Collaborative Spectrum Sensing for Opportunistic Access in Fading Environments

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Abstract— **Traditionally, frequency spectrum is licensed to users by government agencies in a fixed manner where licensee has exclusive right to access the allocated band. This policy has been de jure practice to protect systems from mutual interference for many years. However, with increasing demand for the spectrum and scarcity of vacant bands, a spectrum policy reform seems inevitable. Meanwhile, recent measurements suggest the possibility of sharing spectrum among different parties subject to interference-protection constraints. In this paper we study spectrum-sharing between a primary licensee and a group of secondary users. In order to enable access to unused licensed spectrum, a secondary user has to monitor licensed bands and opportunistically transmit whenever no primary signal is detected. However, detection is compromised when a user experiences shadowing or fading effects. In such cases, user cannot distinguish between an unused band and a deep fade. Collaborative spectrum sensing is proposed and studied in this paper as a means to combat such effects. Our analysis and simulation results suggest that collaboration may improve sensing performance significantly.**

I. Introduction

Recent years have witnessed a dramatic increase in the demand for radio spectrum. This is partly due to the increasing interest of consumers in wireless services which in turn is driving the evolution of wireless networks toward high-speed data networks. With the emergence of new applications and the compelling need for mobile Internet access, demand for the spectrum is expected to grow even more tremendously in the coming years.

Spectrum is inherently a limited natural resource access to which is regulated by government agencies such as Federal Communications Commission (FCC) in the United States. Traditional approach to spectrum management is very inflexible in the sense that frequency bands are exclusively licensed to users and each system has to operate within a limited frequency band. However, with most of the spectrum being already allocated, it is becoming exceedingly hard to find vacant bands to either deploy new services or to enhance the existing ones. This spectrum limitation has had profound impacts on the research directions of wireless communications community. Within the past decade a great deal of research has been done to squeeze every bit per second out of a given channel.

On the other hand, recent measurements by Spectrum Policy Task Force (SPTF) within FCC indicate that many portions of the licensed spectrum are not used for significant periods of time [1]. In another experiment, spectrum occupancy between 30 MHz and 3 GHz in New York City in September 2004 was studied by Shared Spectrum Company [2]. The average duty cycle during the measurement period (approximately 30 hours) was only 13%. Evidently, there are many ”white spaces” in the spectrum which are not utilized. This finding suggests that currently spectrum scarcity is largely due to the inefficient fixed frequency assignments rather than physical shortage of the spectrum. Thus, an alternate remedy to spectrum scarcity is to allow other systems to access such under-utilized licensed bands dynamically (i.e. whenever/wherever licensee is not fully using its spectrum).

FCC's initiative to open up TV bands for unlicensed access [3] along with several other projects including Defense Advanced Research Projects Agency (DARPA)'s ”Next Generation” (XG) program [4] and national science foundation's ”NeTS-ProWiN” project [5] signal a paradigm shift in the spectrum access policy. Meanwhile, IEEE has formed a new working group on wireless regional area networks (IEEE 802.22) whose goal is to develop a standard for unlicensed access to TV spectrum on a non-interfering basis [6]. This raises several new technical and regulatory issues to be addressed by the academia as well as the policy-makers. Interested reader is referred to [7]- [8] for general overview of issues associated with the spectrum access policy reform.

In its report to the commission, SPTF proposed secondary access to already-licensed spectrum as a means to mitigate spectrum shortage. However, such *spectrum-sharing* should be carried out in a controlled fashion so that primary licensee's operation in the band is not compromised. Therefore, a secondary user trying to access the licensed spectrum should consider the impact of its transmission on the reception quality of the primary licensee.

In absence of cooperation or signalling between primary licensee and secondary user(s), spectrum availability for secondary access may be determined by direct spectrum sensing. In this case, a secondary user monitors a licensed frequency band and opportunistically transmits when it does not detect presence of any primary users.

When the structure of primary signal is known to the

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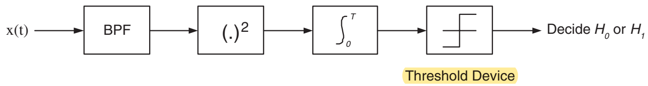

Fig. 1. Block diagram of an energy detector

secondary user, the optimal detector in stationary Gaussian noise is a matched-filter followed by a threshold test. However, implementing this type of coherent detector is difficult since a secondary user would need extra dedicated circuitry to achieve synchrony with each type of primary licensee [9]. Moreover, there may be cases in practice where matched-filter detector is ruled out due to the lack of knowledge about primary signal's structure. In such scenarios, a general-purpose detector would be much more desirable.

A common method for detection of unknown signals in noise is energy detection (a.k.a. radiometry) [10]. Fig. 1 depicts block-diagram of an energy detector. The input band-pass filter selects the center frequency, f_s, and 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. Finally, output of the integrator, Y, is compared with a threshold, λ, to decide whether signal is present or not.

While energy-detectors have been extensively studied in the past, performance under channel randomness has been only recently considered [11]. Simulation results of [11] along with those provided later in this paper suggest that performance of energy-detector degrades in shadowing/fading environments.

In order to improve spectrum sensing, several authors have recently proposed collaboration among secondary users [9], [12], [13]. Fig. 2 shows a scenario where only one secondary user may be able to detect the primary signal and the other users have no way of distinguishing between a white space or a deep shadowing effect. In such cases, collaboration may enhance secondary spectrum access significantly.

Most of the proposed methods are ad hoc solutions and a more general model incorporating different parameters such as number of secondary users, detection and false-alarm probabilities and more importantly propagation characteristics is still lacking. In this paper we quantify performance of spectrum sensing in fading environments and study effect of collaboration.

Remainder of this extended abstract is organized as follows. In section 2, performance of local spectrum sensing under shadowing/fading is characterized while collaborative spectrum sensing is outlined in section 3. Finally some concluding remarks and further research directions are discussed in section 4. Simulation results accompany analysis wherever applicable.

II. Local Spectrum Sensing in Fading Channels

The goal of spectrum sensing is to decide between the following two hypotheses,

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

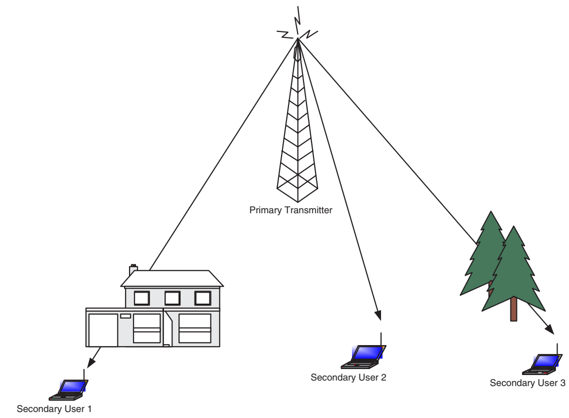

Fig. 2. Collaborative spectrum sensing in a shadowed environment. In this case only the middle secondary user may be able to detect the primary signal.

where $x(t)$ is the signal received by secondary user and $s(t)$ is primary users's transmitted signal, $n(t)$ is the additive white Gaussian noise (AWGN) and h is the amplitude gain of the channel. We also denote by γ the signal-to-noise ratio (SNR).

We denote the output of integrator in Fig. 1 by Y which serves as decision statistic. Following the work of Urkowitz [10], Y may be shown to have the following distribution,

$$Y \sim \begin{cases} \mathcal{X}^2_{2TW}, & H_0 \\ \mathcal{X}^2_{2TW}(2\gamma), & H_1 \end{cases}$$

where $\mathcal{X}^2_{2TW}$ and $\mathcal{X}^2_{2TW}(2\gamma)$ denote central and non-central chi-square distributions respectively, each with $2TW$ degrees of freedom and a non-centrality parameter of 2γ for the latter distribution. For simplicity we assume that time-bandwidth product, TW, is an integer number which we denote by m.

In a non-fading environment where h is deterministic, probabilities of detection and false alarm are given by the following formulas [11],

$$P_d = P\{Y > \lambda | H_1\} = Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) \qquad (1)$$

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

where $\Gamma(.)$ and $\Gamma(.,.)$ are complete and incomplete gamma functions respectively [14] and $Q_m(.,.)$ is the generalized Marcum Q-function [15] defined as follows,

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

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

The fundamental tradeoff between $P_m = 1 - P_d$ (probability of missed detection) and P_f has different implications in the context of dynamic spectrum-sharing. A high P_m would result in missing the presence of primary user with high probability which in turn increases interference to primary licensee. On the other hand, a high P_f would result in low

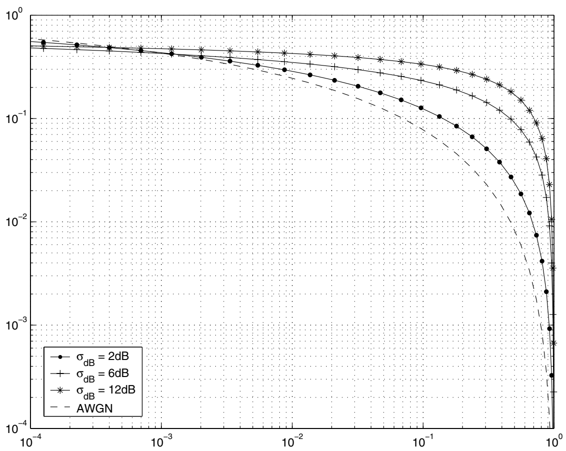

Fig. 3. Complementary ROC (P_m vs. P_f) under log-normal shadowing with different dB-spreads ($\overline{\gamma} = 10$ dB, $m = 5$). AWGN curve is provided for comparison.

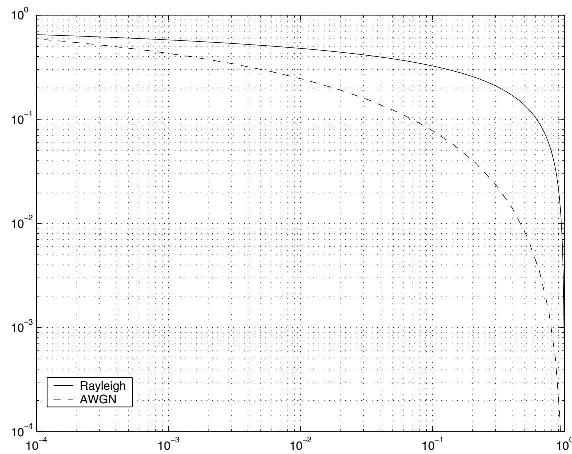

Fig. 4. Complementary ROC (P_m vs. P_f) under Rayleigh fading ($\overline{\gamma} = 10$ dB, $m = 5$). AWGN curve is provided for comparison.

spectrum utilization since false alarms increase 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/fading, (1) gives probability of detection *conditioned* on the instantaneous SNR, γ. In this case, average probability of detection (which with an abuse of notation is denoted by P_d) may be derived by averaging (1) over fading statistics,

$$P_d = \int_x Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) f_\gamma(x) dx \tag{3}$$

where $f_\gamma(x)$ is the probability distribution function (pdf) of SNR under fading.

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

A. Log-normal Shadowing

Empirical measurements suggest that medium-scale variations of the received-power, when represented in dB units, follow a normal distribution (see e.g. [16]). In other words, the linear (as opposed to dB) channel gain may be modelled by a log-normal random variable, e^X, where X is a zero-mean Gaussian r.v. with variance σ^2. Log-normal shadowing is usually characterized in terms of its dB-spread, σ_{dB}, which is related to σ by $\sigma = 0.1 \ln(10)\sigma_{dB}$.

When γ is log-normally distributed due to shadowing, (3) may be evaluated numerically. Fig. 3 shows complementary ROC curves for three different dB-spreads. Average SNR, $\overline{\gamma}$, and m are assumed to be 10 dB and 5 respectively. A plot for non-fading (pure AWGN) case is also provided for comparison.

Comparing the AWGN curve with those corresponding to shadowing, we observe that for regions of practical interest, spectrum sensing is harder in presence of shadowing. Moreover, as shadowing becomes more intense (higher dB-spread), energy-detector's performance degrades.

B. Rayleigh Fading

Under Rayleigh fading, γ would have an exponential distribution. In this case, a closed-form formula for P_d may be obtained (after some manipulation) by substituting $f_\gamma(x)$ in (3) [11],

$$\begin{aligned} P_d &= e^{-\frac{\lambda}{2}} \sum_{k=0}^{m-2} \frac{1}{k!}\left(\frac{\lambda}{2}\right)^k + \left(\frac{1+\overline{\gamma}}{\overline{\gamma}}\right)^{m-1} \\ &\times \left(e^{-\frac{\lambda}{2(1+\overline{\gamma})}} - e^{-\frac{\lambda}{2}} \sum_{k=0}^{m-2} \frac{1}{k!}\left(\frac{\lambda\overline{\gamma}}{2(1+\overline{\gamma})}\right)^k\right) \end{aligned} \tag{4}$$

Fig. 4 provides plots of complementary ROC curve under AWGN and Rayleigh fading scenarios. $\overline{\gamma}$ and m are assumed to be 10 dB and 5 respectively. We observe that Rayleigh fading degrades 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.

III. Collaborative Spectrum Sensing in Fading Channels

In order to improve performance of spectrum sensing, we allow different secondary users to collaborate by sharing their information. In order to minimize the communication overhead, users only share their final 1-bit decisions (H_0 or H_1) rather than their decision statistics.

Let n denote the number of users collaborating. For simplicity we assume that all n users experience independent and identically distributed (iid) fading/shadowing with same average SNR. A fundamental result in distributed binary hypothesis testing is that when sensors are conditionally

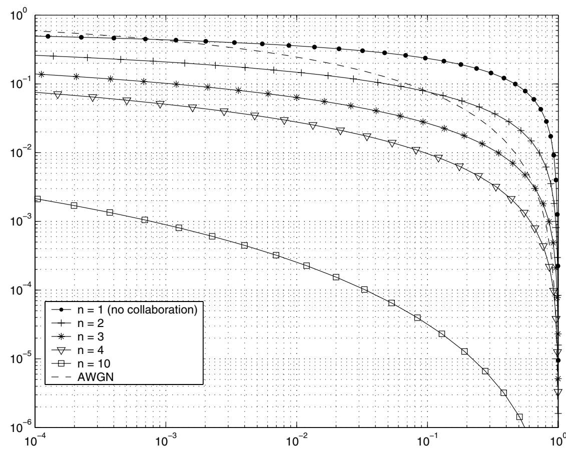

Fig. 5. Q_m vs. Q_f under iid log-normal shadowing ($\sigma_{dB} = 6$ dB) for different number of collaborative spectrum sensors ($\overline{\gamma} = 10$ dB, $m = 5$)

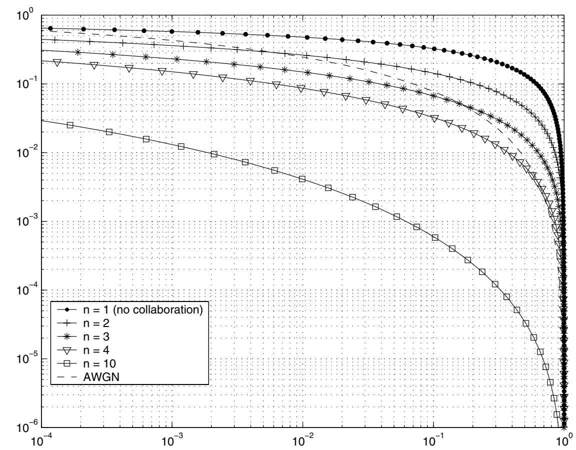

Fig. 6. Q_m vs. Q_f under iid Rayleigh fading for different number of collaborative spectrum sensors ($\overline{\gamma} = 10$ dB, $m = 5$)

independent (as in our case), optimal decision rule for individual sensors is likelihood ratio test (LRT) [17]. However, optimum individual thresholds are not necessarily equal and it is generally hard to derive them. We assume that all users employ energy-detection rather than LRT and use the same decision rule (i.e. same threshold λ). While these assumptions render our scheme sub-optimum, they facilitate analysis as well as practical implementation.

A secondary user receives decisions from $n-1$ other users and decides H_1 if any of the total n individual decisions is H_1. This fusion rule is known as the OR-rule or 1-out-of-n rule [17]. Probabilities of detection and false-alarm for the collaborative scheme (denoted by Q_d and Q_f respectively) may be written as follows,

$$Q_d = 1 - (1 - P_d)^n \tag{5}$$

$$Q_f = 1 - (1 - P_f)^n \tag{6}$$

where P_d and P_f are the individual probabilities of detection and false-alarm as defined by (3) and (2) respectively. It may be seen from (5) and (6) that compared to local sensing, this collaborative scheme increases probability of detection as well as probability of false-alarm . However, the net effect is an improvement in detection performance as seen in simulations.

Fig. 5 and 6 show complementary ROC for different number of collaborating users under independent log-normal shadowing ($\sigma_{dB} = 6$ dB) and Rayleigh fading respectively. As before $\overline{\gamma} = 10$ dB and $m = 5$. In both cases non-fading AWGN curve is shown for comparison.

As seen in these figures, fusing decisions of different secondary users cancels deleterious impact of shadowing/fading effectively. Moreover, with increasing n, collaborative scheme is capable of outperforming AWGN local sensing ($n = 1$). This is due to the fact that for larger n, with high probability there will be a user with a channel better than that of the non-fading AWGN case.

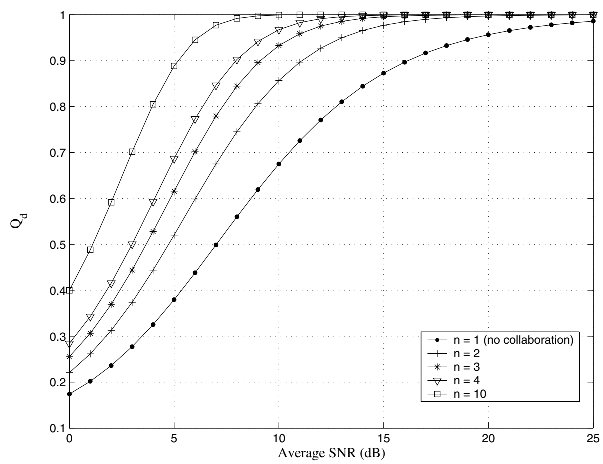

Fig. 7. Q_d vs. $\overline{\gamma}$ under iid Rayleigh fading for different number of collaborative spectrum sensors ($Q_f = 10^{-1}$, $m = 5$)

Fig. 7 shows Q_d versus $\overline{\gamma}$ under iid Rayleigh fading for different number of collaborative spectrum sensors. For each curve, decision threshold, λ, is chosen such that $Q_f = 10^{-1}$. Time-bandwidth product, m, is set to 5 as before.

Results indicate a significant improvement in terms of required average SNR for detection. In particular, for a probability of detection equal to 0.9, local spectrum sensing requires $\overline{\gamma} \simeq 16$ dB while collaborative sensing with $n = 10$ only needs an average SNR of 5 dB for individual users.

IV. Collaborative Spectrum Sensing Under Spatially-Correlated Shadowing

Up to this point we have dealt with the case where secondary users experience independent shadowing/fading. While such assumption is reasonable for multi-path fading effects, there is usually a degree of spatial correlation associated with log-normal shadowing [18]. Intuitively, shadowing correlation would degrade performance of collaborative sensing when collaborating users are close. This is due to the fact that

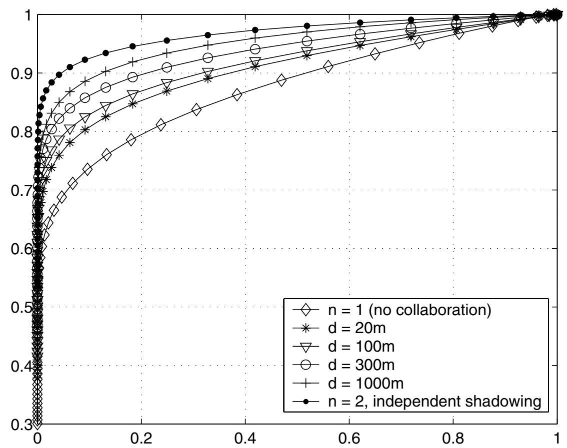

Fig. 8. Q_d vs. Q_f under spatially-correlated log-normal shadowing for different distances between two collaborative spectrum sensors in a suburban environment ($n = 2$, $\overline{\gamma} = 10$dB, $m = 5$). Cases with no-collaboration ($n = 1$) and also independent shadowing ($n = 2$) are shown for comparison.

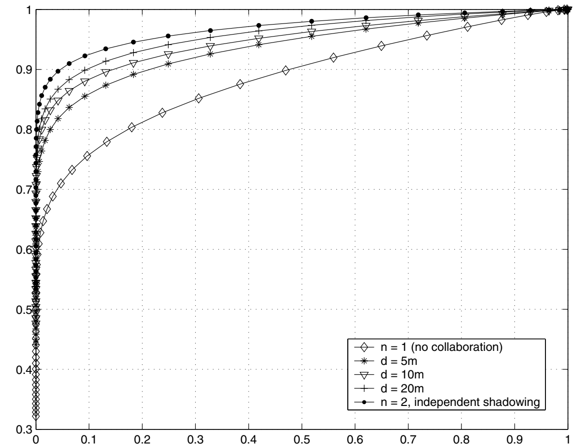

Fig. 9. Q_d vs. Q_f under spatially-correlated log-normal shadowing for different distances between two collaborative spectrum sensors in an urban environment ($n = 2$, $\overline{\gamma} = 10$dB, $m = 5$). Cases with no-collaboration ($n = 1$) and also independent shadowing ($n = 2$) are shown for comparison.

such users are likely to experience similar shadowing effects thereby countering collaboration gain. In this section further analysis and simulation results for the above scenario are provided.

Empirical data suggests an exponential correlation function for shadowing effects [18],

$$R(d) = e^{-ad} \tag{7}$$

where $R(d)$ is the correlation function, d is the distance between two locations and a is a constant depending on the environment. Based on measurements reported in [18], $a = 0.1204$ in urban environments and $a \approx 0.002$ in suburban environments.

In order to quantify the degrading effect of correlated shadowing on detection performance, we consider two collaborating users at different distances. For each distance, two correlated log-normal random variables, with correlation function as given by (7), are generated. In each case ROC is obtained using Monte Carlo simulation.

Fig. 8 and Fig. 9 depict the ROC at different inter-user distances for suburban and urban environments respectively. As expected, correlated shadowing degrades performance of collaborative detection. However, this effect becomes less significant when two users are located further apart. Moreover, it can be seen that to achieve the same performance level, a much larger separation between the two users is required in suburban (as opposed to urban) environments. Thus, when designing collaborative spectrum sensing protocols, relative location of users should be taken into account.

V. Concluding Remarks

In a heavily shadowed/fading environment, different secondary users may need to cooperate in order to detect the presence of a primary user. In such a scenario, a comprehensive model relating different parameters such as detection probability, number and spatial distribution of spectrum sensors and more importantly propagation characteristics is yet to be found.

This paper serves as a first step towards design and analysis of collaborative spectrum sensing schemes. Our results indicate that significant performance enhancements may be achieved through collaboration thereby motivating further research in this area.

It is well-known that energy detector's performance is susceptible to uncertainty in noise power [19]. In such cases, alternate detection schemes such as cyclic feature detection [20] may be employed. Performance analysis of spectrum sensing in this scenario is the subject of our current research.

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