Performance of Maximum Eigenvalue Spectrum Sensing over α-μ, κ-μ and η-μ Fading Channels

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***Abstract*— Eigenvalue spectrum sensing is a powerful technique to search for spectrum holes, with performance similar to the energy detection. Among the eigenvalue-based techniques, the maximum eigenvalue detection (MED), also known as Roy's Largest Root Test (RLRT) is, for a sufficiently large number of samples, the optimum test if there is no *a priori* knowledge on the primary signal. In this paper, the probability of detection of the MED is assessed, assuming that the primary signal is transmitted over the α-μ, κ-μ and η-μ generalized fading channels.**

***Keywords*— Cognitive radio, eigenvalue spectrum sensing, generalized fading channels.**

I. Introduction

The current spectrum allocation policy assigns a specific band to a user inside a certain geographical region in a long-term basis. However, the increasing demand for wireless services and the small portion of frequency bands available for new allocations have caused the problem of spectrum scarcity. The cognitive radio (CR) [1] concept has arisen as a possible solution to this problem, by introducing the approach of opportunistic usage of underutilized frequency bands.

A CR is defined by the International Telecommunication Union (ITU) as "*a radio employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives; and to learn from the results obtained*" [2]. Among the numerous functionalities that fit in the above definition, the *spectrum sensing* aims at monitoring the usage and characteristics of the spectral bands of interest [3], [4]. The CR has to efficiently identify spectrum holes while avoiding harmful interference to licensed users by either switching to an unoccupied band or maintaining the interference below a maximum acceptable level [5]. Common spectrum sensing techniques found in the literature use energy detection, cyclostationary feature detection, matched filter detection, wavelet detection and compressed sensing detection [3]. Eigenvalue-based spectrum sensing [6]–[8] techniques have been recently proposed, and have received a lot of attention from the scientific community in the past few years.

Eigenvalue based detection is a non-coherent technique that uses the eigenvalues of the received signal sample covariance matrix to estimate the channel state. In the absence of a primary user (PU) signal the CRs will receive nothing but noise and the covariance matrix will tend to be diagonal, as the number of signal samples increase, with entries being the noise variance, i.e. the eigenvalues will be equal to the noise variance. If the channel is occupied by a PU signal, some eigenvalues will be spiked and this contrast is the characteristic that is differently explored by the several eigenvalue detection rules. Among these rules, we can mention the maximum eigenvalue detection (MED), the maximum-minimum eigenvalue detection (MMED), and the eigenvalue-based generalized likelihood ratio test (GLRT). The MED uses the noise variance information in the computation of the test statistic, whereas the MMED and GLRT are blind in this sense.

In this paper we are concerned with the MED when applied to a scenario in which the channels between the primary signal source and the secondary cognitive radios are time-varying fading channels modeled by the general distributions α-μ, κ-μ and η-μ .

A. Related Work

To evaluate the performance of a detection technique, two probabilities are usually taken into consideration: the probability of false alarm P_{fa}, and the probability of detection P_{d}. The former is the probability of declaring a channel occupied when it is in fact idle, and the latter is the probability of declaring the channel busy when there is indeed a signal being transmitted by the PU. In the case of MED, these probabilities depend on the distribution of the largest eigenvalue, which in turn relies on the random matrix theory [6], [7], [9].

The exact probability distributions for the largest eigenvalue of a covariance matrix for both the presence and the absence of a primary signal is given in [7]. However, the high complexity of these distributions renders them intractable in most of the mathematical derivations, which brings the need for approximations or asymptotic analyses. Expressions for computing the probabilities of missed-detection ($1 - P_{\mathrm{d}}$) and false alarm using the MMED are given in [6]. The asymptotic performance analyses of the MED and the GLRT are given in [8], considering a large number of samples and sensors.

In the above-mentioned analyses, the matrix that represents the channel gains between the primary transmitter and the secondary receivers are considered random, but fixed during the sensing interval. The unique restriction imposed to it is that it is a full-rank matrix.

A number of references consider that the entries of the channel matrix are independent and identically distributed (i.i.d.) complex Gaussian random variables, which characterizes the short-term behavior of flat Rayleigh fading channels [6]–[8], [10], [11].

The short term fading statistics are characterized by several other distributions such as Rice, Nakagami-*m*, Weibull, and Hoyt [12]. Each of these distributions is suitable for a specific channel condition, but there are conditions in witch none of them accurately fit experimental data. Therefore, a more generic distribution is required to describe the wireless channel. Three general distributions have been proposed for this purpose, the α-μ, the κ-μ and the η-μ [13], [14]. The parameter μ relates to the number of clusters of the multipath waves. The parameter α accounts for the non-linearity of the physical medium, κ is the ratio between the total power of the dominant waves and the total power of the scattered waves, and η is related to the unbalance between the in-phase and quadrature components of the scattered waves. Special cases of these general distributions are the Rice, the Nakagami-*m*, the Hoyt, the Weibull, the Rayleigh, the one-sided Gaussian, the exponential, and the Gamma distribution.

B. Contributions and Paper Structure

In this paper we present an analysis of the MED performance in terms of the probability of detection, P_{d}, considering that the primary signal is transmitted over α-μ, κ-μ and η-μ flat fading channels. To obtain such a performance metric, the probability density function (PDF) of the received signal-to-noise ratio (SNR) must be obtained. Using known results concerning the sum of squared i.i.d. κ-μ and η-μ random variables and a moment matching approach for the sum of α-μ random variables, the probability of detection was numerically computed. To the best of our knowledge, no other work has tackled this scenario before.

The rest of the paper is organized as follows. In Section II we present the basis of the eigenvalue cooperative spectrum sensing with generalized fading channels. The distributions of the SNR are derived for α-μ, κ-μ and η-μ channels in Section III. Section IV is devoted to numerical results and discussions, and Section V concludes the paper.

II. Eigenvalue-Based Cooperative Spectrum Sensing over Generalized Channel

Consider a secondary cognitive network composed of K CRs. Each CR collects N samples of the signal transmitted by a single PU, and forwards these samples to the fusion center (FC). The problem of determining the channel state is a binary hypothesis test with $\mathcal{H}_0$ and $\mathcal{H}_1$ representing, respectively, the absence and the presence of a PU signal. Let $\mathbf{y}(n) = [y_1(n), \ldots, y_K(n)]^T$ be the vector with the samples received by the FC at the n-th discrete-time instant, with $y_i(n)$ being the sample obtained at the i-th CR and n-th time instant. The operation $[\cdot]^T$ means transposition. Under the two hypotheses, $\mathbf{y}(n)$ can be written as

$$\mathbf{y}(n) = \begin{cases} \mathbf{v}(n), & \mathcal{H}_0 \\ \mathbf{h}s(n) + \mathbf{v}(n), & \mathcal{H}_1 \end{cases}, \tag{1}$$

where $\mathbf{v}(n) \sim \mathcal{N}_{\mathbb{C}}(0_{K\times 1}, \sigma_v^2 \mathbf{I}_{K\times K})$, $s(n)$ is the primary signal sample modeled as Gaussian random variable with zero mean and variance σ_s^2 and $\mathbf{h} = [h_1, \ldots, h_K]^T$ is an unknown channel vector with entry h_i being the channel gain between the PU and the i-th CR. The channel is considered memoryless and constant during the sensing interval.

Under $\mathcal{H}_1$, the average received SNR at the FC is defined as

$$\hat{\rho} = \frac{\sigma_s^2}{\sigma_v^2} \frac{\mathbb{E}\left[\|\mathbf{h}\|^2\right]}{K}, \tag{2}$$

where the $\mathbb{E}$ denotes the expected value operator and $\|\mathbf{h}\|$ is the Euclidean norm of $\mathbf{h}$.

The samples received at the FC are stored in a $K \times N$ matrix

$$\mathbf{Y} = [\mathbf{y}(1), \mathbf{y}(2), \ldots, \mathbf{y}(N)] = a\mathbf{h}\mathbf{s} + \mathbf{V} \tag{3}$$

where $\mathbf{s} = [s(1), s(2), \ldots, s(N)]$ is a $1 \times N$ signal vector, $\mathbf{V} = [\mathbf{v}(1), \mathbf{v}(2), \ldots, \mathbf{v}(N)]$ is $K \times N$ noise matrix and $a \in \{0, 1\}$ indicates the absence (0) or presence (1) of a PU signal. The sample covariance matrix is then computed as

$$\mathbf{R} = \frac{1}{N}\mathbf{Y}\mathbf{Y}^{\dagger}, \tag{4}$$

with $\dagger$ denoting the conjugate and transpose operation.

Let $\{\lambda_1 > \lambda_2 > \ldots > \lambda_K\}$ be the ordered eigenvalues of $\mathbf{R}$, and let T be a test statistic, or decision variable, computed from these eigenvalues to distinguish between the hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$. The test statistic is compared with a predefined threshold γ and a decision upon the channel state is made. If $T > \gamma$ the FC decides in favor of $\mathcal{H}_1$, otherwise it decides for $\mathcal{H}_0$. Therefore, the probabilities of false alarm and detection are given by

$$P_{\text{fa}}(\gamma) = \Pr[T > \gamma | \mathcal{H}_0], \tag{5}$$

$$P_{\text{d}}(\gamma) = \Pr[T > \gamma | \mathcal{H}_1]. \tag{6}$$

Usually, the threshold is a function of a target false alarm probability. A low value of P_{fa} is important to increase the throughput of the CR network and a high P_{d} keeps the interference to primary users below a predefined value.

Several tests can be constructed from the eigenvalues of 4, among which the most known are the MED, the MMED and the eigenvalue-based GLRT. In this paper we consider only the maximum eigenvalue detection (MED), for which the test statistic is computed as the ratio between the maximum eigenvalue of $\mathbf{R}$ and the noise variance, that is,

$$T_{\text{MED}} = \frac{\lambda_1}{\sigma_v^2}. \tag{7}$$

In [7], the exact probabilities of false alarm and detection are derived for the MED, from where it can be shown that

$$P_{\text{fa}}(\gamma) = |\det \mathbf{A}|, \tag{8}$$

where $\mathbf{A}$ is a $K \times K$ matrix with entries

$$A_{i,j} = \binom{N - j + i - 1}{i - 1} \gamma_R(N + i - j, N\gamma),$$

with $\gamma_{\text{R}}(s, x)$ being the regularized lower incomplete gamma function defined by

$$\gamma_R(s, x) = \int_0^x t^{s-1} e^{-t} dt.$$

The expression for computing the probability of detection given in [7] is very complex, making any analysis a cumbersome task. In [8], a Gaussian approximation for the probability of detection is given as a function of the decision threshold γ, and conditioned on the received SNR ρ:

$$P_{\mathrm{d}}(\gamma|\rho) \approx Q\left[\sqrt{N}\left(\frac{\gamma}{K\rho+1} - \frac{K-1}{NK\rho} - 1\right)\right], \quad (9)$$

where Q is the standard Gaussian tail probability function.

In order to obtain the unconditional probability of detection, Equation (9) must be averaged over the PDF of the SNR, i.e.

$$P_{\mathrm{d}}(\gamma) = \int_0^\infty P_{\mathrm{d}}(\gamma|\rho) f_{\mathrm{SNR}}(\rho) d\rho \quad (10)$$

where $f_{\mathrm{SNR}}(\rho)$ is the PDF of the signal-to-noise ratio.

In the next section we derive $f_{\mathrm{SNR}}(\rho)$ for the generalized fading channels α-μ, κ-μ and η-μ, so that $P_{\mathrm{d}}(\gamma)$ can be computed.

III. The PDF of the SNR over α-μ, κ-μ and η-μ Channels

The SNR of the received signal at the FC under $\mathcal{H}_1$ defined in (2) can be rewritten by substituting the norm operator by a sum operator, i.e.,

$$\rho = \frac{\sigma_s^2}{\sigma_v^2}\frac{1}{K}\sum_{i=1}^{K} h_i^2. \quad (11)$$

Therefore, the PDF of the SNR is related to the sum of K random variates h_i^2, being h_i the random variate of the channel fading envelope associated to the distributions α-μ, κ-μ or η-μ. In the next subsection we derive the PDF of the SNR for the channels under consideration.

A. The PDF of the SNR for the α-μ channel

The PDF of the signal envelope R following an α-μ distribution with α-root mean square value $\hat{r} = \sqrt[\alpha]{\mathbb{E}[R^\alpha]}$ is given by [13]

$$f_R(x) = \frac{\alpha\mu^\mu x^{\alpha\mu-1}}{\Gamma(\mu)\,\hat{r}^{\alpha\mu}} \exp\left[-\mu\left(\frac{x}{\hat{r}}\right)^\alpha\right], \quad (12)$$

where $\alpha > 0$ is an arbitrary parameter related to the non-linearity of the wireless medium and μ is the inverse of the normalized variance of R^α, i.e.,

$$\mu = \frac{\mathbb{E}^2[R^\alpha]}{\mathbb{V}[R^\alpha]}, \quad (13)$$

with $\mathbb{E}[\cdot]$ and $\mathbb{V}[\cdot]$ being the expectation and variance operators, respectively.

The derivation of the PDF of the sum of α-μ random variates through the exact solution is cumbersome and sometimes no closed form expression can be obtained. However, this PDF can be well approximated by another α-μ distribution through moment matching. In [15], [16], the procedure for computing the parameters of an α-μ distribution to approximate the density of the sum α-μ and Nakagami-m random variates respectively are described. This method can be adapted to the approximate of the sum of α-μ random variates, as follows.

Consider the random variable $H = h^2$, with h having an α-μ distribution. By means of a simple transformation of random variables, it can be shown that the PDF of H is

$$f_H(x) = \frac{\alpha\mu^\mu x^{\frac{\alpha\mu}{2}-1}}{2\Gamma(\mu)\hat{r}^{\frac{\alpha\mu}{2}}} \exp\left(-\mu\left(\frac{x}{\hat{r}}\right)^{\alpha/2}\right), \quad (14)$$

with generalized moments

$$\mathbb{E}(H^n) = \hat{r}^n \frac{\Gamma(\mu + 2n/\alpha)}{\mu^{2n/\alpha}\Gamma(\mu)}, \quad (15)$$

where $\Gamma(\cdot)$ is the gamma function.

Let $S = \sum_{i=0}^{K} H_i$, with H_i being i.i.d. variates, each with distribution (14). The n-th moment of S can be obtained in closed form through [15], [16]

$$\mathbb{E}\left(S^n\right) = \sum_{n_1=0}^{n}\sum_{n_2=0}^{n_1}\cdots\sum_{n_{K-1}=0}^{n_{K-2}} \binom{n}{n_1}\binom{n_1}{n_2}\binom{n_{K-2}}{n_{K-1}} \times\mathbb{E}\left(H^{n-n_1}\right)\mathbb{E}\left(H^{n_1-n_2}\right)\mathbb{E}\left(H^{n_{K1-1}}\right) \quad (16)$$

The moment matching technique aims at estimating the parameters of a given distribution as a function of moments of the random variable. The generalized parameter μ defined in [13] , which is parameterized by the β-th and 2β-th moments of the underlying random variable, that is,

$$\beta\mu = \frac{\mathbb{E}^2[H^\beta]}{\mathbb{E}[H^{2\beta}] - \mathbb{E}^2[H^\beta]}. \quad (17)$$

By matching the generalized parameter μ of an α-μ distribution to the generalized parameter μ of the random variable S for different values of β (e.g.: one and two), a system of transcendental equations arises, from which the parameters α and μ of the approximated distribution can be numerically calculated. The system of equations is formed from

$$\frac{\mathbb{E}^2[S^\beta]}{\mathbb{E}[S^{2\beta}] - \mathbb{E}^2[S^\beta]} = \frac{\Gamma^2\left(\frac{\beta}{\alpha_s} + \mu_s\right)}{\Gamma(\mu_s)\Gamma\left(\frac{2\beta}{\alpha_s} + \mu_s\right) - \Gamma^2\left(\frac{\beta}{\alpha_s} + \mu_s\right)}, \quad (18)$$

where the α_s and μ_s are the parameters to be obtained for the approximate PDF of S.

The α-root mean square value is then estimated from

$$\hat{r}_s = \mu_s^{1/\alpha_s} \sqrt[\beta]{\frac{\Gamma(\mu_s)\mathbb{E}(S^\beta)}{\Gamma(\mu_s + \beta/\alpha_s)}}. \quad (19)$$

With the estimated parameters α_s, μ_s and $\hat{r}_s$, the approximated FDP of the SNR can be obtained by a simple change of variables and is given by

$$f_{\mathrm{SNR}}(\rho) = \frac{\alpha_s\mu_s^{\mu_s}}{\Gamma(\mu_s)}\frac{\rho^{\alpha_s\mu_s-1}}{\hat{\rho}^{\alpha_s\mu_s}} \exp\left[-\mu_s\left(\frac{\rho}{\hat{\rho}}\right)^{\alpha_s}\right], \quad (20)$$

with

$$\hat{\rho} = \frac{\sigma_s^2\hat{r}_s}{\sigma_v^2 K} \quad (21)$$

being the average SNR.

B. The PDF of the SNR for the κ-μ channel

The κ-μ distribution is used to represent the small scale fading of a signal envelope in the line-of-sight condition. If R is the envelope of the signal under κ-μ fading, the PDF of the normalized envelope $P = R/\sqrt{\mathbb{E}(R^2)}$ is given by [14]

$$f_P(r) = \frac{2\mu(1+\kappa)^{\frac{\mu+1}{2}}}{\kappa^{\frac{\mu-1}{2}}\exp(\mu\kappa)} r^{\mu}\exp\left[-\mu(1+\kappa)r^2\right] \times I_{\mu-1}\left[2\mu r\sqrt{\kappa(1+\kappa)}\right], \quad (22)$$

where $\kappa > 0$ is the ratio between the total power of the dominant components and the total power of the scattered components, $\mu > 0$ is given by

$$\mu = \frac{\mathbb{E}^2\left(R^2\right)}{\mathbb{V}\left(R^2\right)}\frac{1+2\kappa}{(1+\kappa)^2},$$

and $I_\nu(\cdot)$ is the modified Bessel function of the first kind and order ν [17]. The sum of K κ-μ random variables squared has a κ-μ distribution with parameters $\kappa_s = \kappa$ and $\mu_s = K\mu$ [14]. Therefore, after some simple algebraic manipulations, the PDF of the SNR can be written as

$$f_{\text{SNR}}(\rho) = \frac{K\mu(1+\kappa)^{\frac{K\mu+1}{2}}}{\kappa^{\frac{K\mu-1}{2}}\exp\left[K\mu\kappa\right]}\frac{\rho^{\frac{K\mu-1}{2}}}{\hat{\rho}^{\frac{K\mu+1}{2}}}\exp\left[-K\mu\frac{\rho}{\hat{\rho}}(1+\kappa)\right] \times I_{K\mu-1}\left[2K\mu\sqrt{\kappa(1+\kappa)\frac{\rho}{\hat{\rho}}}\right], \quad (23)$$

with $\hat{\rho}$ being the average SNR, as given by (21)

C. The PDF of the SNR for the η-μ channel

The η-μ distribution is a general fading distribution best suited to represent the small scale variation of a fading signal envelope R in a non-line-of-sight condition. In this case, the PDF of the normalized envelope $P = R/\sqrt{\mathbb{E}(R^2)}$ is [14]

$$f_P(r) = \frac{2(\eta-1)^{1/2-\mu}(\eta+1)^{1/2+\mu}\sqrt{\pi}}{\exp\left[(1+\eta)^2\mu r^2/2\eta\right]\sqrt{\eta}\Gamma(\mu)} \times \mu^{1/2+\mu}r^{2\mu}I_{\mu-1/2}\left(\frac{(\eta^2-1)\mu r^2}{2\eta}\right), \quad (24)$$

where $\eta > 0$ is the scattered-wave power ratio between the in-phase and quadrature components of each cluster of multipath, $I_\nu(\cdot)$ is the modified bessel function of the first kind and order ν [17], and

$$\mu = \frac{\mathbb{E}^2(R^2)}{\mathbb{V}(R^2)}\frac{1+\eta^2}{(1+\eta)^2}.$$

The PDF of the sum of K squared η-μ random variables has a η-μ distribution with parameters $\eta_s = \eta$ and $\mu_s = K\mu$ [14]. Then, it can be shown that the PDF of the SNR when the channel fading is characterized by an η-μ distribution is

$$f_{\text{SNR}}(\rho) = \frac{\sqrt{\pi}(K\mu)^{K\mu+1/2}\left(2+\eta^{-1}+\eta\right)^{K\mu}}{\Gamma(K\mu)\left(\eta^{-1}-\eta\right)^{K\mu-1/2}}\frac{\rho^{K\mu-1/2}}{\hat{\rho}^{K\mu+1/2}} \times \exp\left[-K\mu\left(\frac{2+\eta^{-1}+\eta}{2}\right)\frac{\rho}{\hat{\rho}}\right] \times I_{K\mu-1/2}\left(K\mu\frac{\eta^{-1}-\eta}{2}\frac{\rho}{\hat{\rho}}\right) \quad (25)$$

where $\hat{\rho}$ is the average SNR, computed from (21)

IV. NUMERICAL RESULTS

In this section, the probability of detection of the MED is assessed, considering that the primary user signal is transmitted over the generalized fading channels α-μ, κ-μ and η-μ. The theoretical results were obtained by numerically evaluating (10) for the SNR densities derived in Section III. The Monte Carlo simulation results were obtained by counting a minimum of 500 detection events or 50000 simulation runs, whichever occurs first, for each decision threshold. We have considered a cognitive network with $K = 6$ CRs, each one collecting $N = 400$ samples. The primary signal was modeled as a Gaussian random process with zero mean and variance $\sigma_s^2 = 1$, and the additive Gaussian noise variance was set to $\sigma_v^2 = 1$. In this case, the second moment of the channel gains was set according to (2) to produce the desired average SNR of -10 dB. This value was chosen so as to represent the important condition of low SNR, which is particularly challenging for any spectrum sensing technique.

Figure 1 shows the probability of detection as a function of the decision threshold for the α-μ channel with $\mu = 2$ and some different values of α. Its noteworthy that in the region of most practical interest, which corresponds to high probabilities of detection, the larger the value of α the higher will be the probability of detection for the same threshold. This is consistent with the fact that a higher α are associated with better channel conditions. Recall that the probability of false alarm is independent of the channel, thus the probability of detection unveils the spectrum sensing performance.

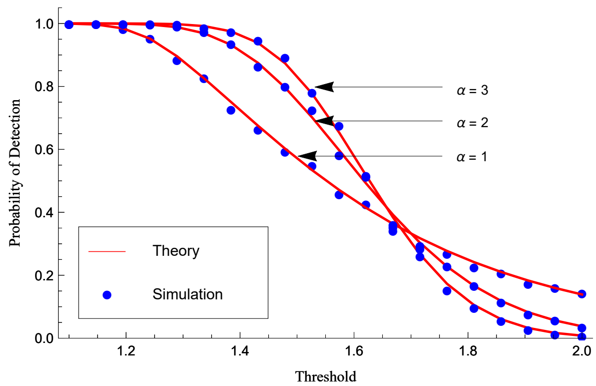

Fig. 1. Probability of detection versus threshold for the MED under the α-μ fading, for $\mu = 2$ and variable α.

In Figure 2 it is shown the probability of detection as a function of the decision threshold for the κ-μ channel with $\kappa = 1$ and some different values of μ. Now, in the region of high probabilities of detection, the larger the value of μ the higher will be the performance for the same threshold. This is consistent with the fact that a higher μ are associated with better channel conditions

In Figure 3, the probability of detection versus the decision threshold is shown for the MED over a η-μ channel, for $\eta = 0.2$ and variable μ. Again considering the region with high probability of detection, the higher the value of μ the better is the performance of the spectrum sensing.

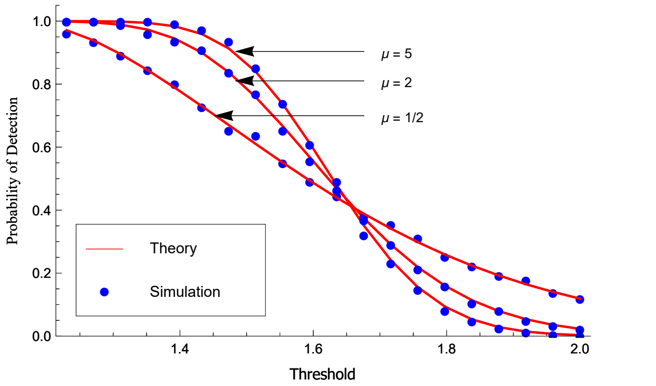

Fig. 2. Probability of detection versus threshold for the MED under the κ-μ fading, for $\kappa = 1$ and variable μ.

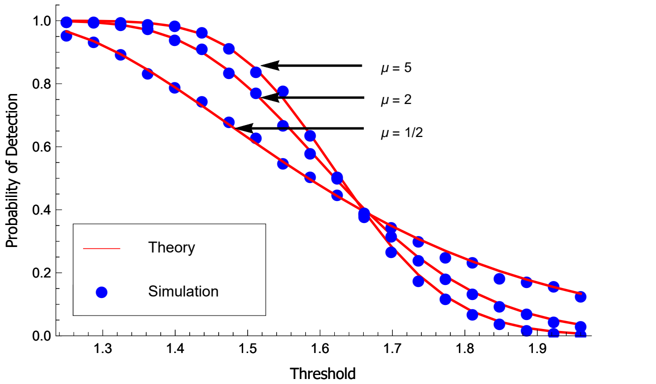

Fig. 3. Probability of detection versus threshold for the MED under the η-μ fading, for $\eta = 0.2$ and variable μ.

Finally, in Figure 4 we show the influence of the number of coopering CRs on the spectrum sensing performance. The probability of detection versus the threshold is depicted in η-μ (for lack of space, the figure for α-μ and κ-μ were omitted) channel with $K = 2, 4, 6, 8$. Increasing the number of cognitive radios leads to a better performance, but, on the other hand, it also leads to a greater complexity of the eigenvalues computation and to a overuse of the reporting control channel.

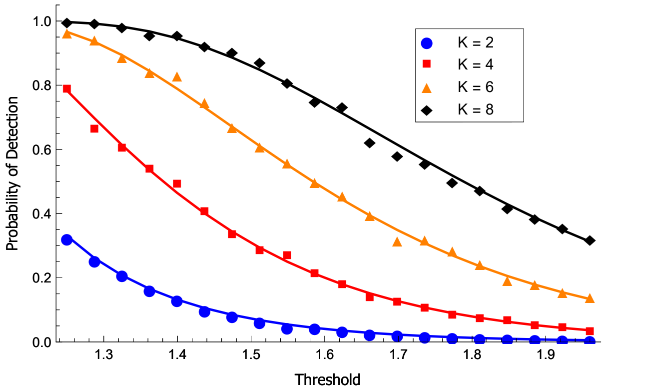

Fig. 4. Probability of detection versus threshold for the MED under the η-μ fading, for $\eta = 0.2$ and $\mu = 0.5$

V. Conclusion

In this paper, non-closed form expressions for the probability of detection of the maximum eigenvalue detection technique were derived and numerically computed, assuming that the channels between the primary transmitter and the cognitive radios are modeled by the generalized fading distributions α-μ, κ-μ and η-μ. We have shown that the theoretical results are in close agreement with simulation results. The performance analysis of the spectrum sensing over such channel models is of more practical appeal, since the most common analysis that consider pure AWGN channels lead to better, but unrealistic performances.

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