Spectrum Sensing via Restricted Neyman-Pearson Approach in the Presence of Non-Gaussian Noise

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***Abstract*—In this paper, spectrum sensing in cognitive radio systems is studied for non-Gaussian channels in the presence of prior distribution uncertainty. In most practical cases, some amount of prior information about signals of primary users is available to secondary users but that information is never perfect. In order to design optimal spectrum sensing algorithms in such cases, we propose to employ the restricted Neyman-Pearson (NP) approach, which maximizes the average detection probability under constraints on the worst-case detection and false-alarm probabilities. We derive a restricted NP based spectrum sensing algorithm for additive Gaussian mixture noise channels, and compare its performance against the generalized likelihood ratio test (GLRT) and the energy detector. Simulation results show that the proposed spectrum sensing algorithm provides improvements over the other approaches in terms of minimum (worst-case) and/or average detection probabilities.**

***Index Terms*– Cognitive radio, spectrum sensing, detection, Neyman-Pearson, Gaussian mixture, likelihood ratio.**

I. Introduction

Cognitive radio has emerged as a promising approach to solve the conflicts between spectrum under-utilization and spectrum scarcity [1]. In cognitive radio systems, secondary users are allowed to access and communicate over the frequency bands assigned to primary users as long as they do not cause any (significant) interference to primary users. Therefore, secondary users should be able to detect the presence of primary users reliably. Hence, spectrum sensing is a very crucial task in cognitive radio systems.

Common spectrum sensing methods are based on matched filtering, energy detection, and cyclostationary detection [2]-[5]. Usually energy detection is preferred in the absence of prior information about signals of primary users [6]. Although there are various approaches in the literature, a complete statistical framework, which considers *uncertainties* in the knowledge of prior distributions of any unknown system parameters, is not available. In [7], fundamental bounds on detection performance are obtained for low signal-to-noise ratio (SNR) scenarios in the presence of noise uncertainty. Specifically, the noise is modeled to be white, and its distribution is known only within a particular set. A spectrum sensing method based on the eigenvalues of the covariance matrix of the received signal is proposed in [8]. The ratio of the maximum eigenvalue to the minimum eigenvalue is used to detect signals of primary users. In [9], generalized likelihood ratio tests (GLRTs) are developed for the spectrum sensing problem. Iterative and simple non-iterative GLRT based algorithms are developed for slow and fast fading channels, respectively. In [10], the concept of soft sensing is considered, which employs the decision test statistic in the spectrum sensing problem as a confidence measure. Detailed surveys on spectrum sensing can be found in [11] and [12].

In this paper, we propose an optimal spectrum sensing approach in the presence of prior distribution uncertainty (i.e., imperfect prior information) based on the restricted Neyman-Pearson (NP) approach [13]-[15]. Specifically, a composite hypothesis-testing problem in the NP framework is formulated, and uncertainties in prior distributions are taken into account via the restricted NP approach. A restricted NP based spectrum sensing algorithm is obtained for additive Gaussian mixture noise channels in the presence of imperfect prior information about signals of primary users. In addition, the proposed algorithm is compared against the GLRT and energy detection approaches, and its advantages are illustrated in terms of the minimum (worst-case) and/or average detection probabilities.

This paper is organized as follows. We describe the system model and present the problem formulation of the restricted NP approach for spectrum sensing in Section II. Numerical results are provided and discussed in Section III. Finally, some conclusions are drawn in Section IV.

II. Spectrum Sensing via Restricted NP

Spectrum sensing in cognitive radio systems can be formulated as a binary hypothesis-testing problem [19] in which hypothesis $\mathcal{H}_0$ and hypothesis $\mathcal{H}_1$ correspond to the absence and presence of primary users, respectively. Assuming that M observations are available to the secondary user, the following hypothesis-testing problem can be stated:

$$\begin{aligned} &\mathcal{H}_0 : \mathbf{x} = \mathbf{n} \\ &\mathcal{H}_1 : \mathbf{x} = \boldsymbol{\theta} + \mathbf{n} \end{aligned} \qquad (1)$$

where $\mathbf{x}$ is an M-dimensional vector representing the measurements (observations) for spectrum sensing, $\boldsymbol{\theta}$ denotes the unknown parameter due to primary users, and $\mathbf{n}$ is the noise that is assumed to consist of independent and identically

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distributed components. For the probability distribution of the noise components, a generic Gaussian mixture model is employed; that is, each element of $\mathbf{n}$ has the following probability density function (PDF):

$$p_n(n) = \sum_{i=1}^{L} \frac{\nu_i}{\sqrt{2\pi}\,\varepsilon_i} \exp\left(-\frac{(n-\mu_i)^2}{2\varepsilon_i^2}\right) \tag{2}$$

where L is the number of components in the mixture, and μ_i, ε_i^2, and ν_i are the mean, variance, and weight of each component, respectively.[1] It is noted that the noise model in (2) is quite generic since it can approximate various noise PDFs by suitable selection of its parameters [20]. In addition, as mentioned in [21]-[23], the received signal in a cognitive radio receiver can be corrupted by non-Gaussian noise as a result of man-made impulsive noise and interference, and the noise can be modeled as Gaussian mixture noise as in (2).

In practice, some prior information about the probability distribution of $\boldsymbol{\theta}$ in (1) is available to secondary users. This prior knowledge is usually obtained by using previous measurements and/or by utilizing pilot signals. However, that prior information is never perfect and can include certain errors. Therefore, the aim in this study is to perform optimal spectrum sensing in the presence of uncertainties in the prior distribution of the unknown parameter related to the primary users. To achieve this aim, we adopt the restricted NP approach [13], [15] for this problem.

In the restricted NP framework, there exists some imperfect prior information about the unknown parameter. For the model in (1), let $w(\boldsymbol{\theta})$ denote the imperfect PDF of parameter $\boldsymbol{\theta}$, which does not necessarily correspond to the true prior distribution; i.e., can include certain errors. A restricted NP decision rule maximizes the average detection probability, which is obtained based on the imperfect PDF $w(\boldsymbol{\theta})$, under constraints on the worst-case detection and false-alarm probabilities. Mathematically stated, it is obtained as the solution of the following optimization problem [15]:

$$\underset{\phi}{\text{maximize}} \int_{\Lambda} P_D(\phi;\boldsymbol{\theta}) w(\boldsymbol{\theta}) d\boldsymbol{\theta} \tag{3}$$

$$\text{subject to } P_D(\phi;\boldsymbol{\theta}) \geq \beta, \quad \forall \boldsymbol{\theta} \in \Lambda \tag{4}$$

$$P_F(\phi) \leq \alpha \tag{5}$$

where Λ is the parameter space for $\boldsymbol{\theta}$, $P_D(\phi;\boldsymbol{\theta})$ is the detection probability of the decision rule ϕ for a given parameter value $\boldsymbol{\theta}$, $P_F(\phi)$ is the false-alarm probability of the decision rule, α is the false-alarm constraint, and β is the design parameter to compensate for the uncertainties in $w(\boldsymbol{\theta})$. It is noted that parameter β is adjusted according to the amount of uncertainty in $w(\boldsymbol{\theta})$. In particular, as the amount of uncertainty decreases (increases), a smaller (larger) value of β is employed.

[1]For simplicity of expressions, the parameters of the noise are assumed to be known. However, any uncertainties in the noise parameters can also be incorporated into the proposed restricted NP based spectrum sensing algorithm by considering the generic formulation in [15].

Alternatively, the problem in (3)-(5) can be expressed as

$$\underset{\phi}{\text{maximize}}\ \lambda \int_{\Lambda} P_D(\phi;\boldsymbol{\theta}) w(\boldsymbol{\theta}) d\boldsymbol{\theta} + (1-\lambda) \min_{\boldsymbol{\theta}\in\Lambda} P_D(\phi;\boldsymbol{\theta})$$
$$\text{subject to } P_F(\phi) \leq \alpha \tag{6}$$

where $\lambda \in [0,1]$ is a design parameter that is set according to β [15].

Based on (1), the detection probability and the false-alarm probability in (6) are given by

$$P_D(\phi;\boldsymbol{\theta}) = \int_{\Gamma} \phi(\mathbf{x}) p_{\mathbf{n}}(\mathbf{x}-\boldsymbol{\theta}) d\mathbf{x}\ , \quad \text{for } \boldsymbol{\theta} \in \Lambda \tag{7}$$

$$P_F(\phi) = \int_{\Gamma} \phi(\mathbf{x}) p_{\mathbf{n}}(\mathbf{x}) d\mathbf{x} \tag{8}$$

where Γ represents the observation space, $p_{\mathbf{n}}(\mathbf{x})$ is the PDF of noise $\mathbf{n}$, and $\phi(\mathbf{x})$ denotes the decision rule that maps $\mathbf{x}$ into a real number in $[0,1]$, representing the probability of selecting $\mathcal{H}_1$ [19].

The optimal solution to the problem in (3)-(5) is in the form of an NP decision rule corresponding to the least-favorable distribution [13]-[15]. The least-favorable distribution can be obtained by combining the uncertain PDF $w(\boldsymbol{\theta})$ with another PDF $\mu(\boldsymbol{\theta})$ as $v(\boldsymbol{\theta}) = \lambda w(\boldsymbol{\theta}) + (1-\lambda)\mu(\boldsymbol{\theta})$, and by obtaining the PDF $v(\boldsymbol{\theta})$ that corresponds to the minimum average detection probability [15]. Based on the NP lemma [19], the solution of (3)-(5) is then in the form of a likelihood ratio test (LRT) as follows:

$$\phi^*(\mathbf{x}) = \begin{cases} 1\,, & \int_{\Lambda} p_{\mathbf{n}}(\mathbf{x}-\boldsymbol{\theta}) v(\boldsymbol{\theta}) d\boldsymbol{\theta} \geq \eta\, p_{\mathbf{n}}(\mathbf{x}) \\ 0\,, & \int_{\Lambda} p_{\mathbf{n}}(\mathbf{x}-\boldsymbol{\theta}) v(\boldsymbol{\theta}) d\boldsymbol{\theta} < \eta\, p_{\mathbf{n}}(\mathbf{x}) \end{cases} \tag{9}$$

where the threshold η is chosen such that the false-alarm rate is equal to α, that is, $P_F(\phi^*) = \alpha$. In addition, $v(\boldsymbol{\theta})$ is calculated as described before; i.e., $v(\boldsymbol{\theta}) = \lambda w(\boldsymbol{\theta}) + (1-\lambda)\mu(\boldsymbol{\theta})$, where $\mu(\boldsymbol{\theta})$ is obtained for the least-favorable distribution [15].

The following algorithm proposed in [15] can be employed to obtain the optimal restricted NP decision rule for the spectrum sensing problem:

1) From (7), calculate $P_D(\phi^*_{\boldsymbol{\theta}_1};\boldsymbol{\theta})$ for all $\boldsymbol{\theta}_1 \in \Lambda$, where $\phi^*_{\boldsymbol{\theta}_1}$ represents the α-level NP decision rule corresponding to $v(\boldsymbol{\theta}) = \lambda w(\boldsymbol{\theta}) + (1-\lambda)\delta(\boldsymbol{\theta}-\boldsymbol{\theta}_1)$ as in (9).
2) Obtain $\boldsymbol{\theta}_1^* = \arg\min_{\boldsymbol{\theta}_1\in\Lambda} f(\boldsymbol{\theta}_1)$, where

$$f(\boldsymbol{\theta}_1) = \lambda \int_{\Lambda} w(\boldsymbol{\theta}) P_D(\phi^*_{\boldsymbol{\theta}_1};\boldsymbol{\theta}) d\boldsymbol{\theta} + (1-\lambda) P_D(\phi^*_{\boldsymbol{\theta}_1};\boldsymbol{\theta}_1). \tag{10}$$

3) If $P_D(\phi^*_{\boldsymbol{\theta}_1^*};\boldsymbol{\theta}_1^*) = \min_{\boldsymbol{\theta}\in\Lambda} P_D(\phi^*_{\boldsymbol{\theta}_1^*};\boldsymbol{\theta})$, $\phi^*_{\boldsymbol{\theta}_1^*}$ is the solution of the restricted NP problem. Otherwise, no solution exists.

Detailed explanations about this algorithm and its modifications for more generic scenarios can be found in [15]. As discussed in [15], the solution exists and it is unique in all practical cases.

Based on (9) and the algorithm above, the proposed decision rule for the spectrum sensing problem can be expressed as

$$\frac{\lambda \int_\Lambda p_{\mathbf{n}}(\mathbf{x}-\boldsymbol{\theta})w(\boldsymbol{\theta})d\boldsymbol{\theta} + (1-\lambda)p_{\mathbf{n}}(\mathbf{x}-\boldsymbol{\theta}_1^*)}{p_{\mathbf{n}}(\mathbf{x})} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta \tag{11}$$

where $\boldsymbol{\theta}_1^*$ is obtained as described above, and η is selected such that the false-alarm probability is equal to α.

As observed from (11), the proposed spectrum sensing algorithm is in the form of an LRT in which the PDF in the numerator corresponds to the mixture of the observation PDF for a specific (least-favorable) parameter value and the observation PDF averaged over the imperfect prior distribution. As a special case, if the prior distribution is perfect, $\lambda = 1$ is employed and the test reduces to the classical LRT. However, for imperfect prior distribution, the use of nonzero λ can be more advantageous, as discussed in the next section.

Although the decision rule in (11) is generic for any noise PDF and any prior distribution of the parameter, we can obtain specific expressions for it in the case of the Gaussian mixture model in (2) and a uniform prior distribution. In particular, we assume that the components of parameter $\boldsymbol{\theta}$ are independent and the kth component, θ_k, is uniformly distributed between a_k and b_k for $k = 1, \ldots, M$; that is, $\theta_k \sim \mathcal{U}[a_k, b_k]$ [16]. Then, the decision rule in (11) becomes

$$\lambda \frac{\prod_{k=1}^M \frac{1}{b_k - a_k} \int_{a_k}^{b_k} \sum_{i=1}^L \frac{\nu_i}{\sqrt{2\pi}\,\varepsilon_i} \exp\left(-\frac{(x_k-\theta_k-\mu_i)^2}{2\varepsilon_i^2}\right) d\theta_k}{\prod_{k=1}^M \sum_{i=1}^L \frac{\nu_i}{\sqrt{2\pi}\,\varepsilon_i} \exp\left(-\frac{(x_k-\mu_i)^2}{2\varepsilon_i^2}\right)}$$
$$+ (1-\lambda) \frac{\prod_{k=1}^M \sum_{i=1}^L \frac{\nu_i}{\sqrt{2\pi}\,\varepsilon_i} \exp\left(-\frac{(x_k-\theta_{1,k}^*-\mu_i)^2}{2\varepsilon_i^2}\right)}{\prod_{k=1}^M \sum_{i=1}^L \frac{\nu_i}{\sqrt{2\pi}\,\varepsilon_i} \exp\left(-\frac{(x_k-\mu_i)^2}{2\varepsilon_i^2}\right)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta \tag{12}$$

where $\theta_{1,k}^*$ is the kth element of $\boldsymbol{\theta}_1^*$ in (11).

In order to compare the performance of the proposed spectrum sensing algorithm in (12) against the other common algorithms in the literature, we consider the GLRT and energy detection approaches [17], [18]. In the GLRT, the maximum likelihood estimate of the unknown parameter is calculated and an LRT is formed based on that estimate [19]. From (1) and (2), the GLRT for the spectrum sensing problem can be obtained as follows:

$$\max_{\boldsymbol{\theta}} \frac{\prod_{k=1}^M \sum_{i=1}^L \frac{\nu_i}{\sqrt{2\pi}\,\varepsilon_i} \exp\left(-\frac{(x_k-\theta_k-\mu_i)^2}{2\varepsilon_i^2}\right)}{\prod_{k=1}^M \sum_{i=1}^L \frac{\nu_i}{\sqrt{2\pi}\,\varepsilon_i} \exp\left(-\frac{(x_k-\mu_i)^2}{2\varepsilon_i^2}\right)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta_g \tag{13}$$

where θ_k is the kth element of $\boldsymbol{\theta}$, and η_g is chosen such that the false alarm probability is equal to α.

On the other hand, the energy detector compares the total energy of the observations against a threshold; i.e,

$$\|\mathbf{x}\|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta_e \tag{14}$$

where the threshold η_e is chosen such that the false alarm probability is equal to α; that is,

$$\Pr\left\{\|\mathbf{x}\|^2 > \eta_e \,\middle|\, \mathcal{H}_0\right\} = \alpha\ . \tag{15}$$

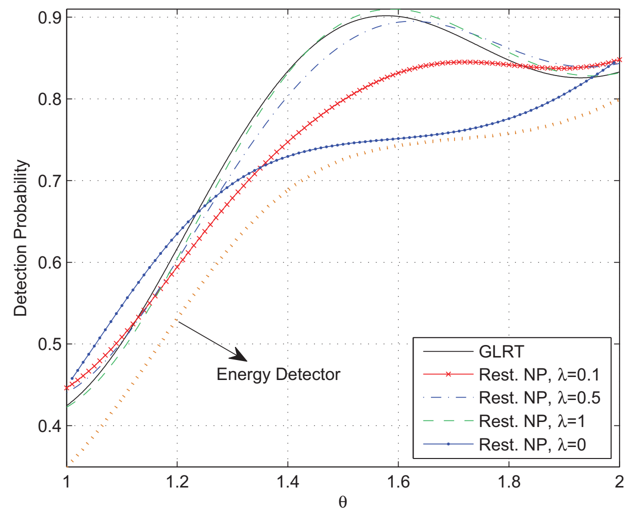

Fig. 1. Probabilities of detection versus θ for the restricted NP, GLRT, and energy detection approaches, where the parameters of the Gaussian mixture noise are set to $L = 3$, $\nu_1 = \nu_3 = 0.25$, $\nu_2 = 0.5$, $\mu_1 = -\mu_3 = 1$, $\mu_2 = 0$, and $\varepsilon_i = 0.2\ \forall i$.

III. Performance Evaluation

In this section, simulation results are presented in order to illustrate the accuracy and robustness of the proposed restricted NP based spectrum sensing algorithm in various scenarios. For comparison purposes, performance of the GLRT and energy detection approaches is evaluated as well. In the simulations, the false alarm constraint in (5) is set to $\alpha = 0.1$. In addition, parameter $\boldsymbol{\theta}$ is modeled as a scalar random variable that lies in the interval $\Lambda = [a, b]$, where $a = 1$ and $b = 2$. The imperfect prior distribution for $\boldsymbol{\theta}$ is specified by a uniform distribution over Λ; that is, $w(\boldsymbol{\theta}) = 1$ for $\boldsymbol{\theta} \in [1, 2]$, and $w(\boldsymbol{\theta}) = 0$ otherwise. In other words, the secondary user has the prior distribution information about $\boldsymbol{\theta}$ as $\boldsymbol{\theta} \sim \mathcal{U}[1, 2]$; however, this information is not perfect and can include certain errors. Such a scenario can be encountered in practice for example when there is some information about the value of parameter $\boldsymbol{\theta}$ (which can be obtained from previous measurements or based on the knowledge of a pilot signal transmitted by the primary user) and the uncertainty around this value is modeled by a uniform distribution [16]. Although a uniform distribution is considered in this example, the theoretical analysis in Section II can also be employed for any other distribution.

For the first set of simulations, the parameters of the Gaussian mixture noise in (2) are set to $L = 3$, $\nu_1 = \nu_3 = 0.25$, $\nu_2 = 0.5$, $\mu_1 = -\mu_3 = 1$, $\mu_2 = 0$, and $\varepsilon_i = 0.2\ \forall i$. This mixture noise can correspond to the sum of zero-mean Gaussian noise and interference which is due to two users that result in signal values of ± 0.5 with equal probabilities at the

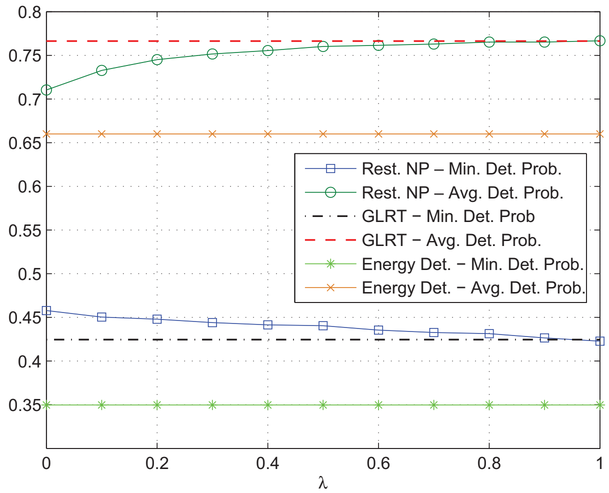

Fig. 2. Probabilities of detection versus λ for the restricted NP, GLRT, and energy detection approaches, where the parameters of the Gaussian mixture noise are set to $L = 3$, $\nu_1 = \nu_3 = 0.25$, $\nu_2 = 0.5$, $\mu_1 = -\mu_3 = 1$, $\mu_2 = 0$, and $\varepsilon_i = 0.2\ \forall i$.

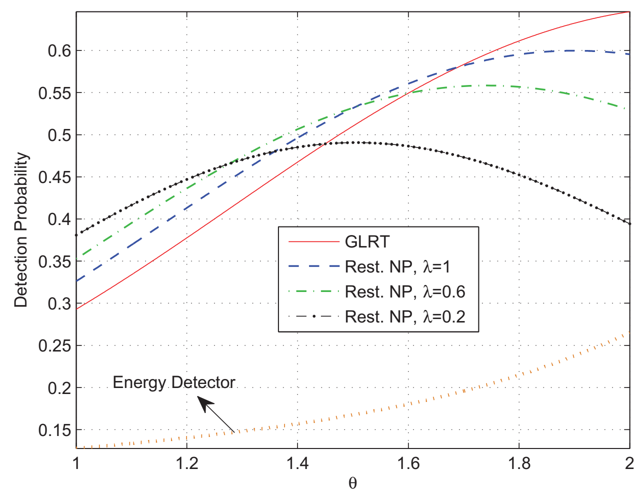

Fig. 3. Probabilities of detection versus θ for the restricted NP, GLRT, and energy detection approaches, where the parameters of the Gaussian mixture noise are $L = 2$, $\nu_1 = \nu_2 = 0.5$, $\mu_1 = \mu_2 = 0$, $\varepsilon_1 = 0.5$, and $\varepsilon_1 = 2$.

receiver. In Fig. 1, detection probabilities are plotted versus $\boldsymbol{\theta}$ for the energy detector, the GLRT, and the proposed restricted NP based algorithm with various values of λ. It is observed that the energy detector has the worst performance for all parameter values. On the other hand, the restricted NP based approach provides higher and lower detection probabilities than the GLRT approach depending on the value of the parameter. In order to compare the performance of the algorithms in more detail, Fig. 2 illustrates the average and minimum detection probabilities versus λ for all the approaches, where λ is the design parameter in the restricted NP based approach (see (6)). It is observed that the restricted NP based spectrum sensing algorithm provides a tradeoff between the average and the minimum (i.e., worst-case) detection probabilities. For example, in order to achieve a larger minimum (average) detection probability, the restricted NP based approach with a smaller (larger) value of λ can be employed. Such a tradeoff is not present in the GLRT and the energy detection approaches. Since the prior distribution information is imperfect, the average detection probabilities shown in Fig. 2 may not be the true average detection probabilities; hence, the robustness of the restricted NP based approach (i.e., having larger minimum detection probabilities) can be crucial in practice.

Next, the parameters of the Gaussian mixture noise are set to $L = 2$, $\nu_1 = \nu_2 = 0.5$, $\mu_1 = \mu_2 = 0$, $\varepsilon_1 = 0.5$, and $\varepsilon_2 = 2$. The noise model employed in this scenario is practically important since the mixture of zero-mean Gaussian random variables with different variances is often used to model man-made noise, impulsive phenomena, and certain sorts of ultra-wideband interference [21]. In Fig. 3 and Fig. 4, the detection probabilities are plotted versus $\boldsymbol{\theta}$ and λ, respectively. It is observed in this scenario that the restricted NP approach can outperform the GLRT approach in terms of *both* the minimum and average detection probabilities. After approximately $\lambda = 0.55$, both the minimum and average detection probabilities of the restricted NP approach are larger than those of the GLRT approach. For example, when $\lambda = 0.6$, the average detection probability of the restricted NP test is slightly larger than that of the GLRT, and its minimum detection probability (0.353) is significantly larger than that of the GLRT (0.293). Therefore, the restricted NP based approach provides improved accuracy and robustness in this scenario.

IV. Concluding Remarks

The restricted NP approach has been employed to solve the spectrum sensing problem in cognitive radio systems in the presence of imperfect prior information about unknown parameters of primary users. A restricted NP based spectrum sensing algorithm has been proposed for Gaussian mixture noise, which is encountered in cognitive radio systems in the presence of man-made noise and interference. It has been shown that the proposed approach can provide improvements over the GLRT approach in terms of the minimum (worst-case) detection probability and/or the average detection probability depending on the amount of uncertainty in the prior information. Since prior information is imperfect in all practical scenarios, the proposed approach is well-suited for the spectrum sensing problem in order to provide robust and accurate detection of primary users.

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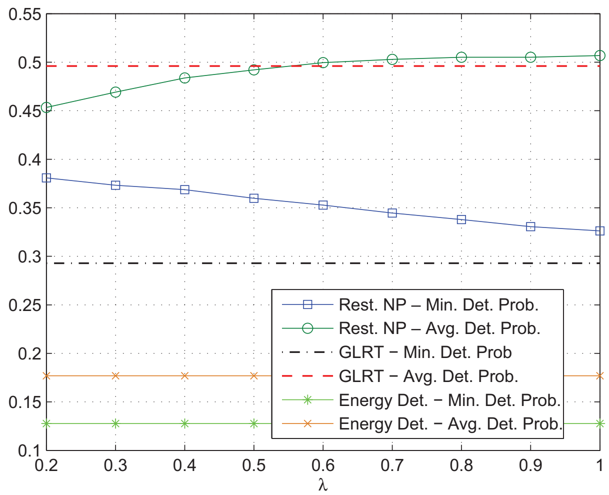

Fig. 4. Probabilities of detection versus λ for the restricted NP, GLRT, and energy detection approaches, where the parameters of the Gaussian mixture noise are $L = 2$, $\nu_1 = \nu_2 = 0.5$, $\mu_1 = \mu_2 = 0$, $\varepsilon_1 = 0.5$, and $\varepsilon_1 = 2$.

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