A Locally Optimal Soft Linear-Quadratic Scheme for CR Systems in Shadowing Environments

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***Abstract*—In this letter, we analyze the problem of detecting spectrum holes in cognitive radio systems under the Neyman-Pearson scenario. We consider that a group of unlicensed users use non-coherent energy detectors to sense the radio signal and design a soft locally optimal linear-quadratic statistic based on the deflection coefficient. Each unlicensed user transmits the processed data to a central entity, where the decision about the presence or not of licensed users is made. Using the method of Monte Carlo, we show that the proposed statistic outperforms previous ones available in the literature in a wide range of shadow-fading scenarios and it is robust against parameters errors.**

***Keywords*—Distributed detection; Cognitive radio; Spectrum sensing; Wireless sensor networks;**

I. Introduction

Wireless spectrum is a vital resource required for radio communications. Worldwide, radio frequency bands are assigned to the licensed holders of the bands in large geographic areas. Within this paradigm, the wireless spectrum is a scarce resource in high demand for current and future technologies. However, measurements campaigns have suggested that much of the licensed spectrum is frequently under-utilized in vast areas at different times [1]. In recent years, cognitive radio (CR) systems has emerged as a possible solution for the spectrum shortage (see [2]–[4] and references therein). In CR systems, unlicensed, or secondary users (SU), sense the spectrum in a particular place and time and wish to detect the presence or absence of the licensed, or primary users (PU), in order to use the spectrum when it is available. In Fig. 1, we show a possible scenario of CR. A PU transmits to its intended receivers located inside the primary range R_p, defined as the maximum distance between two PUs. The SUs sense the spectrum and decide if they are out of the *protected region* of the primary system which would allow them to use the spectrum without causing harmful interference to the PUs. R_s is the interference range of the SUs.

Although each SU may sense the spectrum alone and make a decision, the typical low signal-to-noise ratio (SNR) of the PU signal at the SU receiver makes it difficult to develop reliable detection schemes. Additionally, the so-called hidden-terminal problem arises in environments with shadow fading: a SU could receive an undetectable very weak signal from the PU, decide to transmit and produce interference to the PUs.

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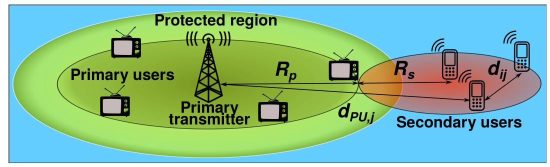

Fig. 1. A CR network with spectrum sensing devices.

A way to tackle these issues is to allow SUs cooperating with each other to detect the PU signal. While some of the SUs receivers could be shadowed from the PU signal, it is unlikely that all of them are in a deep shadow simultaneously.

Several previous works have considered the shadowing effect in the sensing channel. In [5], the measurements of the SUs are quantized to 1-bit and sent to the fusion center (FC), where the final decision is made. A linear-quadratic detector is proposed as a decision fusion rule, based on the deflection coefficient (DC), to study its performance in correlated log-normal shadowing environments. In [6], the performance degradation of collaborative sensing is characterized due to correlated shadowing by deriving a lower-bound on the false alarm probability. In [7], an amplify-and-forward scheme is analyzed in a correlated log-normal sensing and reporting channel. Although this kind of schemes have been frequently used in previous works (see also [8]), the required reporting channel bandwidth could be prohibitive for CR systems if the SUs transmit one symbol per each symbol received. In order to save this valuable resource, the SUs should process locally a set of measurements and send only a summary of them to the FC. Respect to small-scale fading environments, in [9] the authors have developed several cooperative schemes for 1-bit, multi-bit and soft data fusion based in the likelihood functions with unknown parameters. In [10] an optimal linear soft fusion scheme of energy measurements is obtained based on the so-called modified deflection coefficient (MDC). However, the scenario with both shadowing and fading effects deserves more study.

Considering that the SUs in general do not know the transmission scheme used by the PUs, demodulation of the PU signal is unfeasible. Therefore, non-coherent energy detectors are used in the previous mentioned works and they are typically employed in the SUs receivers. The instantaneous energy of the signal received by the SUs variates due to either the fading channel and/or the modulation scheme used by the PU (e.g., PAM, QAM or OFDM). This feature of the received signal, often overlooked, could be beneficially exploited in the SUs to further improve the detection performance. For example, one could consider not only linear combinations but also higher orders terms of the instantaneous energy to capture fluctuations of the PU signal energy at the SU.

In this letter, we propose a locally optimal soft linear-quadratic (LQ) distributed detection scheme to process the measurements of the SUs, based on the MDC criterion. In this scheme, the SUs gather a set of measurements delivered by their non-coherent energy detectors, perform some processing and transmit the analog result (sometimes called soft decision) through a noisy communication channel to the FC. The FC makes a decision about the state of the PU through a threshold test, and then, broadcasts it to the SUs. Soft decisions typically produce better performances. It is sometimes argued that using soft decisions significantly increases the amount of data to be transmitted and, hence, the required bandwidth. However, this is not entirely true since there may be significant overhead related to the protocol used in transmitting the sensing results to the FC. That overhead will be present even if only binary decisions are transmitted. Therefore, the difference in the transmission and bandwidth requirements between hard and soft decision statistics may be small [2].

Guided by the generalized likelihood ratio test (GLRT), we propose a LQ scheme whose parameters are selected to maximize the local MDC. Given that these parameters are a function of the first two moments of the energy measurements, we suggest a simple but effective estimation scheme to perform this task. Monte Carlo numerical experiments show that the proposed soft distributed scheme has a superior performance in shadow-fading environments, compared to schemes presented previously in the literature.

Next, we present the signal model, derive the proposed statistic, analyze the results and, finally, elaborate the conclusions of this letter.

II. Signal Model

The basic task of the FC is to decide if the SUs are located inside the protected region or not (see Fig. 1). Thus, we have a binary hypothesis testing problem. Under $\mathcal{H}_1$, we consider that the PU is ON and the SUs are inside the protected region. In this case, the energy that the SUs measure will correspond mainly to the PU signal, assumed to be affected by both path loss and shadow-fading effects. The power received in a given SU P_r (in dBm) separated from the PU in a distance d is modeled by [11]

$$P_r(d) = P_t + K_{\text{dB}} - 10p\log_{10}(d/d_0) - \psi_{\text{dB}} \tag{1}$$

where P_t (in dBm) is the transmitted power, K_{dB} is an unitless constant, p is the path loss exponent, d_0 is a reference distance, and ψ_{dB} is a random variable that models the shadow-fading effect. We adopt the popular log-normal model for the shadow-fading meaning that the random variable expressed in dB ψ_{dB} is a zero-mean Gaussian random variable with variance σ^2_{SH}. In a wireless scenario, the signal power measured by two receivers close to each other presents certain correlation. We model the correlation between two SUs to decay exponentially with the distance d between them, validated empirically in [12]. Thus, the autocorrelation function is $R(d) = \sigma^2_{\text{SH}} e^{-d/d_c}$ where d_c is the decorrelation distance. Under $\mathcal{H}_0$, when the PU is OFF or the SUs are outside the protected region, we assume that the noise power dominates the behavior, can only be known with a certain degree of accuracy and is log-normally distributed with mean m_0 and variance σ_0^2 [5]. In this work, we will assume that the measurements at different times at each SU are independent and identically distributed (iid). Under $\mathcal{H}_1$, we can justify this assumption based on the fact that the small-scale fast fading will produce uncorrelated fluctuations in the signal. Additionally, the symbols transmitted by the PU can be considered uncorrelated, which reinforces the assumption. Under $\mathcal{H}_0$, the measurements are dominated by the thermal noise which is uncorrelated in time. Consider that each SU can subtract the mean value[1] m_0 (in dBm) to its energy measurements captured in each time slot to obtain the set of observations $\{y_{ij}\}_{i=1}^m$, where the indexes i and j identify the time slot, and the SU, respectively, and m is the number of measurements taken by each SU. Let $\boldsymbol{y}_j = [y_{1j}, \ldots, y_{mj}]^T$ be the vector of observations collected by the j-th SU during m time slots and define the whole vector of measurements collected by n SUs as $\boldsymbol{y} = [\boldsymbol{y}_1^T, \ldots, \boldsymbol{y}_n^T]^T$. The hypothesis testing problem selects $\mathcal{H}_0$ or $\mathcal{H}_1$:

$$\begin{cases} \mathcal{H}_0: & \boldsymbol{y} \sim \mathcal{N}(\boldsymbol{0}, \sigma_0^2 I_{nm}) \\ \mathcal{H}_1: & \boldsymbol{y} \sim \mathcal{N}(\boldsymbol{\mu} \otimes \boldsymbol{1}, \Sigma_1 \otimes I_m), \end{cases} \tag{2}$$

where $\mathcal{N}(\boldsymbol{a}, B)$ denotes the Gaussian distribution with mean $\boldsymbol{a}$ and covariance matrix B, $\boldsymbol{\mu} = [\mu_1, \ldots, \mu_n]^T$, with $\mu_j = P_r(d_{\text{PU},j}) - m_0$ and $d_{\text{PU},j}$ is the distance between the PU and the j-th SU receiver; $\otimes$ is the Kronecker product and $\boldsymbol{1}$ is a column vector of m ones. We assume that both the measurement inaccuracy and the shadow-fading effects are additive in the dB scale, therefore, $\Sigma_1 = \sigma_0^2 I_n + \Sigma_{\text{SH}}$, where I_n is the identity matrix of dimension n, Σ_{SH} is the $n \times n$ covariance matrix given by the shadow-fading, i.e., $(\Sigma_{\text{SH}})_{ij} = \sigma^2_{\text{SH}} e^{-d_{ij}/d_c}$, and d_{ij} is the distance between the i-th and j-th SU. We also define $(\Sigma_1)_{jj} = \sigma^2_{1,j}$.

III. The Proposed Linear Quadratic Statistic

In this section, we first propose a linear-quadratic statistic motivated by the GLLR statistic and then optimize its parameters using the MDC [10] at each SU. The deflection criterion was used vastly in the literature of detection theory [13]. When the distribution under both hypotheses are Gaussian, the deflection is proportional the Chernoff distance between both distributions, which means that a better performance is obtained if we maximize the deflection. On the other hand, when the distributions are not Gaussian, the deflection cannot be related to a true distance although it has been shown using numerical simulations that a better performance is obtained for greater deflections. Therefore, the proposed statistic can also be used in non-Gaussian scenarios. We will show that the proposed soft distributed detector has a better performance than previous schemes presented in the literature and exhibits a robust behavior against parameter estimation errors.

[1]If m_0 is estimated with some error, the same hypothesis testing problem (2) can be performed considering that the estimation error is absorbed by the mean under $\mathcal{H}_1$.

We analyze the problem under the Neyman-Pearson framework, which minimizes the miss-detection probability while satisfying a certain false alarm probability level P_{f0}. Let $\mathbb{P}_j(\cdot)$ be the probability measure under $\mathcal{H}_j$, $j = 0, 1$, let $\hat{\mathcal{H}}$ be the decision made by the FC and assume that the SUs transmit their own data if they detect the spectrum to be free. Given a statistic T, it is compared against a predefined threshold τ. The FC decides $\hat{\mathcal{H}} = \mathcal{H}_1$ if $T > \tau$, and $\hat{\mathcal{H}} = \mathcal{H}_0$ otherwise. The miss-detection and false alarm probabilities are, respectively, $P_{\mathrm{m}} = \mathbb{P}_1(\hat{\mathcal{H}} = \mathcal{H}_0) = \mathbb{P}_1(T \leq \tau)$ and $P_{\mathrm{f}} = \mathbb{P}_0(\hat{\mathcal{H}} = \mathcal{H}_1) = \mathbb{P}_0(T > \tau)$, where the threshold τ computed numerically to satisfy $P_{\mathrm{f}} \leq P_{\mathrm{f0}}$.

Considering the model (2), and letting $\hat{\Sigma}_1$ and $\hat{\boldsymbol{\mu}}$ be the maximum likelihood estimations (MLE) of the mean and covariance matrix of $[y_{i1}, \ldots, y_{in}]^T$, $i = 1, \ldots, m$, respectively, the (normalized) GLRT statistic is $T_{\mathrm{GLRT}}(\boldsymbol{y}) = \frac{1}{nm} \log \frac{p_1(\boldsymbol{y}; \hat{\Sigma}_1, \hat{\boldsymbol{\mu}})}{p_0(\boldsymbol{y})}$,

$$T_{\mathrm{GLRT}}(\boldsymbol{y}) = \boldsymbol{y}^T \tfrac{1}{2} \left({\sigma_0}^{-2} I_{nm} - \hat{\Sigma}_1^{-1} \otimes I_m \right) \boldsymbol{y} + (\hat{\boldsymbol{\mu}} \otimes \mathbf{1})^T \boldsymbol{y} \quad (3)$$

$$\approx \frac{1}{n} \sum_{j=1}^{n} \left[\tfrac{1}{2} \left(\tfrac{1}{\sigma_0^2} - \tfrac{1}{\hat{\sigma}_{1,j}^2} \right) \tfrac{\|\boldsymbol{y}_j\|^2}{m} + \hat{\mu}_j \tfrac{\mathbf{1}^T \boldsymbol{y}_j}{m} \right], \quad (4)$$

where $p_j(\boldsymbol{y})$ is the probability density function of $\boldsymbol{y}$ under $\mathcal{H}_j$, $j = 0, 1$. In (3) we have omitted the constant terms that do not modify the statistics performance. To compute this statistic in the FC, each of the n SUs should employ m channel uses[2] to transmit its whole set of measurements, which is energy and bandwidth costly. Instead, we propose to transmit a summary of the set of measurements that uses only one channel use per SU. In (4) we have approximated $\hat{\Sigma}_1$ by its main diagonal matrix $\mathrm{diag}(\hat{\sigma}_{1,1}^2, \ldots, \hat{\sigma}_{1,n}^2)$, valid if the spatial correlation is a mild one [7]. In view of (4), we propose the following LQ local statistic

$$T_{\mathrm{LQ},j}(\boldsymbol{y}_j) = \alpha_j \frac{\|\boldsymbol{y}_j\|^2}{m} + \beta_j \left(\frac{\mathbf{1}^T \boldsymbol{y}_j}{m} \right)^2 + \gamma_j \frac{\mathbf{1}^T \boldsymbol{y}_j}{m}, \quad (5)$$

where the second term appears if μ_j is unknown and it is replaced by the sample mean $\hat{\mu}_j$, while the third term models the situation where μ_j is known. Thus, β_j and γ_j balance the confidence on the estimation of the mean. Then, the local parameters $(\alpha_j, \beta_j, \gamma_j)$ are optimized maximizing the local MDC defined by $D(T_{\mathrm{LQ},j}) = \frac{(\mathbb{E}_1(T_{\mathrm{LQ},j}) - \mathbb{E}_0(T_{\mathrm{LQ},j}))^2}{\mathbb{V}\mathrm{ar}_1(T_{\mathrm{LQ},j})}$, where $\mathbb{E}_j(\cdot)$ and $\mathbb{V}\mathrm{ar}_j(\cdot)$ are the expectation and the variance operators under $\mathcal{H}_j$, $j = 0, 1$. The MDC can be expressed as

$$D_j = \frac{(\boldsymbol{a}^T \boldsymbol{x}_j)^2}{\boldsymbol{x}_j^T B \boldsymbol{x}_j} = \left(\left(B^{-\frac{1}{2}} \boldsymbol{a} \right)^T \frac{\tilde{\boldsymbol{x}}_j}{\|\tilde{\boldsymbol{x}}_j\|} \right)^2 \quad (6)$$

where $\boldsymbol{x}_j = [\alpha_j, \beta_j, \gamma_j]^T$, $\boldsymbol{a}$ and B are easily computed and B is a 3×3 positive definite symmetric matrix. Calling $\tilde{\boldsymbol{x}}_j = B^{\frac{1}{2}} \boldsymbol{x}_j$, the second equality in (6) is obtained, which involves a scalar product and is maximized when $B^{-\frac{1}{2}} \boldsymbol{a}$ and $\tilde{\boldsymbol{x}}_j$ are collinear, i.e., the optimum parameter vector is $\tilde{\boldsymbol{x}}_j^* = c B^{-\frac{1}{2}} \boldsymbol{a}$, where c is any constant. Returning to the original vector, $\boldsymbol{x}_j^* = c B^{-1} \boldsymbol{a}$, whose components are $\alpha_j^* = 1$, $\beta_j^* = -m\mu_j^2 / \sigma_{\mathrm{SH}}^2$ and $\gamma_j^* = 2\mu_j(m\mu_j^2 + \sigma_0^2)/\sigma_{\mathrm{SH}}^2$, and where, without loss of optimality, we have chosen c such that $\alpha_j^* = 1$. Once each SU processes locally its measurements, it sends the analog result to the FC through orthogonal additive white Gaussian noise (AWGN) channels: $z_j = T_j(\boldsymbol{y}_j) + w_j$, where w_j is a zero-mean Gaussian noise with variance $\sigma_{w,j}^2$. The use of AWGN channel model is justified by assumptions on analog-forwarding schemes and SU-FC channels with high coherence time relative to the reporting time. Guided by (4), we build the final statistic averaging the information received by the FC:

$$T_{\mathrm{FC}} = \frac{1}{n} \sum_{j=1}^{n} z_j = \frac{1}{n} \sum_{j=1}^{n} T_{\mathrm{LQ},j}(\boldsymbol{y}_j) + \frac{1}{n} \sum_{j=1}^{n} w_j. \quad (7)$$

A. Local Parameters Estimation

The parameters α_j^*, β_j^* and γ_j^* depend on σ_0^2, $\sigma_{1,j}^2$ and μ_j, which are typically unknown and must be estimated. To perform this task, at the beginning of the detection procedure, the SUs use the LQ statistic with the parameters set to a fixed value, independent of the required moments, e.g., $\alpha_j = \beta_j = \gamma_j = 1$, such that the FC makes a decision and communicates it to the SUs. Then, the SUs are able to classify and store the current data in a *presence* or *absence* vector for future reference, accordingly to the FC's decision. Let $M_{p,\mu}$, M_{p,σ^2} and $M_{a,\mu}$, M_{a,σ^2} be two presence and absence first-in-first-out (FIFO) memories of length L, available in each SU. If the FC decides that the PU is present, each SU stores the sample mean and the sample variance in $M_{p,\mu}$ and M_{p,σ^2}, respectively, otherwise, it stores the corresponding estimations in $M_{a,\mu}$ and M_{a,σ^2}. Then, the moments are estimated averaging the available data as follows. Let l be the present time, the recursive algorithm of the j-th sensor is $a_j(l) = \frac{L-1}{L} a_j(l-1) + \frac{1}{L}(b_j(l-1) - b_j(l-1-L))$, where $a_j(l) = \frac{1}{L} \sum_{k=l-L}^{l-1} b_j(k)$ and $b_j(k)$ is either the sample mean $\hat{\mu}_j(k) = \mathbf{1}^T \boldsymbol{y}_j(k)/m$ or the sample variance $\hat{\sigma}_j^2(k) = \|\boldsymbol{y}_j(k)\|^2/m - \hat{\mu}_j^2(k)$ recovered from the memories, and $\boldsymbol{y}_j(k)$ is the vector corresponding to the k-th set of measurements. We will show that, although the arbitrary selection of the LQ's parameters is suboptimal, its performance allows to initialize correctly the memories, and then to switch to the optimal LQ statistic using the estimated parameters. The size of the block of measurements to average should be selected considering the rate of change of the CR system parameters.

IV. Analysis of the Results

In this section, we compare the performance of the proposed LQ statistic against several statistics, which are introduced as follows: i) an asymptotically GLRT equivalent test called *linear* (GLR-L) test proposed in [9], which only needs to know the mean and variance under $\mathcal{H}_0$. ii) a *simplified linear* test called GLR-SL derived also in [9]. The GLR-L statistic is $T_{\mathrm{GLR\text{-}L}}(\boldsymbol{y}_j) = (\hat{\boldsymbol{\theta}}_{1,j} - \boldsymbol{\theta}_0)^T \partial \log p_1(\boldsymbol{y}_j; \boldsymbol{\theta}) / \partial \boldsymbol{\theta} |_{\boldsymbol{\theta} = \boldsymbol{\theta}_0}$, where $\hat{\boldsymbol{\theta}}_{1,j}$ is the MLE of the unknown parameter vector $\boldsymbol{\theta}_{1,j} = [\mu_j, \sigma_{1,j}^2]^T$, and $\boldsymbol{\theta}_0 = [0, \sigma_0^2]^T$ is assumed to be known. For the model (2), it results in $T_{\mathrm{GLR\text{-}L}}(\boldsymbol{y}_j) = \frac{m}{\sigma_0^2}((\mathbf{1}^T \boldsymbol{y}_j / m)^2 +$

[2]A channel use takes place when a symbol is transmitted.

$(\|\boldsymbol{y}_j\|^2/m - (\mathbf{1}^T\boldsymbol{y}_j/m)^2 - \sigma_0^2)(1 + \|\boldsymbol{y}_j\|^2/(m\sigma_0^2))/2)$ which involves up to fourth powers of the energy measurements y_{ij}. On the other hand, the GLR-SL statistic is intended for cases where the MLE estimation $\boldsymbol{\theta}_1$ is unfeasible, defined by $T_{\text{GLR-SL}}(\boldsymbol{y}_j) = \mathbf{1}^T \partial \log p_1(\boldsymbol{y}_j; \boldsymbol{\theta})/\partial \boldsymbol{\theta}|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$. For the model (2), it results in a particular case of the LQ statistic proposed here: $T_{\text{GLR-SL}}(\boldsymbol{y}_j) = \frac{m}{\sigma_0^2}(\mathbf{1}^T\boldsymbol{y}_j/m + \|\boldsymbol{y}_j\|^2/(2m\sigma_0^2) + 1/2)$. We assume that both statistics are transmitted to the FC through an AWGN channel, and that the FC averages the received measurements as in (7) to make a decision.

We consider that the SUs are uniformly distributed in a square of edge $2R_s = 0.1$, and that the distance between the center of this square and the PU is $R_p = 1.1$. For each statistic, we compute the sample error probability averaged with the spatial distribution of SUs using the method of Monte Carlo. The sensing SNR (in dB) coincides with the difference of means under $\mathcal{H}_1$ and $\mathcal{H}_0$, i.e., $\text{SNR}_{s,j} = \mu_j$. The parameters used are $P_t = 1.4$ dBm, $d_0 = 1$, $d_c = 0.1$, $p = 3.3$, $K_{\text{dB}} = 0$ dB, $L = 5$, $n = 6$, $m = 20$, $\sigma_0 = 3$ dB and $\text{SNR}_c = 5$ dB is the SNR of the communication channel. Notice that the decorrelation distance selected coincides with the edge of the square, so, we will have relatively high correlated measurements.

In Fig. 2, we plot the complementary receiver operating characteristic (ROC) of the three distributed statistics considered here with perfect knowledge of the parameters and also with the statistics estimated with the method described in Sec. III-A. We see that the LQ statistic has significant gains in terms of miss probability for any target false alarm probability in the range considered. Notice also the robustness of the LQ statistics against parameter error estimation.

In Fig. 3 we plot the miss probability against the shadowing standard deviation σ_{SH} for a low sensing SNR. As we can see, the LQ statistic has a superior performance in the whole range. It is worth to mention that most empirical studies for outdoor channels support σ_{SH} ranging from 4 dB to 13 dB [11]. This makes the LQ statistic suitable for different shadowing environments. Notice that in low sensing SNR scenarios as the tested here, the shadowing effect improves the detection performance of the PU, given that makes more distinctive the PU signal from the noise signal.

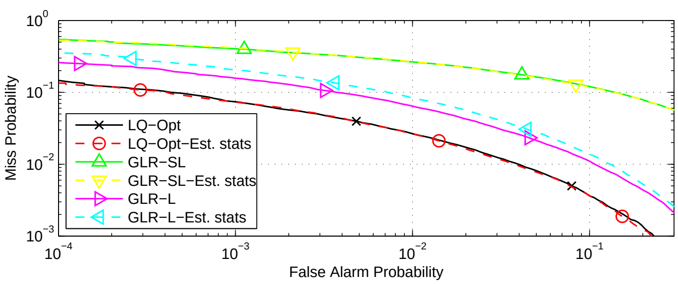

Fig. 2. Complementary ROC of the statistics with $\sigma_{\text{SH}} = 6$ dB.

V. Conclusions

Considering the shadowing effect and based on the deflection criterion, we have designed a soft local statistic that optimally combines the linear and quadratic terms of the energy measurements delivered by the non-coherent receiver suitable for detecting spectrum holes in cognitive radio systems. Numerical results show that the proposed statistic is suitable for a wide range of shadowing scenarios and it is robust against errors in its parameters.

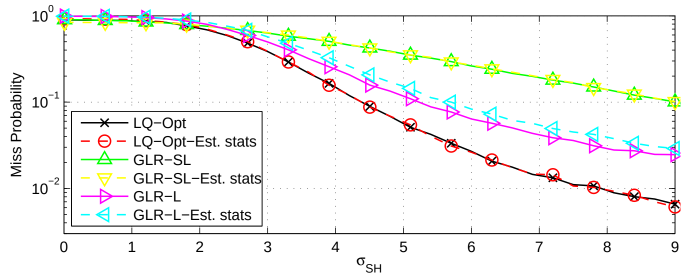

Fig. 3. Miss probability for $P_{f0} = 0.01$.

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