementation.

In what follows, the two extremes of the information-sharing are considered. First we assume that the central user has full knowledge of all the individual measurements (soft decisions). However, the measured energy, Y, takes on a continuous range of values and has to be quantized using a sufficient number of bits before being transmitted to the central user. Therefore, having precise replicas of the measurements at the band manager is not appealing from the implementation point of view due to the communication overhead. A more favorable choice, in this respect, is for the individual users to communicate only their final 1-bit (hard) decisions (i.e. H_0 or H_1) to the band manager.

A. Linear Soft-Decision Combining

It is well-known that among different linear diversity combining schemes, the Maximal-Ratio Combining (MRC) provides a better performance [23]. However, it requires the fading-channel gain at different branches (users in our case) to be estimated. On the other hand, the Equal-Gain Combining (EGC) is known to perform only slightly inferior to MRC while the channel estimation is no longer required.

Under EGC, the band manager decides between H_0 and H_1 by comparing the sum of measured energies to a threshold. The decision statistic is thus,

$$Y_0 \triangleq \sum_{i=1}^{n} Y_i \tag{8}$$

The sum of n independent chi-square random variables is another chi-square variate with its degree of freedom and non-centrality parameter equal to the sum of n individual degrees of freedom and n non-centrality parameters, respectively [24]. Therefore, the pdf of the combiner output under each hypothesis is given by,

$$f_{Y_0|H_0}(y) = \frac{y^{nm-1}e^{-y/2}}{\Gamma(nm)2^{nm}} \quad (9)$$

$$f_{Y_0|H_1}(y) = \frac{y^{m-1}e^{-(y+2m\sum_{i=1}^{n}\gamma_i)/2}}{\Gamma(nm)2^{nm}} \times {}_0F_1\left(nm, \frac{my\sum_{i=1}^{n}\gamma_i}{2}\right) \quad (10)$$

Thus, the probability of detection (conditioned on the SNR of fading channels) and the probability of false-alarm are given by,

$$Q_d = P\{Y_0 > \lambda | H_1, \gamma_1 = l_1, \ldots, \gamma_n = l_n\} = Q_{nm}\left(\sqrt{2m\sum_{i=1}^{n} l_i}, \sqrt{\lambda}\right) \quad (11)$$

$$Q_f = P\{Y_0 > \lambda | H_0\} = \frac{\Gamma(nm, \lambda/2)}{\Gamma(nm)} \quad (12)$$

where we have used Q_d and Q_f to distinguish the corresponding quantities from their single-user non-collaborative counterparts and they should not be confused with the Marcum Q-function, $Q_m(.,.)$. The average probability of detection is obtained by un-conditioning (11) with respect to γ_i's. We note, however, that the conditional Q_d is only a function of $\gamma_0 \triangleq \sum_{i=1}^{n}\gamma_i$ and we may write,

$$Q_d = \int_{\gamma_0} Q_{nm}\left(\sqrt{2mx}, \sqrt{\lambda}\right) f_{\gamma_0}(x)dx \quad (13)$$

where, with an abuse of notation, Q_d denotes the average probability of detection as well.

Under Rayleigh fading, γ_0 is the sum of n i.i.d. exponential random variables and may be readily shown to follow a Gamma distribution [25],

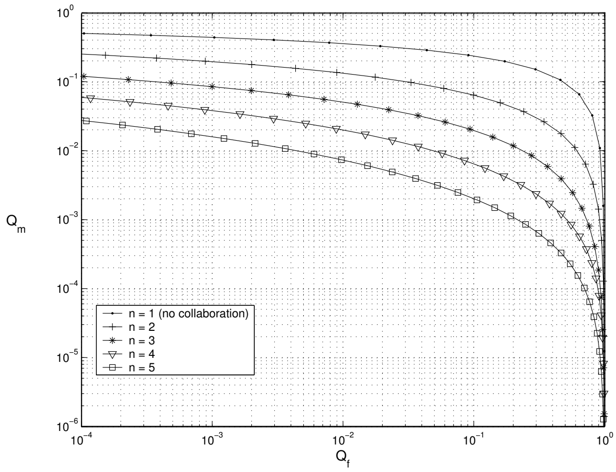
$$f_{\gamma_0}(x) = \frac{x^{n-1}e^{-x/\overline{\gamma}}}{(n-1)!\overline{\gamma}^n} \quad (14)$$

Substituting $f_{\gamma_0}(x)$ from (14) into (13) and after some manipulation one may arrive at a closed-form expression for Q_d [20] which will be used to obtain the complementary ROC curve.

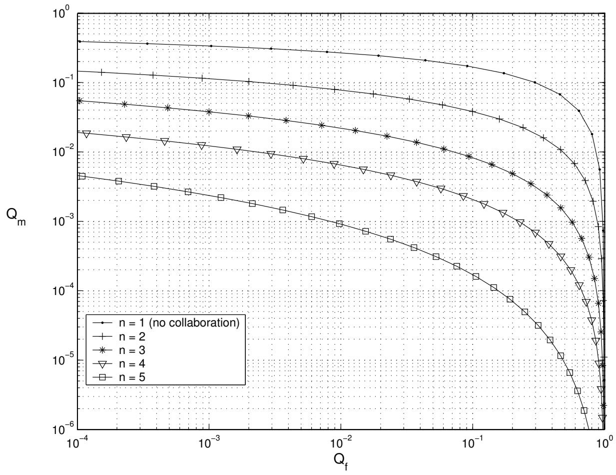
Under i.i.d. log-normal shadowing, the complementary ROC curve is obtained numerically. Fig. 4 (a) and Fig. 4 (b) show the complementary ROC curves under i.i.d. Rayleigh fading and i.i.d. log-normal shadowing ($\sigma_{dB} =$ 6dB), respectively. It is observed that given a required probability of non-interference, Q_d, collaboration results in a significantly higher probability of detecting the white spaces (i.e. a lower Q_f).

B. Hard-Decision Combining

In quantifying the performance of collaborative sensing above, it was assumed that all the measured energies are known exactly at the band manager. While rendering the final decision optimum, providing the band manager with perfect information demands a relatively high volume of communication among users. In order to minimize the communication overhead, let us consider the other extreme where users only share their final 1-bit (hard) decisions (H_0 or H_1) rather than their decision statistics. Let u_i denote the 1-bit decision of the ith user, defined as,



(a)



(b)

Figure 4. The complementary ROC (Q_m vs. Q_f) of the EGC under i.i.d. (a) Rayleigh fading (b) log-normal shadowing ($\sigma_{dB} = 6$dB). ($\overline{\gamma} =$ 5 dB, $m = 5$).

$$u_i = \begin{cases} 0, & \text{Decide } H_0 \text{ if } y_i < \lambda_i \\ 1, & \text{Decide } H_1 \text{ if } y_i > \lambda_i \end{cases} \qquad i = 1, \ldots, n$$

When the individual measurements, conditioned on each hypothesis, are mutually independent, it may be shown that the Neyman-Pearson criterion results in the following combining rule [22],

$$\sum_{i=1}^{n} u_i \log_e\left[\frac{P_{d_i}(1-P_{f_i})}{(1-P_{d_i})P_{f_i}}\right] \underset{H_0}{\overset{H_1}{\gtrless}} \Lambda \quad (15)$$

where P_{d_i} and P_{f_i} denote the individual probabilities of detection and false-alarm. That is, the band manager makes its decision by comparing a weighted sum of the individual hard decisions to a threshold, assigning

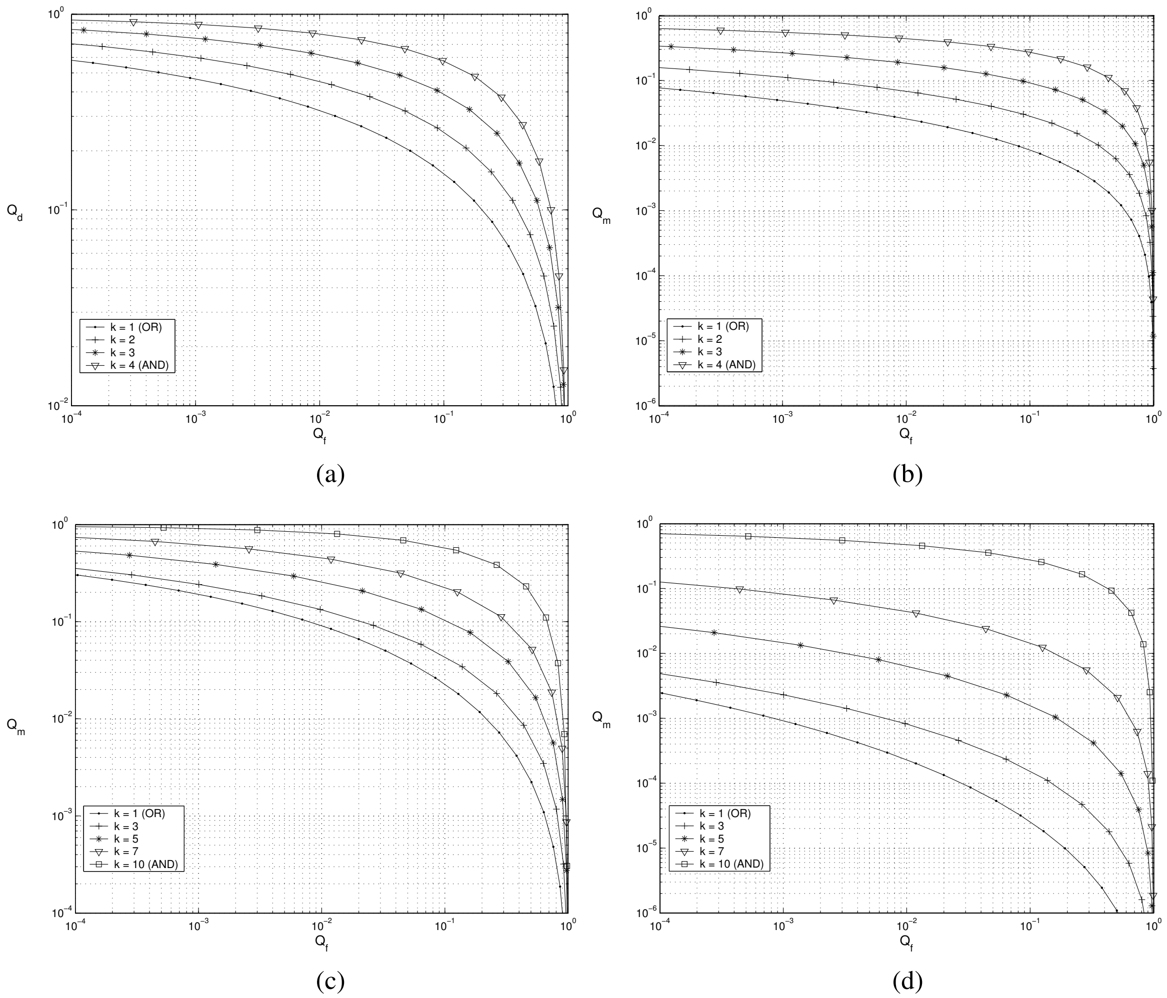


Figure 5. The complementary ROC for different k-out-of-n rules in i.i.d. Rayleigh fading with $m = 5$ and (a) $n = 4, \overline{\gamma} = 0$dB (b) $n = 4, \overline{\gamma} = 5$dB (c) $n = 10, \overline{\gamma} = 0$dB (d) $n = 10, \overline{\gamma} = 5$dB

a larger weight to more reliable measurements. In order to simplify the implementation, we assume that all users employ the same decision threshold λ. As before, let us also assume that all collaborating users experience the same path-loss effect (i.e. $\overline{\gamma_i} = \overline{\gamma}, i = 1, \ldots, n$). Under these conditions, different users have equal probabilities of detection and false-alarm (i.e. $P_{d_i} = P_d, P_{f_i} = P_f,\ i = 1, \ldots, n$), which in turn results in the equal weighting of the individual decisions in (15) by the band manager. Thus, based on the chosen threshold Λ, the band manager implements a k-out-of-n rule[2] where it decides H_1 if k or more local decisions are equal to 1 [22].

The average probabilities of detection and false-alarm for the k-out-of-n rule are related to their single-user counterparts through,

$$Q_d = \sum_{i=k}^{n} \binom{n}{i} P_d^i (1 - P_d)^{n-i} \qquad (16)$$

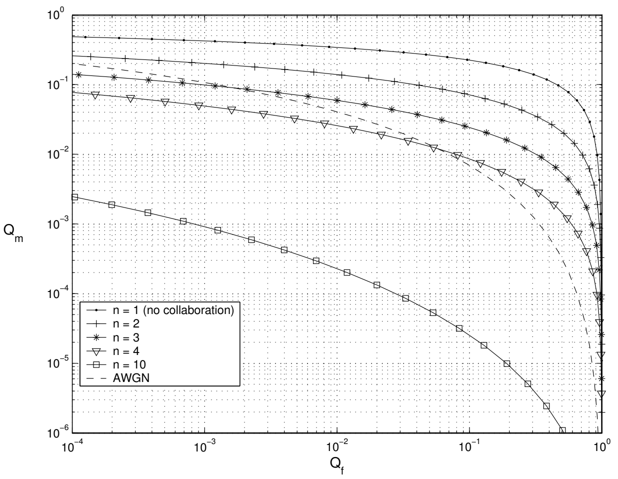
$$Q_f = \sum_{i=k}^{n} \binom{n}{i} P_f^i (1 - P_f)^{n-i} \qquad (17)$$

where P_d and P_f are the individual probabilities of detection and false-alarm as defined by (6) and (4), respectively.

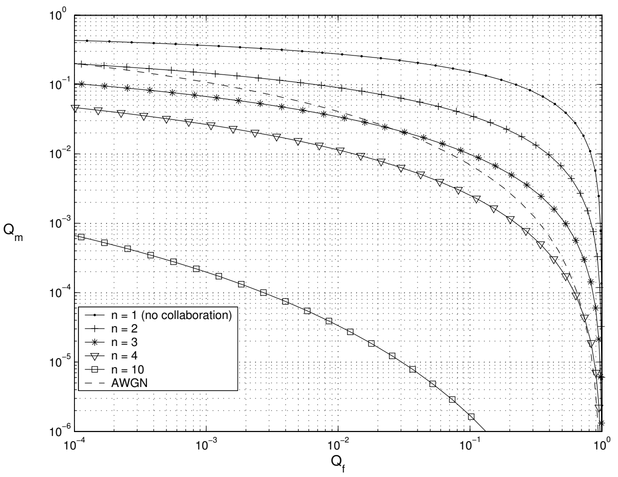
The complementary ROC curves under different k-out-of-n rules in i.i.d. Rayleigh fading are plotted in Fig. 5. These along with other simulation results, not reported here, indicate that for many cases of practical interest, the 1-out-of-n (a.k.a. OR) rule delivers a better performance. Therefore, the band manager should declare the band occupied if any secondary user detects the primary signal. We point out, however, that the OR rule is not necessarily optimum in general and the optimum k-out-of-n rule has to be determined numerically.

Fig. 6 (a) and Fig. 6 (b) show the complementary ROC for the OR rule with different number of collaborating users under i.i.d. Rayleigh fading and i.i.d. log-normal shadowing ($\sigma_{dB} = 6$ dB), respectively. As before, $\overline{\gamma} = 5$ dB and $m = 5$. In both cases, the non-fading AWGN curve is shown for comparison.

[2] For example, $0 < \Lambda < \log_e[P_d(1-P_f)/(1-P_d)P_f]$ results in the 1-out-of-n (OR) rule while $(n-1)\log_e[P_d(1-P_f)/(1-P_d)P_f] < \Lambda < n\log_e[P_d(1-P_f)/(1-P_d)P_f]$ gives rise to the n-out-of-n (AND) rule.



(a)



(b)

Figure 6. The complementary ROC (Q_m vs. Q_f) of the OR rule with $\overline{\gamma} = 5$ dB and $m = 5$ under i.i.d. (a) Rayleigh fading (b) log-normal shadowing ($\sigma_{dB} = 6$dB). The AWGN curve is provided for comparison.

As seen in these figures, fusing the decisions of different secondary users cancels the deleterious impact of shadowing/fading effectively. Moreover, with increasing n, the collaborative scheme is even capable of outperforming the AWGN (non-fading) local sensing ($n = 1$). Informally speaking, this stems from the fact that with more secondary users there is a higher chance of having a user with its SNR well above the average. Thus, we conclude that channel fading, if properly exploited, is advantageous to the sensing-based opportunistic spectrum access.

Comparing figures 4 and 6 for the same number of collaborating users, as expected, there is a loss of performance when employing the hard-decision combining (HDC) with OR rule instead of the EGC. However, in practice, HDC may still be the better choice due to its significantly lower communication overhead. This becomes more important when dealing with autonomous users (i.e. when collaboration is voluntary rather than enforced). In this case, more users will be willing to cooperate if they do not have to consume a lot of their own resources for the collaboration. Therefore, in the remainder of the paper we limit our analysis to HDC with the OR rule.

IV. Asymptotic Performance Under i.i.d. Fading

In this section we characterize the asymptotic performance of the collaboration protocol proposed in Section III in terms of the spectrum utilization, sensitivity, detection time/bandwidth and robustness to noise uncertainty.

A. Spectrum Utilization

As stated before, the percentage of the correctly identified white spaces is determined by $1-P_f$ ($1-Q_f$ in the collaborative case). While in practice such white spaces may not be fully utilized due to the various overheads, their percentage provides a reasonable measure of the spectrum utilization. In what follows, we show that under i.i.d. fading, while maintaining the required interference-protection level, Q_f can be made arbitrarily small by having more collaborating users.

The asymptotic behavior of k-out-of-n fusion rules under i.i.d. observations has been studied in [26]. It was shown that while maintaining Q_d at a constant level for any k-out-of-n rule with finite k (or finite $n-k$), the probability of false-alarm will go to zero asymptotically if and only if the following condition is satisfied [26],

$$\begin{cases} \left.\frac{\partial P_d}{\partial P_f}\right|_{P_f=0} = \infty, & \text{finite } k \\ \left.\frac{\partial P_d}{\partial P_f}\right|_{P_f=1} = 0, & \text{finite } n-k \end{cases} \tag{18}$$

From (6) and applying the chain rule we obtain (19) (shown on the next page) where,

$$R \triangleq \sqrt{2mxG_m^{-1}(P_f)}$$

Therefore, we may write,

$$\begin{aligned} \left.\frac{\partial P_d}{\partial P_f}\right|_{P_f=0} &\stackrel{a}{=} \int_\gamma 2^{m-2}\,\Gamma(m)e^{-mx}\left.\frac{I_{m-1}(R)}{R^{m-1}}\right|_{R=\infty} f_\gamma(x)dx \\ &\stackrel{b}{=} \int_\gamma \frac{\Gamma(m)e^{-mx}}{2}\sum_{i=0}^{\infty}\left.\frac{(R^2/4)^i}{i!\Gamma(m+i)}\right|_{R=\infty} f_\gamma(x)dx \\ &= \infty \end{aligned} \tag{20}$$

where the equality in (a) is due to the fact that $R|_{P_f=0} = \lim_{P_f\to 0} G_m(P_f) = \infty$ and (b) results from the series expansion of the modified Bessel function of the first kind.

Thus, employing any k-out-of-n rule with finite k (e.g., the OR rule), the first condition in (18) is met by our system under i.i.d. fading or shadowing. Therefore, while keeping Q_d fixed, Q_f goes to zero asymptotically by increasing the number of collaborating users.

The impact of collaboration on Q_f, under i.i.d. Rayleigh fading and log-normal shadowing, has been depicted in Fig. 7. We observe that with these parameters, requiring $Q_d = 0.9$ for a single user in Rayleigh fading

$$
\begin{aligned}
\frac{\partial P_d}{\partial P_f} &= \int_\gamma \frac{\partial}{\partial P_f} Q_m\left(\sqrt{2mx}, \sqrt{G_m^{-1}(P_f)}\ \right) f_\gamma(x)dx \\
&= \int_\gamma \Bigg[-\frac{\left(G_m^{-1}(P_f)\right)^{m/2}}{(2mx)^{\frac{m-1}{2}}} \exp\Big\{ -\big(2mx + G_m^{-1}(P_f)\big)/2 \Big\} I_{m-1}\Big(\sqrt{2mxG_m^{-1}(P_f)}\ \Big) \frac{1}{2\sqrt{G_m^{-1}(P_f)}} \\
&\quad \times \frac{-2^{m-1}\Gamma(m)}{\Big(G_m^{-1}(P_f)\Big)^{m-1} \exp\big\{ -G_m^{-1}(P_f)/2 \big\}} \Bigg] f_\gamma(x)dx \ = \int_\gamma 2^{m-2}\ \Gamma(m) e^{-mx}\ \frac{I_{m-1}(R)}{R^{m-1}} f_\gamma(x)dx \qquad (19)
\end{aligned}
$$

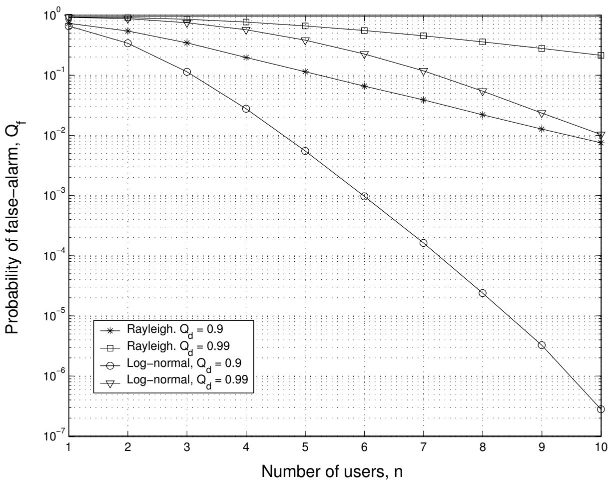


Figure 7. Q_f vs. the number of collaborating users under i.i.d. Rayleigh fading and log-normal shadowing with $\sigma_{dB} = 6$dB ($\overline{\gamma} = 0$dB, $m = 5$).

($\overline{\gamma} = 0$dB) results in $Q_f > 0.75$, thereby defeating the idea of opportunistic spectrum access. On the other hand, having 10 users, more than 99% of the white spaces can be correctly detected.

B. Required SNR

A fundamental parameter determining the quality of detection is the average SNR, $\overline{\gamma}$, which mainly depends on the primary user's transmitted power as well as its distance to the secondary users. A viable spectrum-sensing scheme should be able to operate at low SNR levels (e.g., due to a low-power primary transmission or large path-loss) without compromising the primary system. This requirement may be fulfilled through collaboration as we shall illustrate shortly.

Since our goal is to quantify the collaboration gain, let us assume the time-bandwidth product to be unity (i.e. removing the non-coherent integration gain). Setting m in (4) and (7) equal to 1 and combining the results gives rise to the following simple characterization of the ROC,

$$P_d = e^{\frac{\log_e P_f}{1+\overline{\gamma}}} \qquad (21)$$

Therefore, the average SNR required to maintain a given Q_d and Q_f under i.i.d. Rayleigh fading is given by,

$$\overline{\gamma} = \frac{\log_e\left(1 - \sqrt[n]{1-Q_f}\right)}{\log_e\left(1 - \sqrt[n]{1-Q_d}\right)} - 1 \qquad (22)$$

Differentiating $\overline{\gamma}$ in (22) with respect to n, we arrive at (23) where $g(x) = \frac{x\log_e(x)}{(1-x)\log_e(1-x)}$ is a monotonically decreasing function for $x \in [0,1]$ and,

$$A = \frac{\log_e(1 - \sqrt[n]{1-Q_f})}{n\log_e(1 - \sqrt[n]{1-Q_d})} > 0$$

Therefore, $\frac{\partial\overline{\gamma}}{\partial n} < 0$ if and only if $\sqrt[n]{1-Q_f} > \sqrt[n]{1-Q_d}$ or equivalently $Q_f < Q_d$. Since the latter condition holds for any system of practical interest, $\overline{\gamma}$ is a monotonically decreasing function of n.

Now we proceed to show that for a given set of parameters Q_d, Q_f and m, the limit of $\overline{\gamma}$ as n goes to infinity is zero. Applying L'Hopital's rule to (22) repeatedly,

$$
\begin{aligned}
\lim_{n\to\infty}\overline{\gamma} &= \lim_{n\to\infty} \frac{\sqrt[n]{1-Q_f}\left(1-\sqrt[n]{1-Q_d}\right)\log_e(1-Q_f)}{\sqrt[n]{1-Q_d}\left(1-\sqrt[n]{1-Q_f}\right)\log_e(1-Q_d)} \\
&\quad -1 \\
&= \lim_{n\to\infty} \frac{\sqrt[n]{1-Q_f}\,\sqrt[n]{1-Q_d}}{\sqrt[n]{1-Q_d}\,\sqrt[n]{1-Q_f}} - 1 \\
&= 0 \qquad (24)
\end{aligned}
$$

Therefore, it is possible to deliver the desired performance at arbitrarily low SNR levels as long as there are sufficient number of users with i.i.d. fading channels.

Fig. 8 provides plots of $\overline{\gamma}$ versus the number of collaborating users in i.i.d. Rayleigh fading and log-normal shadowing where the latter plot has been obtained numerically. For each curve, the decision threshold, λ, is chosen such that[3] $Q_f = 0.01$.

Results indicate a significant improvement in terms of the average SNR required for detection. In particular, to achieve $Q_d = 0.99$ and $Q_f = 0.01$ with $m = 100$, local spectrum sensing requires $\overline{\gamma} \simeq 14$dB while collaborative sensing with $n = 10$ only needs an average SNR of -5dB for the individual users.

C. Required Observation Time and Bandwidth

After detecting a white space, the secondary users must continue to monitor the spectrum to be able to vacate the band as soon as the primary user starts to transmit. This may be done by either constantly monitoring a small portion of the primary spectrum, set aside for this

[3]For a fixed Q_f, λ is an increasing function of n given by $\lambda(n) = G_m^{-1}(1 - \sqrt[n]{1-Q_f}) \simeq G_m^{-1}(Q_f/n)$, with $G_m(.)$ as defined in (4).

$$\frac{\partial \overline{\gamma}}{\partial n} = \frac{1}{\left[n \log_e(1-\sqrt[n]{1-Q_d})\right]^2} \left[\frac{\sqrt[n]{1-Q_f}\log_e(1-Q_f)\log_e(1-\sqrt[n]{1-Q_d})}{1-\sqrt[n]{1-Q_f}} - \frac{\sqrt[n]{1-Q_d}\log_e(1-Q_d)\log_e(1-\sqrt[n]{1-Q_f})}{1-\sqrt[n]{1-Q_d}} \right]$$
$$= A\left[g\left(\sqrt[n]{1-Q_f}\right) - g\left(\sqrt[n]{1-Q_d}\right)\right] \quad (23)$$

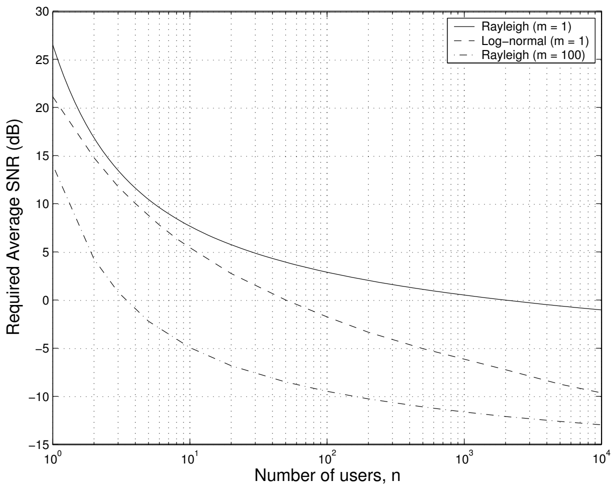


Figure 8. The required average SNR vs. the number of collaborating users under i.i.d. Rayleigh fading and log-normal shadowing with $\sigma_{dB} = 6$dB ($Q_d = 0.99$, $Q_f = 0.01$).

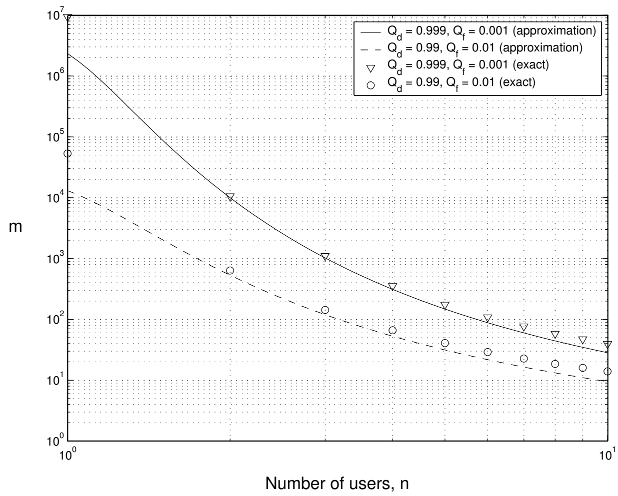


Figure 9. The required time-bandwidth product vs. the number of collaborating users in i.i.d. Rayleigh fading ($\overline{\gamma} = 0$dB).

purpose, or having periodic sensing intervals. In either case, the time or bandwidth allocated for sensing is wasted in the sense that it may not be used for the secondary transmission. Moreover, the time required to identify a *reappearing* primary transmission determines the delay experienced by the primary system in accessing its spectrum. As a result, depending on the type of primary application (e.g., its delay sensitivity), there may be a very stringent constraint on this time period. In what follows, we show that collaboration may be used to lower the required observation time and bandwidth, thereby increasing both agility and efficiency of the sensing-based access.

Under i.i.d. Rayleigh fading and relatively small[4] $\overline{\gamma}$, we have the following approximation for the required time-bandwidth product (see [27] for the derivation),

$$m \simeq 2\left[\frac{\mathrm{Erfc}^{-1}\left(\frac{2Q_f}{n}\right)}{\overline{\gamma}\log_e\left(1-\sqrt[n]{1-Q_d}-\frac{Q_f}{n}\right)}\right]^2 \triangleq \hat{m} \quad (25)$$

where $\mathrm{Erfc}^{-1}(.)$ is the inverse of the complementary error function defined as $\mathrm{Erfc}(x) = \frac{2}{\sqrt{\pi}}\int_x^{\infty} e^{-t^2}dt$.

The formula in Eq. (25) suggests that m should be increased whenever a higher Q_d is desired. Moreover, m is proportional to $1/\overline{\gamma}^2$. Therefore, at low SNR levels, the detection will be significantly delayed in order to collect sufficient energy. On the other hand, it may be easily shown that $\hat{m}$ is a decreasing function of n hence, collaboration can maintain the required time-bandwidth product at a reasonable level.

Fig. 9 shows plots of $\hat{m}$ versus the number of collaborating users in i.i.d. Rayleigh fading. For comparison, we have also plotted the exact values of m, obtained by numerically solving (4) and (7) for m and λ. It is observed that $\hat{m}$ closely approximates m for $n \geq 2$ even at a moderate SNR level. Results suggest a significant gain in terms of time and bandwidth, even with only two collaborating users.

We conclude that, maintaining the global probabilities of detection and false-alarm at a desired level, collaboration enables users to employ less sensitive detectors by lowering the required time-bandwidth product for the individual energy detectors. Therefore, from a policy-making perspective, dynamic spectrum access for a network of collaborating secondary users should be regulated based on their capabilities as a group rather than separate individuals. In that sense, a group of secondary users may be able to *collaboratively* access a licensed band, restricted to any one of them individually. Furthermore, a less stringent sensitivity requirement is particularly appealing from the implementation point of view due to the reduced hardware cost and complexity.

D. Robustness to Noise Power Uncertainty

The derivation of the energy detector's decision statistic, Y, involves normalization by $N_0/2$. In our analysis

[4]Low average SNR levels increase the required time-bandwidth product significantly. Therefore, it makes sense to study the impact of collaboration in such cases.

thus far, we have assumed perfect knowledge of the noise power at each secondary user. However, such a priori knowledge is not usually available in practice and noise power has to be estimated by the receiver.

The authors in [12] investigated the worst-case impact of imperfect noise power estimation on the energy detection of spread-spectrum signals. In particular, they established that, when the noise power is only known to be contained within a bounded interval (but unknown otherwise) and the decision threshold is set to guarantee an upper-bound on P_f, achieving a desired P_d requires the SNR to be higher than a minimum level. Moreover, this minimum SNR is only a function of the noise uncertainty and does not depend on either P_f , P_d or the time-bandwidth product, m.

Adopting the uncertainty model of [12], we analyze the impact of noise power uncertainty on the spectrum utilization. However, we take a slightly different approach from that of [12] by guaranteeing a lower-bound on Q_d rather than upper-bounding Q_f. As argued before, this is a more sensible choice in a spectrum-sharing context. Moreover, instead of deriving a minimum average SNR to satisfy a desired Q_f, we will assume a constant $\overline{\gamma}$ and will study the degradation of Q_f. That is, we analyze the worst-case effect of noise uncertainty on the spectrum-utilization, subject to a guaranteed interference-protection level (i.e. a lower-bound on Q_d).

Let us assume the noise power estimate, $\hat{N}_0$, is at most U/2 dB away from the actual N_0 (i.e. a peak-to-peak uncertainty of U dB). Then,

$$\frac{1}{\alpha} \leq \frac{\hat{N}_0}{N_0} \leq \alpha \tag{26}$$

where $\alpha = 10^{U/20} \geq 1$.

An *overestimate* of the noise power results in the normalized decision statistic, Y, becoming smaller, which in turn reduces the probability of detection and its average (with respect to the fading statistics) in (3) and (6), respectively. Since the global probability of detection, Q_d, is an increasing function of P_d, the worst-case scenario (minimum Q_d) happens when all the collaborating users overestimate the noise power by a factor of α. Therefore, in order to guarantee the same level of interference-protection as when the noise power is exactly known, the decision threshold should be modified as,

$$\hat{\lambda} = \frac{\lambda}{\alpha} \tag{27}$$

We note, however, that maintaining a lower-bound on Q_d by reducing the decision-threshold gives rise to a higher probability of false-alarm in (4). This in turn results in lower spectrum utilization since Q_f is an increasing function of P_f. Denoting the output of the integrator in Fig. 1 by Z, the individual probability of false-alarm under $\hat{\lambda}$ is given by,

$$P_f = P\{Y > \hat{\lambda}|H_0\} = P\left\{\frac{Z}{\hat{N}_0/2} > \frac{\lambda}{\alpha}\Big|H_0\right\} \tag{28}$$

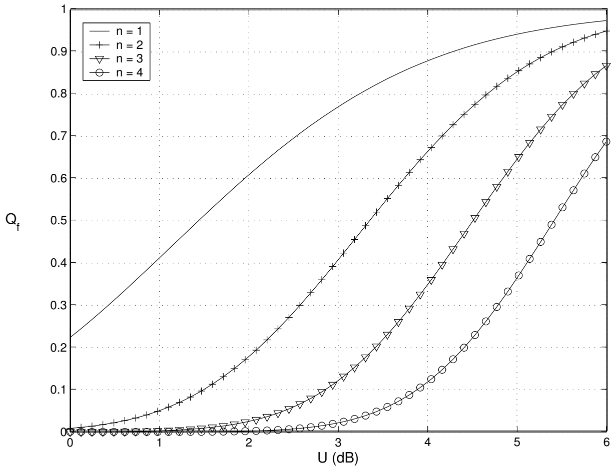


Figure 10. $Q_{f,\text{worst-case}}$ vs. the peak-to-peak noise uncertainty in i.i.d. log-normal shadowing (σ_{dB} = 6dB) for different number of collaborating spectrum sensors ($Q_{d,\text{worst-case}} = 0.9, \overline{\gamma} = 5$dB, $m = 5$).

The spectrum utilization is minimized when all the collaborating users operate at their maximum P_f. This happens when all users *underestimate* the noise power by a factor of α. Therefore, the worst-case Q_f is given by,

$$Q_{f,\text{worst-case}} = 1 - (1 - P_{f,\text{worst-case}})^n \tag{29}$$

where,

$$\begin{aligned} P_{f,\text{worst-case}} &= P\left\{\frac{Z}{(N_0/\alpha)/2} > \frac{\lambda}{\alpha}\Big|H_0\right\} \\ &= P\left\{\frac{Z}{N_0/2} > \frac{\lambda}{\alpha^2}\Big|H_0\right\} \end{aligned} \tag{30}$$

Fig. 10 depicts $Q_{f,\text{worst-case}}$ as a function of the noise uncertainty, U, in i.i.d. log-normal shadowing (σ_{dB} = 6dB) for different number of collaborating users. In each case, the decision threshold is modified such that $Q_{d,\text{worst-case}} = 0.9$. Results indicate that noise uncertainty has a significant negative impact on the efficiency of the local spectrum sensing. However, we also observe that sensing becomes more robust toward uncertain noise power with increasing n. In what follows, this observation is made rigorous by proving that $\lim_{n\to\infty} Q_{f,\text{worst-case}} = 0$ subject to $Q_{d,\text{worst-case}} = \beta$ ($\beta < 1$).

Let there be a finite peak-to-peak noise power uncertainty, $U = 20\log_{10}\alpha$ where $1 \leq \alpha < \infty$. Recall that in this case, λ should be replaced by λ/α to compensate for the maximum overestimate of the noise power, $\alpha N_0/2$. From (30),

$$\begin{aligned} P_{f,\text{worst-case}} &= P\left\{\frac{Z}{N_0/2} > \frac{\lambda}{\alpha^2}\Big|H_0\right\} \\ &= G_m\left(\frac{\lambda}{\alpha^2}\right) \end{aligned} \tag{31}$$

or equivalently, $\lambda = \alpha^2 G_m^{-1}(P_{f,\text{worst-case}})$ where $G_m(.)$ is defined as in (4).

$$\begin{aligned} P_{d,\text{worst-case}} &= 1 - \sqrt[n]{1-\beta} \\ &= \int_\gamma P\Big\{\frac{Z}{\alpha N_0/2} > \frac{\lambda}{\alpha}\Big|H_1\Big\} f_\gamma(x)dx \\ &= \int_\gamma P\Big\{Y > \lambda|H_1\Big\} f_\gamma(x)dx \\ &= \int_\gamma Q_m(\sqrt{2mx}, \sqrt{\lambda}) f_\gamma(x)dx \\ &= \int_\gamma Q_m\Big(\sqrt{2mx}, \sqrt{\alpha^2 G_m^{-1}(P_{f,\text{worst-case}})}\Big) \\ &\quad \times f_\gamma(x)dx \end{aligned} \quad (32)$$

From (29), the necessary and sufficient condition for $\lim_{n\to\infty} Q_{f,\text{worst-case}} = 0$ is,

$$\lim_{n\to\infty} n \log(1 - P_{f,\text{worst-case}}) = 0 \quad (33)$$

which may be rewritten as,

$$\lim_{P_{d,\text{worst-case}}\to 0} \frac{\log(1-\beta)}{\log(1-P_{d,\text{worst-case}})} \log(1 - P_{f,\text{worst-case}}) = 0 \quad (34)$$

Applying L'Hopital's rule to (34), we arrive at the same condition defined in (18) for the finite k. However, inspecting (32) shows that $\frac{\partial P_{d,\text{worst-case}}}{\partial P_{f,\text{worst-case}}}$ has a form similar to that derived in (19) if R is replaced by $R' = \alpha R$. Therefore, the first condition in (18) is satisfied for any finite $\alpha > 1$ and $\lim_{n\to\infty} Q_{f,\text{worst-case}} = 0$. That is, under i.i.d. fading or shadowing, the degradation due to noise uncertainty may be completely overcome by having an asymptotically large number of collaborating users.

V. Effect of Spatially-Correlated Shadowing

Up to this point, we have dealt with the case where the secondary users experience independent shadowing or fading. While such assumption is reasonable for the multi-path fading effects, there is usually a degree of spatial correlation associated with the log-normal shadowing [28]. Intuitively, correlated shadowing will degrade the performance of collaborative sensing when the collaborating users are located close to each other. This is due to the fact that such users are likely to experience similar shadowing effects, thereby countering the collaboration gain. In this section, further simulation results for the above scenario are provided.

The empirical data suggests an exponential correlation function for the shadowing effects at different locations [28],

$$R(d) = e^{-ad} \quad (35)$$

where $R(d)$ is the correlation function, d is the distance between the two locations and a is a constant depending on the environment. Based on the measurements reported in [28], $a \approx 0.12$ in urban environments and $a \approx 0.002$ in suburban environments.

In order to quantify the impact of spatially-correlated shadowing on the collaboration gain, we consider a one-dimensional uniform distribution of n secondary users within a fixed distance D. Then, the exponential correlation model of (35) is used to generate the log-normal shadowing effects. For each n, the average SNR required to achieve $Q_d = 0.99$ and $Q_f = 0.01$ with $m = 1$, is found via Monte Carlo simulation with 10000 trials. Note that since the measurements are still i.i.d. under H_0, the decision threshold guaranteeing $Q_f = 0.01$, for each n, will be the same as the corresponding one used to obtain the log-normal curve in Fig. 8.

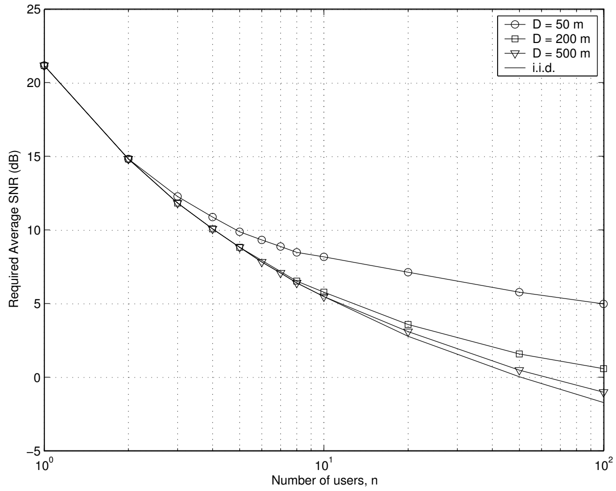


Figure 11. The required average SNR vs. the number of collaborating users under exponentially-correlated log-normal shadowing (σ_{dB} = 6dB) in urban environment ($Q_d = 0.99$, $Q_f = 0.01$, $m = 1$).

The average SNR required for the detection has been plotted in Fig. 11 as a function of the number of collaborating users. As expected, correlated shadowing degrades the performance of collaborative detection in all cases. This effect becomes more significant when users are dispersed over a smaller distance. We observe that for a given average SNR, a larger number of users will be needed to deliver the same performance as the size of the sensing network shrinks. The results shown in Fig. 11 suggest that having a few number of users dispersed over a large distance is more effective than a dense sensing network confined to a small area.

VI. Concluding Remarks

In this paper we studied collaborative sensing as a means to improve the performance of sensing-based opportunistic spectrum access under fading. As indicated by the presented results, even with very simple local detectors along with a low-overhead communication protocol, user collaboration may result in significant performance enhancements. In particular, by increasing the number of collaborating users under i.i.d. fading, the probability of missing the white spaces may be made arbitrarily small while providing the primary user with its desired level of interference-protection. Moreover, the degradation due to noise uncertainty may be compensated for by having more users.

Alternatively, maintaining the global probabilities of detection and false-alarm at a desired level, collaboration enables users to employ less sensitive detectors, thereby reducing the hardware cost and complexity. Collaboration may also be used to enhance the agility of the secondary network by reducing the time required for the detection of the primary signal. This is particularly important during the ongoing secondary transmissions where fast detection of the reappearing primary users is very critical.

While we studied the negative impact of spatially-correlated shadowing through simulation, more research needs to be done to develop efficient collaborative sensing schemes in such setting. It is of particular interest to characterize the performance based on the spatial distribution of the users and the correlation structure of the shadowing.

REFERENCES

[1] Federal Communications Commission, "Spectrum policy task force report (ET Docket No. 02-135)," available online: http://hraunfoss.fcc.gov/edocs_public/attachmatch/DOC-228542A1.pdf, November 2002.

[2] Shared Spectrum Company, "Spectrum Occupancy Report for New York City during the Republican Convention August 30 - September 1, 2004," available online at: http://www.sharedspectrum.com/?section=measurements, January 2005.

[3] Federal Communications Commission, "Notice of Proposed Rule-making, in the matter of unlicensed operation in the TV broadcast bands (ET Docket No. 04-186) and additional spectrum for unlicensed devices below 900 MHz and in the 3 GHz band (ET Docket No. 02-380), FCC 04-113," May 2004.

[4] DARPA XG Working Group, "The XG Vision, Request for Comments," prepared by BBN Technologies, July 2003.

[5] National Science Foundation, "Networking Technology and Systems (NeTS) Program Solicitation," available online at: http://www.nsf.gov/pubs/2005/nsf05505/nsf05505.htm.

[6] IEEE 802.22, Working Group on Wireless Regional Area Networks (WRAN), http://grouper.ieee.org/groups/802/22/.

[7] J. M. Peha, "Approaches to spectrum sharing," *IEEE Communications Magazine*, pp. 10–11, February 2005.

[8] W. D. Horne, "Adaptive spectrum access: using the full spectrum space," *31st Annual Telecommunications Policy Research Conference (TPRC'03)*, October 2003.

[9] I. F. Akyildiz *et al.*, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey," *Computer Networks*, vol. 50, no. 13, pp. 2127–2159, September 2006.

[10] D. Čabrić, S. M. Mishra and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," *in Proc. Asilomar Conference on Signals, Systems, and Computers*, 2004.

[11] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proceedings of IEEE*, vol. 55, pp. 523–231, April 1967.

[12] A. Sonnenschein and P. M. Fishman, "Radiometric detection of spread-spectrum signals in noise," *IEEE Transactions on Aerospace Electronic Systems*, vol. 28, no. 3, pp. 654–660, July 1992.

[13] W. A. Gardner, "Signal interception: a unifying theoretical framework for feature detection," *IEEE Transactions on Communications*, vol. 36, no. 8, pp. 897–906, August 1988.

[14] A. Ghasemi and E. S. Sousa, "Collaborative spectrum sensing for opportunistic access in fading environments," *in Proc. IEEE 1st Symposium on Dynamic Spectrum Access Networks (DySPAN'05)*, pp. 131–136, Baltimore, November 2005.

[15] E. Visotsky, S. Kuffner and R. Peterson, "On collaborative detection of TV transmissions in support of dynamic spetrum sharing," *in Proc. IEEE 1st Symposium on Dynamic Spectrum Access Networks (DySPAN'05)*, Baltimore, November 2005.

[16] S. M. Mishra, A. Sahai and R. W. Brodersen, "Cooperative sensing among cogniive radios," *in Proc. IEEE International Conference on Communications (ICC'06)*, Istanbul, June 2006.

[17] A. Ghasemi and E. S. Sousa, "Impact of user collaboration on the performance of opportunistic spectrum access," *in Proc. IEEE Vehicular Technology Conference (VTC Fall'06)*, Montreal, September 2006.

[18] I. S. Gradshteyn and I. M. Ryzhik, *Table of Integrals, Series, and Products*, 5th ed. Academic Press, 1994.

[19] A. H. Nuttall, "Some integrals involving the Q_M function," *IEEE Transactions on Information Theory*, vol. 21, no. 1, pp. 95–96, January 1975.

[20] F. F. Digham, M.-S. Alouini and M. K. Simon, "On the energy detection of unknown signals over fading channels," *in Proc. of IEEE International Conference on Communications (ICC'03)*, pp. 3575–3579, May 2003.

[21] V. Erceg, *et al.*, "An empirically based path loss model for wireless channels in suburban environments," *IEEE Journal on Selected Areas in Communications*, vol. 17, no. 7, pp. 1205–1211, July 1999.

[22] P. K. Varshney, *Distributed detection and data fusion*. New York: Springer-Verlag, 1997.

[23] D. G. Brennan, "Linear diversity combining techniques," *Proceedings of IRE*, vol. 47, pp. 1075–1102, June 1959.

[24] N. L. Johnson, S. Kotz and N. Balakrishnan, *Continuous Univariate Distributions*, 2nd ed. New York: John Wiley and sons, 1995, vol. 2.

[25] J. G. Proakis, *Digital Communications*, 4th ed. McGraw-Hill, 2001.

[26] R. Viswanathan and V. Aalo, "On counting rules in distributed detection," *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 37, no. 5, pp. 772–775, May 1989.

[27] A. Ghasemi and E. S. Sousa, "Spectrum sensing in cognitive radio networks: the cooperation-processing tradeoff," *Wiley Journal on Wireless Communications and Mobile Computing, Special issue on cognitive radio, software-defined radio, and adaptive wireless systems*, to appear.

[28] M. Gudmundson, "A correlation model for shadow fading in mobile radio," *Electronic Letters*, vol. 27, pp. 2146–2147, November 1991.

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