Performance of Centralized Data-fusion Cooperative Eigenvalue-based Spectrum Sensing under Shadowed Fading

Roberto César Dias Vilela Bomfin
National Institute of
Telecommunications - Inatel
Santa Rita do Sapucaí, MG, Brazil
Email: roberto@gee.inatel.br

Rausley Adriano Amaral de Souza
National Institute of
Telecommunications - Inatel
Santa Rita do Sapucaí, MG, Brazil
Email: rausley@inatel.br

Dayan Adionel Guimarães
National Institute of
Telecommunications - Inatel
Santa Rita do Sapucaí, MG, Brazil
Email: dayan@inatel.br

Abstract*—Cooperative eigenvalue-based spectrum sensing techniques under the multipath (short-term) fading assumption have been extensively analyzed in the literature. However, when evaluating the performance of wireless communication systems, it is of paramount importance to consider the combined effect of the multipath fading and shadowing (long-term fading) on the received signal. In this context, this paper aims at investigating the performance of four eigenvalue-based techniques for centralized data-fusion cooperative spectrum sensing in cognitive radio networks, taking into account both short-term and long-term fading. The channel model assumes that the shadowing is a random variable lognormally distributed about the area-mean signal strength and that the multipath fading is Rayleigh distributed. The detection techniques considered are the generalized likelihood ratio test (GLRT), the maximum-minimum eigenvalue detection (MMED), the maximum eigenvalue detection (MED) and the energy detection (ED). The results show that i) under shadowing, the decisions of the spectrum sensing become less accurate, ii) under severe shadowing, the performance can significantly depart from the one in which only the multipath fading is present, and iii) in terms of ranking, the MED outperforms all the remaining techniques, followed by the ED, the GLRT and the MMED.

I. Introduction

Currently, there is a growing demand for effective use of spectrum and spectral-efficient management strategies in the context of the fast developing wireless communications systems. The spectrum resources have become scarce, and at the same time there is a natural increasing demand for better quality of service, as well as higher transmission rates. Nevertheless, in fact there is an artificial scarcity of spectrum, since there are bands that are not actually used during all time in a given region [1]. The cognitive radio (CR) concept proposed in the Mitola's seminal work [2] can be applied to this context, aiming at using the electromagnetic spectrum more efficiently. A CR system uses advanced techniques that optimize the occupation of the bands, and spectrum sensing techniques to find the so-called spectral opportunities or spectral holes within bands of interest in a given area and in a given time. Hence, a CR system makes it possible to use the available spectrum in temporal, spatial and frequency dimensions, without causing interference to licensed systems.

The importance of studies involving spectrum sensing techniques is undeniable and, now, even more pronounced since that recently, actually this year, the IEEE announced the creation of the IEEE 802.22 Spectrum Occupancy Sensing (SOS) Study Group [3]. As stated by the chair of the working group, "standardization could lead to the more efficient use of spectrum, especially in places where the information about the primary users is difficult to find". Yet, "individual and collaborative spectrum sensing is one of the tools to complement the information contained in databases to create an accurate spectrum occupancy survey, which would combine information from multiple sensors along with local terrain information to predict the spectrum occupancy patterns" [3]. And now, the IEEE 802.22 Revision Project, extending the IEEE Std. 802.22-2011 to other Spectrum Sharing Bands, was approved. The standard specifies operation in the bands that allow spectrum sharing where the communications devices may opportunistically operate in the spectrum of the primary service, such as 1300 MHz to 1750 MHz, 2700 MHz to 3700 MHz and the VHF/UHF TV broadcast bands between 54 MHz to 862 MHz [4].

The choice of the spectrum sensing technique will also influence the detection performance, depending on the cognitive network architecture and the conditions of the channel. Many detection techniques for spectrum sensing have been proposed so far, e.g. the matched filter, the cyclostationary and the energy detection [5], [6]. Among the latest ones are those based on the eigenvalues of the received signal covariance matrix; see [7]–[9] and references therein. These techniques have received a lot of attention mainly because they do not require prior information on the transmitted signal, and, in contrast to the energy detection, some eigenvalue-based schemes do not need to know the noise variance either. As far as the detection technique is concerned, we consider the eigenvalue-based generalized likelihood ratio test (GLRT); the maximum-minimum eigenvalue detection (MMED), also known as the eigenvalue ratio detection (ERD); the maximum eigenvalue detection (MED), also known as Roy's largest root test (RLRT); and the energy detection (ED), applied to a centralized data-fusion cooperative spectrum sensing scheme. ED is not an exclusively eigenvalue-based detection technique, but it can be easily implemented using eigenvalue information. It has been included in the present work for the sake of completeness, also giving support to a broader pool of comparisons.

The scenarios of spectral occupancy differ from one another depending on several factors, such as channel conditions, location and prevailing political control of spectrum usage. This implies greater system complexity, since the cognitive cycle of the CR concept includes a step for learning the channel conditions [2], [10]. Thus, the behavior of the channel, or more precisely the channel model, influences the operation and performance of a CR. Then, evaluating the performance of a CR system under different channel models is of paramount importance. Moreover, no matter the sensing technique adopted, the detection performance depends on the reception conditions of the CRs, and therefore on the propagation environment. For example, in [11] comparisons were made among different models for the energy detector under conditions of additive white Gaussian noise (AWGN) and Rayleigh fading channels. It has been shown that the problem of energy detection lies in the uncertainty of estimating the noise power, which degrades the detection performance [12]–[14]. In [15] the authors analyze the probability of missed detection of the energy detector under Nakagami-*m* fading channels. Recently, in [16] the authors presented a new implementation-oriented model in which typical signal processing tasks of a direct-conversion CR receiver were taken into account considering the multipath Rayleigh fading channel.

It is well-known that in wireless systems, it is frequently observed that the local average power varies randomly from place to place in a given region. This phenomenon has been assigned to the existence of shadowed areas due to the terrain contour, large size vehicles [17], buildings, foliage [18] and other obstacles. A large number of measurements campaigns have suggested that the probability density function (PDF) of the average power can be modeled in terms of a lognormal PDF [18], [19]. However, it is important to consider the simultaneous effect of multipath fading (short-term) and shadowing (long-term) on the received signal. This physical process is known in the specialized literature as shadowed fading, shadow-fading or composite fading. This paper deals with this co-existence of fading effects influencing the performance of different eigenvalue-based spectrum sensing techniques.

Due to the ameliorated detector performance as a result of diversity gain, cooperative spectrum sensing is considered a possible solution for problems experienced by CR networks in a non-cooperative situation, like receiver uncertainty, multipath fading, hidden terminals and shadowing [10]. The later one is the aim of this paper, i.e, we will present the analysis of the cooperative spectrum sensing performance under a shadowed fading condition.

The remainder of the paper is structured as follows. Section II presents the system model for the eigenvalue-based sensing technique and for the shadowed fading channel. Simulation results and discussions concerning the influence of system parameters on the performance of the spectrum sensing are reported in Section III. Finally, Section IV concludes the paper.

II. System Model

A. Centralized Cooperative Eigenvalue Spectrum Sensing

Consider the well-known baseband memoryless linear discrete-time MIMO fading channel model. Assume that there are m single-antenna CRs, each one collecting n samples of the received signal from p primary transmitters during the sensing period, and that these samples are arranged in a matrix $\mathbf{Y} \in \mathbb{C}^{m \times n}$. Similarly, consider that the signal samples from the p primary transmitters are arranged in a matrix $\mathbf{X} \in \mathbb{C}^{p \times n}$, and that $\mathbf{H} \in \mathbb{C}^{m \times p}$ is the channel matrix with elements $\{h_{ij}\}$, $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, p$, representing the channel gain between the j-th primary transmitter and the i-th sensor (CR). The elements of the channel matrix $\mathbf{H}$ simulate a flat shadowed fading channel between each primary transmitter and CR, assumed to be constant during a sensing period and independent from one period to another. This channel will be described with more details in Subsection II-C. Finally, if $\mathbf{V} \in \mathbb{C}^{m \times n}$ represents the matrix containing thermal noise samples that corrupt the received signal, then the matrix of collected samples is given by

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{V}. \tag{1}$$

In eigenvalue-based spectrum sensing, spectral holes are detected by using test statistics based on the eigenvalues of the received signal sample covariance matrix. In a centralized cooperative scheme with data-fusion, matrix $\mathbf{Y}$ is formed at the fusion center (FC), and the sample covariance matrix

$$\mathbf{R} = \frac{1}{n}\mathbf{Y}\mathbf{Y}^{\dagger} \tag{2}$$

is estimated, where $(\cdot)^{\dagger}$ stands for complex conjugate and transpose. The eigenvalues $\{\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m\}$ of $\mathbf{R}$ are then computed, and assuming a single primary transmitter ($p = 1$), the decision variables for the GLRT, the MMED, the MED, and the ED are respectively calculated according to [7]:

$$T_{\text{GLRT}} = \frac{\lambda_1}{\frac{1}{m}\text{tr}(\mathbf{R})} = \frac{\lambda_1}{\frac{1}{m}\sum\limits_{i=1}^{m}\lambda_i} \tag{3}$$

$$T_{\text{MMED}} = \frac{\lambda_1}{\lambda_m} \tag{4}$$

$$T_{\text{MED}} = \frac{\lambda_1}{\sigma^2} \tag{5}$$

$$T_{\text{ED}} = \frac{\|\mathbf{Y}\|_F^2}{mn\sigma^2} = \frac{1}{m\sigma^2}\sum_{i=1}^{m}\lambda_i \tag{6}$$

where σ^2 is the thermal noise power, which is assumed to be known and the same in each sensor input, and $\text{tr}(\cdot)$ and $\|\cdot\|_F$ are the trace and the Frobenius norm of the underlying matrix, respectively. The decision upon the occupation of the sensed channel is attained by comparing the test statistic of choice with a decision threshold.

B. The Spectrum Sensing as a Binary Hypothesis Test

Spectrum sensing can be formulated as a binary hypothesis test problem that can be stated as

$$\begin{aligned} \mathcal{H}_0 &: \quad \text{Primary signal is absent} \\ \mathcal{H}_1 &: \quad \text{Primary signal is present,} \end{aligned} \tag{7}$$

where $\mathcal{H}_0$ is the null hypothesis, meaning that there is no licensed user signal active in a specific sensed band, and $\mathcal{H}_1$ is the alternative hypothesis, which indicates that there is at least one active primary user signal.

Two important parameters associated with the assessment of the spectrum sensing performance are the probability of detection, P_d, and the probability of false alarm, P_fa, which are defined as follows:

$$\begin{aligned} P_\text{d} &= \Pr\{\text{decision} = \mathcal{H}_1|\mathcal{H}_1\} = \Pr\{T > \gamma|\mathcal{H}_1\} \\ P_\text{fa} &= \Pr\{\text{decision} = \mathcal{H}_1|\mathcal{H}_0\} = \Pr\{T > \gamma|\mathcal{H}_0\}, \end{aligned} \tag{8}$$

where $\Pr\{\cdot\}$ is the probability of a given event, T is the test statistic and γ is the decision threshold. The value of γ is chosen depending on the requirements for the spectrum sensing performance, which is typically evaluated from receiver operating characteristic (ROC) curves that show P_d versus P_fa as they vary with the variation of the decision threshold γ. A higher threshold keeps P_fa at low levels, but renders detection difficult. On the other hand, a low threshold favors detection, but increases P_fa. This tradeoff is clearly seen from a ROC curve.

C. Shadowed Fading Channel

Consider the channel matrix in (1) given by

$$\mathbf{H} = \mathbf{H}^\text{f} + \mathbf{H}^\text{s}. \tag{9}$$

The channel matrix $\mathbf{H}^\text{f}$ represents the *multipath fading*, with the elements $|h^\text{f}_{ij}|$ (magnitudes) and $\arg h^\text{f}_{ij}$ (phases) being Rayleigh and uniformly distributed in $(0, 2\pi]$, respectively. The channel matrix $\mathbf{H}^\text{s}$ represents the *shadowing*, with elements $|h^\text{s}_{ij}|$ and $\arg h^\text{s}_{ij}$ being lognormally and uniformly distributed in $(0, 2\pi]$, respectively. Remember that a lognormal variate Z relates to a Gaussian variate Y as $Z = \exp(Y)$. Then, taking into account fading and shadowing simultaneously, it is possible to demonstrate that the elements of $\mathbf{H}$ are random variables with the Rayleigh-lognormal PDF given by [18], [19]

$$\begin{aligned} f(h) = {} & \frac{h}{b_0\sqrt{2\pi d_0}} \times \\ & \int_0^\infty \frac{\mathrm{I}_0(hz/b_0)}{z} \exp\left(-\frac{(\ln z - \mu)^2}{2d_0} - \frac{(h^2+z^2)}{2b_0}\right)\mathrm{d}z \end{aligned} \tag{10}$$

where $h \triangleq |h_{ij}|$ is a random variable representing the shadowed fading channel between each primary transmitter and CR, b_0 represents the average scattered power due to multipath, $\sqrt{d_0}$ and μ are the standard deviation and mean, respectively, of the normal (Gaussian) random process that generates the lognormal distribution or, equivalently, μ is the mean of $\ln z$ and and $\sqrt{d_0}$ is standard deviation of $\ln z$. $\mathrm{I}_0(\cdot)$ is the modified Bessel function of first kind and order 0. Keeping in mind that the Rayleigh and lognormal random processes are additive, it is possible to show that

$$\mathbb{E}(h^2) = 2b_0 + \exp(2\mu + 2d_0), \tag{11}$$

where $\mathbb{E}(\cdot)$ denotes the expectation operator. Concluding, this well-accepted Loo's model assumes that the line-of-sight (LOS) component is subjected to shadowing, resulting in an envelope that follows a lognormal statistic.

III. Simulations Results

This section provides Monte Carlo simulation results and discussions concerning the influence of the shadowed fading on the performance of the spectrum sensing. Before, we show some results used to validate the method for generating the random variables taken into account in the simulations. Figure 1 shows PDFs for the shadowed fading for different values of the fading and shadowing parameters. In this figure, solid lines correspond to the theoretical results, from (10), whereas symbols are associated with the computer-generated random variates, obtained from 10^6 samples. The code was implemented in MATLAB according to the model described in Subsection II-C. One can notice the close agreement between the estimated and the theoretical densities, and that, when the shadowing effect is decreased, the Rayleigh-lognormal PDF exactly overlaps the Rayleigh PDF (dashed line).

With the purpose of simulating the effect of the shadowing for different scenarios, the following parameters have been created: p_S denotes the probability of occurrence of shadowing (lognormal) during a given sensing period, and p_CR represents the fraction of CRs under shadowing. As a consequence, the probability of occurrence of the shadowing is a Bernoulli random variable with probability of success p_S, and the number of CRs independently affected by shadowing is a binomial random variable with parameters m and p_CR.

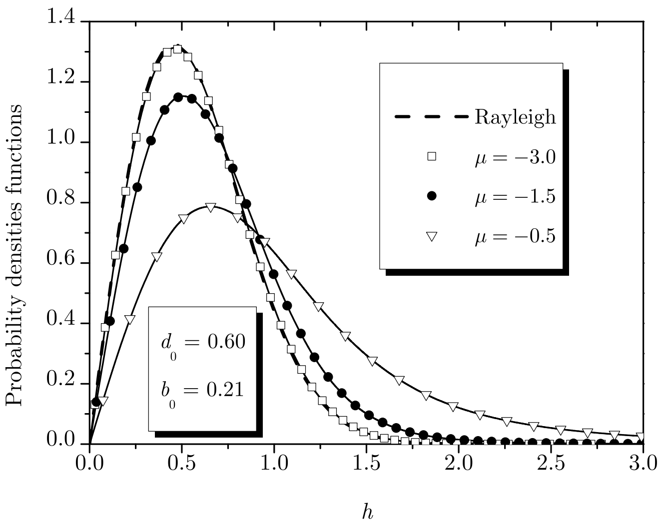

Fig. 1. Empirical and theoretical densities for some values of the shadowing and the fading parameters

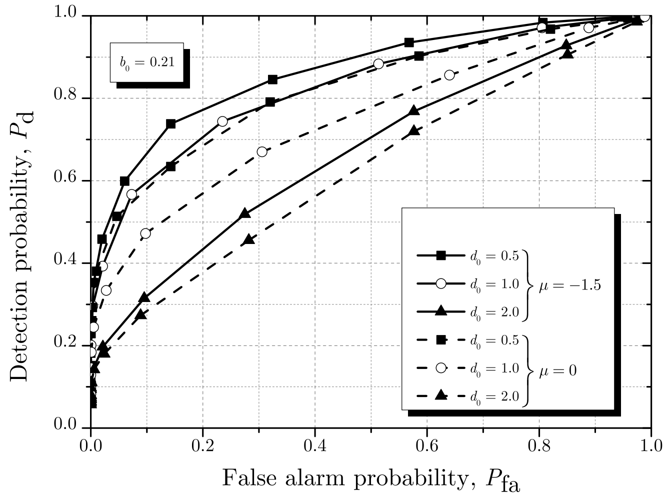

Fig. 2. ROC curves for the MED technique under a shadowed fading channel

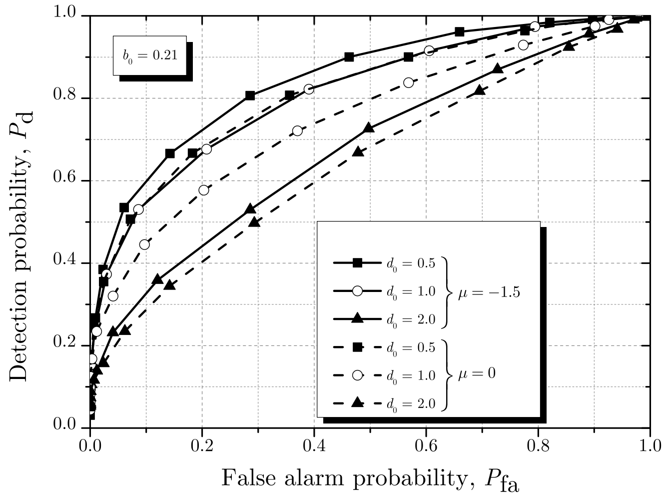

Fig. 3. ROC curves for the ED technique under a shadowed fading channel

We have considered a single primary transmitter ($p = 1$), $m = 6$ single sensor (single antenna) cooperating CRs, each one collecting $n = 50$ samples of the received signal, and a signal-to-noise ratio SNR $= -10$ dB. The primary transmitted signal is assumed to be Gaussian-distributed, which accurately models the envelope fluctuations of most of the digital-modulated signals and, for instance, the envelope of multicarrier signals, such as orthogonal frequency division multiplexing (OFDM) with a large number of subcarries. The desired received SNR, in dB, is guaranteed by making: (i) the transmitted signal power (variance) of the complex Gaussian samples in $\mathbf{X}$ equal to 1, and (ii) the variance of the noise samples equal to $\mathbb{E}(h^2) \times 10^{-\mathrm{SNR}/10}$. The channel was considered static during a sensing period, changing independently and identically distributed from one period to another. The parameters b_0, d_0 and μ are considered the same for all CRs under shadowing. Studies show that the standard deviation of the shadowing fading, $\sqrt{d_0}$, varies from 4 dB to 16 dB [20]–[22]. We used the linear values $\sqrt{0.5}$, $\sqrt{1}$ and $\sqrt{2}$, which corresponds to the values 6.14, 8.68 and 12.28, in dB[1]. Then we characterize the parameters, respectively, as weak, moderate and heavy shadowing.

The ROC curves presented hereafter were obtained via Monte Carlo simulations with 10000 runs. The code was implemented in MATLAB according to the models and test statistics described throughout the paper. The primary radio signal activity was modeled as a Bernoulli random variable with 50% of the time in the ON state (for P_{d} computations) and 50% in the OFF state (for P_{fa} computations).

Figures 2-5 show ROC curves for the MED, the ED, the MMED and the GLRT, respectively, under the Rayleigh-lognormal shadowed fading channel. We consider fixed values for b_0 and variable μ and d_0. It is firstly assumed a worst-case scenario in terms of shadowing, i.e. the probability of occurrence of the shadowing is $p_{\mathrm{S}} = 1$ and all the $m = 6$ CRs are under shadowing conditions, that is, $p_{\mathrm{CR}} = 1$. From these figures one can notice that that the MED technique is better than the ED, which is also the case when only the multipath fading channel is considered. Notice also that the GLRT outperforms the MMED in the Rayleigh-lognormal fading channel, following the same behavior of the multipath Rayleigh fading channel. Observe that, as d_0 increases, the sensing performance decreases. This is an expected result, since a larger d_0 implies a more severe shadowing. The same behavior is produced with an increased value of μ. Additionally, notice the degrading effect of the shadowing in the detection performance of the sensing techniques, even for not too large values of d_0.

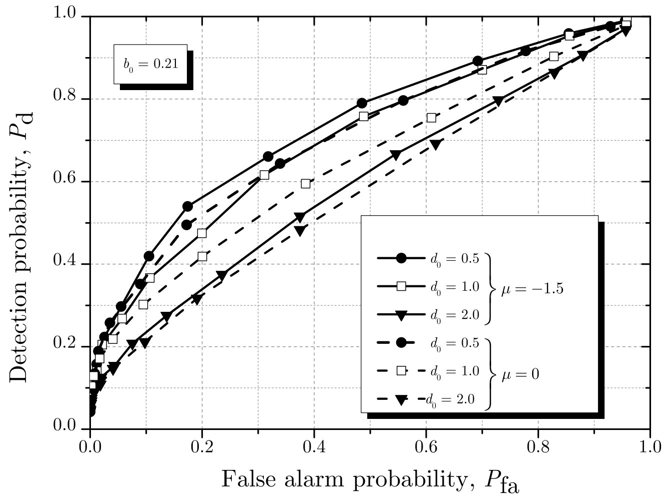

Fig. 4. ROC curves for the MMED technique under a shadowed fading channel

We now consider a more realistic situation in which not all the CRs and under shadowing and the probability of occurrence of the shadowing is smaller than 1. Figures 6 and 7 present a set of ROC curves for known (MED and ED)

[1]Remember that the standard deviation in dB is given by $(20 \log e) d_0$.

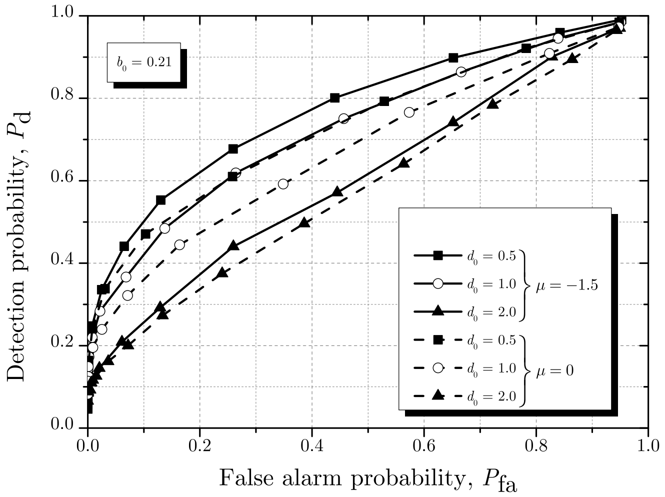

Fig. 5. ROC curves for the GLRT technique under a shadowed fading channel

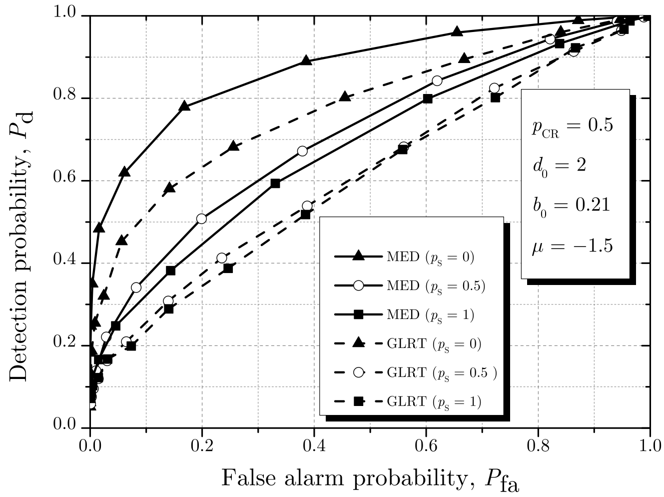

Fig. 7. ROC curves for the MED and for the GLRT techniques considering fixed the fraction of CRs under shadowing of $p_{\text{CR}} = 0.5$

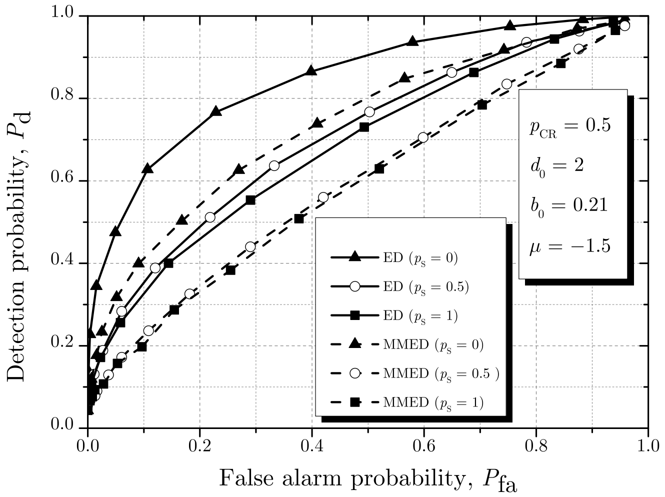

Fig. 6. ROC curves for the ED and for the MMED techniques considering fixed the fraction of CRs under shadowing of $p_{\text{CR}} = 0.5$

and unknown (MMED and GLRT) noise variance techniques, for $\mu = -1.5$, $b_0 = 0.21$, $d_0 = 2$ and variable p_{S}. In this scenario we assume that the fraction of CRs under shadowing is $p_{\text{CR}} = 0.5$. From these figures it is evident the improvement in the detection performance of all techniques, when compared with the worst-case scenario previously taken into account.

In terms of ranking, the MED outperforms all the remaining techniques, followed by the ED, the GLRT and the MMED. When the shadowing parameter μ increases, the performance degradation in terms of the detection probability is almost the same for all eigenvalue-based spectrum sensing techniques considered in this paper. The same conclusion applies to the performance degradation with an increase of the probability of shadowing.

IV. Conclusions and Suggestions for New Research

We have presented a performance analysis of four eigenvalue-based spectrum sensing techniques over the Rayleigh-lognormal shadowed fading channel, allowing for quantifying the adverse impact of concurrent fading and shadowing. The results show that under shadowing, the decisions of the spectrum sensing become less accurate, as expected. Indeed, under severe shadowing, the performance can significantly depart from the one in which only the multipath fading is present.

As a natural extension of this work, scenarios with different composite fading models such as Rice-lognormal, Nakagami-lognormal and the alternative Gamma-shadowed fading models [23], [24] could be considered for applying the eigenvalue-based spectrum sensing. Additionally, it is well-known that the most of the sensing schemes perform satisfactorily for a large number of samples. This is accomplished either by increasing the sensing duration or by oversampling the received signal. The former will increase the frequency of missed opportunities while the latter will cause samples to become usually (possibly highly) correlated. As a consequence, the correlations introduced will degrade the detection performance. This motivates the investigation about other detection schemes that perform well for smaller sample sizes, such as the maximum-eigenvalue-geometric mean (ME-GM) [25]. The continuity of the work also suggests a deeper analysis of the impact of the spatial correlated shadowing [26], [27] and of strategies designed to mitigate the effects of correlated fading, shadowing or both on the performance of cooperative spectrum sensing.

V. Acknowledgment

This work was partially supported by Fapemig (*Fundação de Amparo à Pesquisa do Estado de Minas Gerais*) under Grant TEC-APQ-01255-12.

REFERENCES

[1] D. Čabrić, S. M. Mishra, D. Willkomm, R. Brodersen, and A. Wolisz, "A cognitive radio approach for usage of virtual unlicensed spectrum," in *In Proc. of 14th IST Mobile Wireless Communications Summit 2005*, 2005.

[2] J. Mitola III and G. Q. Maguire Jr., "Cognitive radio: making software radios more personal," *IEEE Personal Commun. Mag.*, vol. 6, no. 4, pp. 13–18, Aug. 1999.

[3] (2014, Jan.). [Online]. Available: http://standards.ieee.org/news/2014/ieee_802_22_sos_study_group.html#sthash.NtA6FtPc.dpuf

[4] (2014, Mar.). [Online]. Available: https://mentor.ieee.org/802.22/dcn/14/22-14-0057-00-0000-802-22-revision-par-document-pdf.pdf

[5] Y. Zeng, Y.-C. Liang, A. Hoang, and R. Zhang, "A review on spectrum sensing for cognitive radio: Challenges and solutions," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, no. 1, p. 381465, 2010. [Online]. Available: http://asp.eurasipjournals.com/content/2010/1/381465

[6] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Commun. Surveys Tuts.*, vol. 11, no. 1, pp. 116 –130, First 2009.

[7] A. Kortun, T. Ratnarajah, M. Sellathurai, C. Zhong, and C. B. Papadias, "On the performance of eigenvalue-based cooperative spectrum sensing for cognitive radio," *Selected Topics in Signal Processing, IEEE Journal of*, vol. 5, no. 1, pp. 49 –55, Feb. 2011.

[8] B. Nadler, F. Penna, and R. Garello, "Performance of eigenvalue-based signal detectors with known and unknown noise level," in *IEEE Int. Conf. Communications*, Jun. 2011, pp. 1–5.

[9] A. Kortun, T. Ratnarajah, and M. Sellathurai, "Exact performance analysis of blindly combined energy detection for spectrum sensing," in *Personal Indoor and Mobile Radio Communications (PIMRC), 2010 IEEE 21st International Symposium on*, Sept 2010, pp. 560–563.

[10] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Elsevier Physical Comm.*, vol. 4, pp. 40–62, Mar. 2011.

[11] S. Ciftci and M. Torlak, "A comparison of energy detectability models for spectrum sensing," in *Global Telecommunications Conference, 2008. IEEE GLOBECOM 2008. IEEE*, Nov. 2008, pp. 1–5.

[12] Y. Zeng and Y.-C. Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio," *IEEE Trans. Commun.*, vol. 57, no. 6, pp. 1784–1793, Jun. 2009.

[13] A. Sahai and D. Cabric, "Spectrum sensing: fundamental limits and practical challenges," in *Proc. IEEE International Symp. New Frontiers Dynamic Spectrum Access Networks (DySPAN)*, Nov. 2005.

[14] D. Cabric, A. Tkachenko, and R. Brodersen, "Spectrum sensing measurements of pilot, energy, and collaborative detection," in *Military Communications Conference, 2006. MILCOM 2006. IEEE*, Oct. 2006, pp. 1–7.

[15] N. Reisi, M. Ahmadian, and S. Salari, "Performance analysis of energy detection-based spectrum sensing over fading channels," in *Wireless Communications Networking and Mobile Computing (WiCOM), 2010 6th International Conference on*, Sep. 2010, pp. 1–4.

[16] D. A. Guimarães and R. A. A. de Souza, "Implementation-oriented model for centralized data-fusion cooperative spectrum sensing," *IEEE Commun. Lett.*, vol. 16, no. 11, pp. 1804–1807, Nov. 2012.

[17] C. Mecklenbrauker, A. Molisch, J. Karedal, F. Tufvesson, A. Paier, L. Bernado, T. Zemen, O. Klemp, and N. Czink, "Vehicular channel characterization and its implications for wireless system design and performance," *Proc. IEEE*, vol. 99, no. 7, pp. 1189–1212, Jul. 2011.

[18] C. Loo, "A statistical model for a land mobile satellite link," *IEEE Trans. Veh. Technol.*, vol. 34, no. 3, pp. 122–127, Aug. 1985.

[19] C. Loo and N. Secord, "Computer models for fading channels with applications to digital transmission," *IEEE Trans. Veh. Technol.*, vol. 40, no. 4, pp. 700–707, Nov. 1991.

[20] V. Erceg, L. Greenstein, S. Tjandra, S. Parkoff, A. Gupta, B. Kulic, A. Julius, and R. Bianchi, "An empirically based path loss model for wireless channels in suburban environments," *IEEE J. Sel. Areas Commun.*, vol. 17, no. 7, pp. 1205–1211, Jul. 1999.

[21] G. R. MacCartney, J. Zhang, S. Nie, and T. S. Rappaport, "Path loss models for 5G millimeter wave propagation channels in urban microcells," in *Global Communications Conference (GLOBECOM), 2013 IEEE*, Dec. 2013, pp. 3948–3953.

[22] S. Seidel and T. Rappaport, "914 MHz path loss prediction models for indoor wireless communications in multifloored buildings," *IEEE Trans. Antennas Propag.*, vol. 40, no. 2, pp. 207–217, Feb. 1992.

[23] P. Shankar, "Statistical models for fading and shadowed fading channels in wireless systems: A pedagogical perspective," *Wireless Personal Communications*, vol. 60, no. 2, pp. 191–213, 2011.

[24] H. Rasheed and N. Rajatheva, "Spectrum sensing for cognitive vehicular networks over composite fading," *International Journal of Vehicular Technology*, vol. 2011, Jan. 2011, available: http://dx.doi.org/10.1155/2011/630467.

[25] N. Pillay and H. Xu, "Eigenvalue-based spectrum 'hole' detection for Nakagami-m fading channels with gaussian and impulse noise," *Communications, IET*, vol. 6, no. 13, pp. 2054–2064, Sep. 2012.

[26] F. M. P. Jr. and P. Cardieri, "Effects of correlated shadowing on cooperative spectrum sensing," in *Collaborative Spectrum Sensing under Spatially Correlated Shadowing Fading (SBRT´12)*. Sociedade Brasileira de Telecomunicações, May 2012.

[27] ——, "Effects of correlated shadowing on cooperative spectrum sensing," in *International Workshop on Telecommunications (IWT´13)*, May 2013.