

Multinode Spectrum Sensing Based on Energy Detection for Dynamic Spectrum Access

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Abstract—Sharing of the frequency spectrum between licensed primary users and unlicensed secondary users (SUs) requires reliable detection of spectrum occupancy by the SUs. Due to fading, single terminal detection is unreliable and results in a high probability of missed detection. This is solved by applying cooperative detection. In this paper two novel energy-based cooperative detection methods using weighted combining for Dynamic Spectrum Access are presented and analyzed. Weighting is based on the local mean SNR and the optimum log-likelihood ratio. Simulation results show a substantial improvement for the proposed weighting methods compared to equal gain combining and hard decision combining.

I. INTRODUCTION

Frequency spectrum is a scarce resource which generally is regulated by governmental agencies. Traditional spectrum management is rather inflexible with exclusive licenses for the use of specific frequency bands. Despite all the frequency bands being already allocated, recent measurements indicate low spatial and/or temporal utilization of parts of the licensed spectrum [1]. A novel way to increase spectrum efficiency is to share the spectrum between licensed primary users (PUs) and unlicensed secondary users (SUs). Unlicensed SUs are allowed to access the spectrum only when they do not interfere with the PU. This sharing is called Dynamic Spectrum Access (DSA).

In the most common scenario there is no cooperation between PUs and SUs. The SU has to determine empty spectrum slot, i.e. a frequency channel which is unused in a certain area and time interval, by sensing a licensed frequency band, and transmit only when it does not detect the PU. A classical technique to detect unknown signals in noise is energy detection [2]. It is simple to implement but suboptimal since no signal signature information is exploited. The detection quality of the SU, indicated by the probabilities of *false alarm*, P_F , and *missed detection*, P_M , is mainly determined by the signal-to-noise ratio of the received PU signal, which is location dependent due to pathloss, shadowing and multipath fading. For a user in a bad location (low signal-to-noise ratio), it will be difficult to make a distinction between an empty channel and an occupied channel. The likelihood that multiple users with independent channels experience a bad channel is

This research was carried out in the Adaptive Ad-Hoc Free Band Wireless Communications (AAF) project funded by the Freeband program of the Dutch Ministry of Economic Affairs.

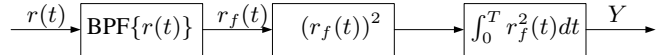


Fig. 1. Block diagram of the energy detector.

smaller than for a single user. Therefore, cooperation between a number of SUs by combining the sensing results taken under the same condition: PU present or PU not present, will enhance the detection performance.

Previous studies on cooperative detection for DSA, i.e. [3], [4], [5], [6], [7], have focused on detection techniques which combine the decisions from the SUs with equal weights. In this paper, we introduce two new techniques for weighted combining of the channel sensing results of users: *weighted gain combining* and *log-likelihood combining*. Due to shadowing, or slow fading, some secondary nodes will receive the PU signal on average with a higher power than others. Since shadowing changes relatively slow over time, it is possible to estimate the expected average signal power at a secondary node. This information, which is a direct measure for the detection quality of the nodes, is exploited by both techniques to weight the information of the SU to enhance the detection quality. We quantify the performance of these techniques with the help of simulations and show the performance increase to hard decision combining and equal gain combining.

The remainder of this paper is organized as follows. Section II describes the performance of single node energy detection in fading channels. The proposed cooperative detection techniques are given in Section III, and accompanied with simulations in Section IV. Finally, this paper is concluded in Section V.

II. ENERGY DETECTION IN FADING CHANNELS AND SYSTEM MODEL

A block diagram of the energy detector is given in Fig. 1. The received signal $r(t)$ can be written as $r(t) = hs(t) + n(t)$, where $s(t)$ is the detected signal waveform, $n(t)$ is additive white Gaussian noise (AWGN) and $h = 0$ under hypothesis H_0 (no PU signal present) and $h = 1$ under hypothesis H_1 (PU signal present). First, the received signal is filtered by an ideal bandpass filter with impulse response $f(t)$ and bandwidth W to limit the noise power. The filtered signal $r_f(t) = f(t) * r(t)$

is squared and integrated over time T resulting in the decision statistic $Y = \int_0^T r_f^2(t)dt$, which is described by [2]

$$Y \sim \begin{cases} \chi_{2u}^2, & \text{under } H_0, \\ \chi_{2u}^2(2\gamma), & \text{under } H_1, \end{cases}$$

where χ_{2u}^2 is a chi-square distribution with $2u$ degrees of freedom, $\chi_{2u}^2(2\gamma)$ is a non-central chi-square distribution with $2u$ degrees of freedom and non-centrality parameter 2γ , $u = TW$ is the time-bandwidth product and $\gamma = \frac{P_s}{N_0}$ is the ratio of signal energy to noise spectral density (SNR). It is assumed that T and W are chosen such that u only takes integer values.

In a non-fading environment the single node probability of detection P_D and the single node probability of false alarm P_F are given by [8]

$$P_D = \Pr(Y > \lambda | H_1) = Q_u(\sqrt{2\gamma}, \sqrt{\lambda}), \quad (1)$$

$$P_F = \Pr(Y > \lambda | H_0) = \frac{\Gamma(u, \lambda/2)}{\Gamma(u)}, \quad (2)$$

where λ is the threshold of the energy detector, $\Gamma(\cdot)$ and $\Gamma(\cdot, \cdot)$ are the complete and upper incomplete gamma function, respectively, and $Q_u(\cdot, \cdot)$ is the generalized Marcum Q-function. From (2) it is clear that the probability of false alarm P_F is independent of γ , since no signal is present under H_0 .

When the receiver is in a fading channel, the received signal energy and SNR are location dependent. Therefore, the average probability of detection P_D is derived by averaging (1) over the fading statistics

$$P_D = \int_0^\infty Q_u(\sqrt{2\gamma}, \sqrt{\lambda}) f_\gamma(x) dx, \quad (3)$$

where $f_\gamma(\gamma)$ is the probability density function (pdf) of the SNR due to fading. The probability of false alarm is the same for all locations, since it does not depend on the SNR.

A. Rayleigh fading

When a signal experiences an NLOS multipath channel, the signal amplitude follows a Rayleigh distribution, and γ is exponentially distributed as $f_\gamma(\gamma) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma}{\bar{\gamma}}\right)$, where $\bar{\gamma}$ is a mean SNR value. A closed-form expression for P_D is obtained, by substituting $f_\gamma(\gamma)$ in (3) [8, Eq. (16)].

B. Shadow fading

Empirical measurements show that on a log scale the attenuation due to shadowing follows a zero mean Gaussian distribution [9], which is characterized by the standard deviation σ_{dB} , or dB-spread. When γ is log-normal distributed the probability of detection can be evaluated numerically.

C. Shadow plus Rayleigh fading

It is likely that a channel will experience both shadowing and multipath fading. The pdf of this composite log-normal

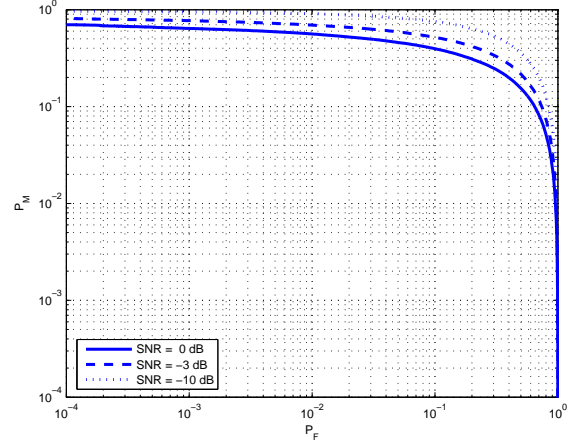


Fig. 2. Complementary ROC curve under log-normal shadowing plus Rayleigh fading at different SNR values for $u = 10$ and $\sigma_{dB} = 6$ dB.

shadowing plus Rayleigh fading channel is found by averaging the log-normal over the exponential distribution, i.e.

$$f_{x_m}(x_m) = \int_0^\infty \frac{1}{x_s} \exp\left(-\frac{x_m}{x_s}\right) \frac{10}{\sigma_{dB} \sqrt{2\pi} \ln(10) x_s} \times \exp\left(-\frac{(10 \log_{10}(x_s) - \mu)^2}{2\sigma_{dB}^2}\right) dx_s.$$

Here x_s is the log-normal random variable, x_m the random variable after shadowing and multipath and μ is the mean of the shadow fading. To the best of the author's knowledge there is no closed form expression for a log-normal plus Rayleigh distribution, and therefore in this paper the performance of local energy detection is evaluated with Monte Carlo simulations.

The performance of the energy detector in this case may be characterized by the complementary receiver operating characteristic (ROC) curve. The complementary ROC, which is a plot of the probability of missed detection $P_M = 1 - P_D$ versus the probability of false alarm P_F , is shown in Fig. 2. These results indicate that the detection performance is degraded by log-normal shadowing plus Rayleigh fading. For example, $P_F > 0.8$ for $P_M < 0.1$, which indirectly results in a low spectrum utilization.

D. System model

A geographical overview of a DSA Network (DSAN) sharing the spectrum with a PU is illustrated in Fig. 3(a). The DSAN, consisting of several SUs, is at a distance d from the primary transmitter (PT). Around the PT there is a region of decodability with a radius of r_{dec} . In the absence of interference and fading a PU receiver can only decode the signal if it is inside this region of decodability. The secondary users are clustered in a DSAN with a radius r_s . We see that all the SUs are within the region of decodability, so they can only use the spectrum when the PT does not transmit.

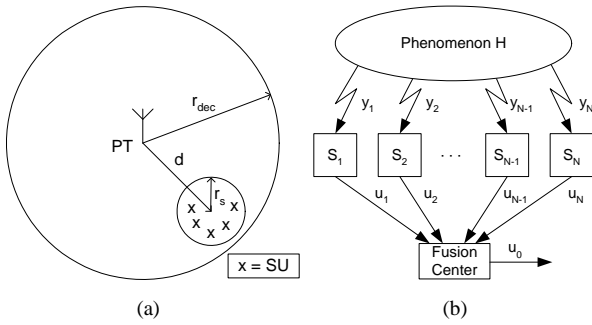


Fig. 3. System model: (a) Geographical overview of the considered network, (b) Parallel cooperative detection topology with fusion center [10, Fig. 1].

III. COOPERATIVE TECHNIQUES

In order to improve the performance of spectrum sensing, the SUs can cooperate to detect the presence of the PU. The detection topology used for cooperative detection is a parallel network with a fusion center as shown in Fig. 3(b). This topology consists of $N \geq 2$ local detectors all observing the same phenomenon. The local detectors transmit their measurement statistics to a fusion center, one dedicated node in the DSAN, which makes a global decision.

It is assumed that all the N SUs experience independent and identically distributed (iid) fading. The sensors are conditionally independent, which means that the SUs' measurements are independent, but that for each SU the same hypothesis $\{H_0, H_1\}$ applies. We now introduce two new cooperative detection techniques: *weighted gain combining* and *log-likelihood combining*.

A. Measurement combining

In measurement combining, the fusion center weights and combines the measurement values of the N local detectors. Based on a threshold test a global decision is generated. The test statistic Y_{WC} is the weighted sum of the N local measurements

$$Y_{WC} = \sum_{n=1}^N w_n Y_n,$$

where Y_n is the non-quantized output of the energy detectors and w_n is the weight for node n .

1) *Weighted gain combining*: In a channel experiencing shadowing, some nodes will have a better location dependent SNR than others. To gain from this SNR diversity, the fusion center can give different weights to different nodes. For *weighted gain combining* (WGC), the proposed SNR dependent weights are given by

$$w_n = \frac{\overline{\gamma}_n}{\sum_{n=1}^N \overline{\gamma}_n},$$

where $\overline{\gamma}_n$, the mean SNR over k measured SNR values of user n , is defined as

$$\overline{\gamma}_n = \frac{1}{2k} \sum_{j=i-k}^i (Y_{n,j} - 2u), \quad (4)$$

and $Y_{n,j}$ is the non-quantized j th measurement of the SU n . This results in a high weight for nodes with a high SNR and low weight for SU nodes with a low SNR. The weights are calculated by the fusion center, since it already receives the SNR measurements of all the nodes. When no information about the nodes' SNRs is available at start-up or after a long time without a signal, the weights are set to $w_n = \frac{1}{N}$. To make WGC adaptive, the fusion center only uses the last k measurements to compute the weights.

2) *Equal gain combining*: A special case of measurement combining is equal gain combining (EGC). In EGC the fusion center combines the measurements with equal weight, e.g. $w_n = 1$ for all n .

The global probability of detection Q_D and global probability of false alarm Q_F for both schemes for the AWGN channel are derived in [8]. However, for the log-normal shadow fading and log-normal plus Rayleigh fading channel Q_D has to be derived numerically.

B. Log-likelihood combining

The optimal solution to the distributed detection problem with conditionally independent sensors, is obtained by applying a likelihood ratio test (LRT) at the fusion center [10]. The LRT performed at the fusion center is given by

$$\Lambda(\mathbf{Y}) = \frac{p(\mathbf{Y}|H_1)}{p(\mathbf{Y}|H_0)} \underset{H_0}{\overset{H_1}{\geq}} \lambda. \quad (5)$$

Here, $\mathbf{Y} = (Y_1, Y_2, \dots, Y_N)$ is the vector of SU energy detector outputs. To employ the LRT, it is assumed that the conditional pdf's $p(Y|H_0)$ and $p(Y|H_1)$ are known. In reality this is not the case because the SNR is not known a priori. To employ the LRT, an estimate of the SNR can be used to derive the pdf's.

We can see that the LRT of the fusion center is the same as a threshold test, and therefore we can use (5) to construct the test statistic Y at the fusion center. Due to the independence assumption (5) can be written as

$$Y_{LLC} = \prod_{n=1}^N \frac{p(Y_n|H_1)}{p(Y_n|H_0)} = \sum_{n=1}^N \log \left[\frac{p(Y_n|H_1)}{p(Y_n|H_0)} \right].$$

In this form, the LRT can be seen as a sum of weights from the local detectors, each given by the local ratio of the likelihood of H_1 and the likelihood of H_0 .

C. Hard decision combining

For comparison, we recall the classical cooperative measurement technique: *hard decision combining*. Here, the local detectors have their own decision rule and make a decision based on their own measurements, which takes the value 0 or 1. Previous studies on cooperative detection for DSA with hard decision detection [3], [4] use energy detection with a fixed threshold identical for all sensors. This cooperative scheme is suboptimal [11], however, the local and global decision rules are simple and easy to implement.

The fusion center decides H_1 if any of the N local decisions decide H_1 . This fusion rule is a threshold rule and is also

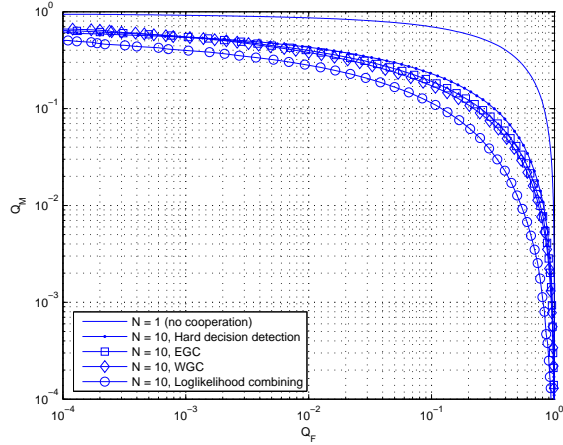


Fig. 4. Complementary ROC curve for the iid composite fading channel for several cooperative techniques with $N = 10$, $\text{SNR} = -8$ dB and $u = 10$.

known as OR-rule or 1-out-of- N rule [11]. In this case the global probability of detection $Q_D = 1 - (1 - P_D)^N$ and global probability of false alarm $Q_F = 1 - (1 - P_F)^N$, where P_D and P_F are given by (1) and (2), respectively.

IV. SIMULATION RESULTS

For most cooperative techniques, closed form solutions for Q_D and Q_F do not exist. Therefore, the performance of the techniques presented in the previous sections are determined from simulations based on the system model as given in Section II-D and using the Monte Carlo method. Except for the simulations showing the influence of the distance, the maximum distance between SUs is assumed much smaller than the distance to the primary transmitter (PT), i.e. $r_s \ll d$. In this case, the differences in the distant dependent path loss between the SUs is relatively small and can be neglected. Unless stated otherwise, the following system parameters are used: the measurement bandwidth of the SU is $W = 100$ kHz, the integration time $T = 0.1$ ms, thus $u = TW = 10$, the number of nodes $N = 10$, and the standard deviation of the shadow fading is $\sigma_{dB} = 6$ dB.

An overview of the performance of the cooperative techniques is given in Fig. 4. The average SNR of the nodes over the whole network is $\bar{\gamma} = -8$ dB. The results indicate that there is an increase in performance for all the cooperative techniques when compared to the single node performance. For $Q_M = 1 - Q_D < 0.1$ the Q_F is reduced from 0.8 for single node detection to 0.1 for 10-node log-likelihood detection. We also see that the more information available for the global decision the larger the performance improvement.

The global probability of false alarm Q_F versus SNR under iid log-normal shadowing plus Rayleigh fading for different cooperative detection techniques and number of sensors is given in Fig. 5. The local and global decision thresholds are chosen such that $Q_D = 0.9$. The results show an improvement in Q_F when cooperative detection is used, and log-likelihood combining shows the best performance for all SNRs. In

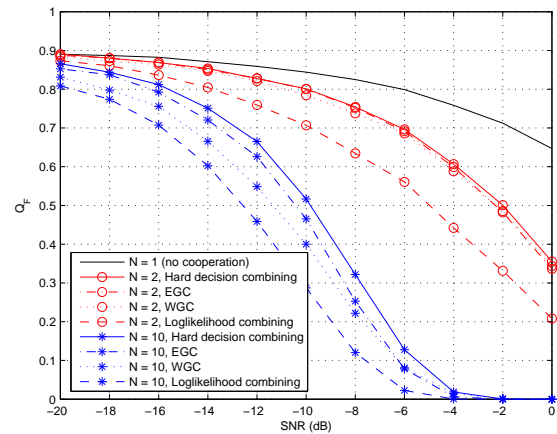


Fig. 5. Probability of false alarm vs SNR under iid log-normal shadowing plus Rayleigh fading for different cooperative techniques and number of sensors, $Q_D = 0.9$.

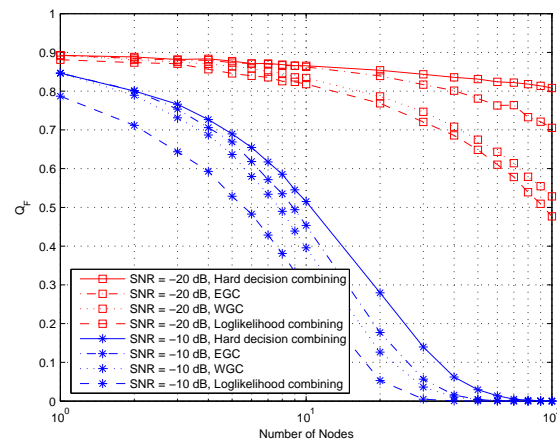


Fig. 6. Probability of false alarm vs the number of nodes under iid log-normal shadowing plus Rayleigh fading for different cooperative techniques and SNR, with fixed probability of detection, $Q_D = 0.9$.

particular for log-likelihood combining with $N = 10$ and $\bar{\gamma} = -10$ dB, Q_F is substantially lower than for hard decision combining and EGC. This improvement can lead indirectly to a higher spectrum efficiency.

The probability of false alarm Q_F versus the number of nodes N under iid log-normal shadowing plus Rayleigh fading is plotted in Fig. 6 for $Q_D = 0.9$. The results show an increase of performance with increasing number of nodes. For low SNR values the increase in performance is less than for higher SNR values. It can also be observed that for low SNR values, log-likelihood combining and WGC perform much better than hard decision combining or EGC.

For a system where the maximum distance between SUs is not much smaller than the distance to the PT, the variation of the SUs' distant dependent path loss can be significant. For a DSAN with a radius of $r_s = 250$ m at a distance $d = 1000$ m from the PT, the difference in SNR can be approximately 9 dB

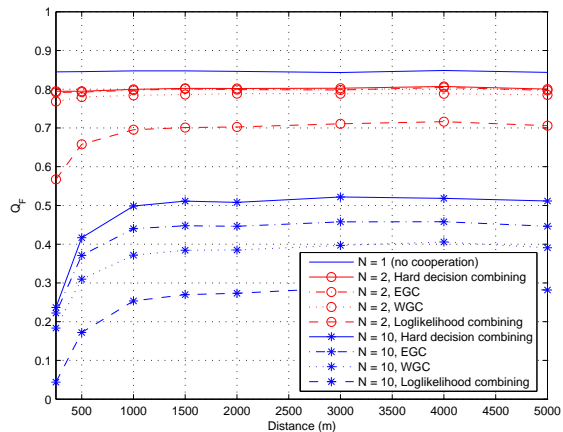


Fig. 7. Probability of false alarm vs distance from the primary transmitter under iid log-normal shadowing plus Rayleigh fading for different cooperative techniques and number of sensors, with fixed probability of detection, $Q_D = 0.9$. For all distances the average SNR at the center of the DSAN is -10 dB.

when the path-loss exponent $n = 4$.

Fig. 7 shows Q_F versus distance under iid log-normal shadowing plus Rayleigh fading for different cooperative techniques and number of sensors for $Q_D = 0.9$. The average SNR at the center of the DSAN is -10 dB. These results show a smaller Q_F at a short distance from the PT because the variation in SNR becomes larger compared to larger distances, which results in improved detection performance. For $r_s = 250$ m, the influence of the distance dependent path loss becomes negligible for $d > 3$ km. In general, it is possible to assume a large distance network for $\frac{r_s}{d} < \frac{1}{12}$.

The local mean SNR $\bar{\gamma}_n$ can be estimated from the last k measurements using (4). The effect of the number of samples to determine $\bar{\gamma}_n$ on the complementary ROC curves for log-likelihood combining under iid log-normal shadowing plus Rayleigh fading is shown in Fig. 8. The mean SNR of the DSAN is -5 dB, and due to shadowing each local sensor experiences a different $\bar{\gamma}_n$. It is assumed that the log-normal shadowing does not change between the k measurements, but the Rayleigh fading is assumed independent for the k measurements. These results indicate that the performance of log-likelihood detection with $k = 1$ is approximately the same as the performance of EGC. It also shows that the performance increases with each additional measurement. For $k \geq 10$ the performance is close to the performance of log-likelihood combining with perfectly known local mean SNR values.

V. CONCLUDING REMARKS

In an environment with severe shadowing plus Rayleigh fading single node detection is not sufficiently reliable for DSA. Thus, secondary users may have to cooperate in sensing the channel state to achieve reliable detection. The techniques proposed in this paper for weighting the channel sensing results from multiple users exploit the knowledge of the local mean SNR, and result in a substantial improvement compared

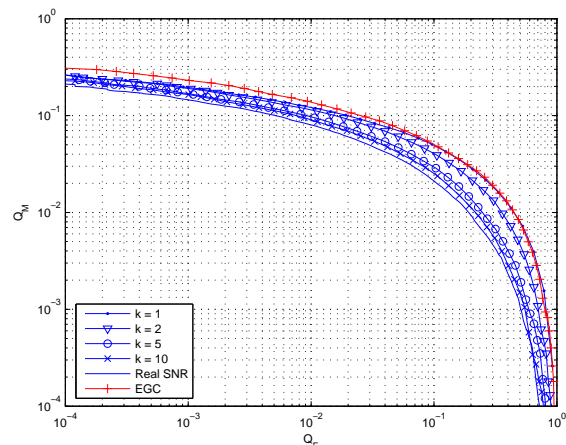


Fig. 8. Complementary ROC curves of log-likelihood combining under iid log-normal shadowing plus Rayleigh fading for different number of SNR estimation steps k , with $N = 10$, $u = 10$. ROC curve of EGC is plotted for comparison.

to existing techniques which do not use this information. Especially, log-likelihood combining outperforms all the other techniques in the case of low SNR and low number of nodes in the network. Interestingly, distant dependent path loss between the SUs, which becomes relevant if the DSAN is close to the primary transmitter, results in improved detection performance due to an increase of the SNR variance. Log-likelihood combining assumes that the pdf of the energy detectors output is known. More research is needed on how to estimate the pdf and its required accuracy.

REFERENCES

- [1] M. A. McHenry, "NSF spectrum occupancy measurements project summary," 2005. [Online]. Available: <http://www.sharedspectrum.com/?section=measurements>
- [2] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proc. IEEE*, vol. 55, no. 4, pp. 523–531, Apr. 1967.
- [3] A. Ghasemi and E. S. Sousa, "Collaborative spectrum sensing for opportunistic access in fading environments," in *Proc. IEEE DySPAN 2005*, Baltimore, MA, Nov. 2005, pp. 131–136.
- [4] E. Visotsky, S. Kuffner, and R. Peterson, "On collaborative detection of TV transmissions in support of dynamic spectrum sharing," in *Proc. IEEE DySPAN 2005*, Baltimore, MA, Nov. 2005, pp. 338–345.
- [5] S. M. Mishra, A. Sahai, and R. W. Brodersen, "Cooperative sensing among cognitive radios," in *Proc. IEEE ICC 2006*, vol. 4, Istanbul, Turkey, 2006, pp. 1658–1663.
- [6] Y.-C. Liang and E. Peh, "Optimization for cooperative sensing in cognitive radio networks," in *Proc. IEEE WCNC 2007*, Hong Kong, China, Mar. 2007, pp. 27–32.
- [7] S. Kyperountas, N. Correal, Q. Shi, and Z. Ye, "Performance analysis of cooperative spectrum sensing in Suzuki fading channels," in *Proc. IEEE CrownCom 2007*, Florida, USA, Aug. 2007.
- [8] F. F. Digham, M.-S. Alouini, and M. K. Simon, "On the energy detection of unknown signals over fading channels," in *Proc. IEEE ICC 2003*, vol. 5, Anchorage, AK, May 2003, pp. 3575–3579.
- [9] T. S. Rappaport, *Wireless Communications: Principles and Practice*. Prentice Hall, 2002.
- [10] R. Viswanathan and P. K. Varshney, "Distributed detection with multiple sensors: Part I—fundamentals," *Proc. IEEE*, vol. 85, no. 1, pp. 54–63, Jan. 1997.
- [11] P. K. Varshney, *Distributed Detection and Data Fusion*. New York: Springer-Verlag, 1996.