Robust Estimator-Correlator for Spectrum Sensing in MIMO CR Networks with CSI Uncertainty

Adarsh Patel, *Student Member, IEEE,* Bhishm Tripathi, *Student Member, IEEE,*
Aditya K. Jagannatham, *Member, IEEE*

***Abstract*—This work introduces novel detection schemes which are robust with respect to the uncertainty in the estimate of the signal covariance matrix for non-coherent spectrum sensing in multiple-input multiple-output (MIMO) cognitive radio networks. We employ an eigenvalue perturbation theory based approach to model the uncertainty in the estimated signal covariance matrix. Subsequently, we derive an optimization framework for the generalized likelihood ratio test (GLRT) based robust test statistic detector (RTSD) and robust estimator-correlator detector (RECD) towards primary user detection, which incorporate the channel state information (CSI) uncertainty inherent in such scenarios. Further, employing the Karush-Kuhn-Tucker (KKT) conditions, we derive closed form expressions for the proposed robust spectrum sensing schemes. Simulation results demonstrate the superior performance of the proposed robust detectors in comparison to the uncertainty agnostic estimator-correlator (EC) detector for spectrum sensing in MIMO cognitive radio networks with CSI uncertainty.**

***Index Terms*—Multiple-Input Multiple-Output (MIMO), Cognitive Radio (CR), Spectrum Sensing.**

I. Introduction

THE ongoing transition from the low rate circuit switched voice call services to the high data rate packet switched multimedia applications has resulted in a steady increase in the demand for higher bandwidth in modern 3G/4G wireless cellular networks. This has led to a scarcity of licensed spectrum bands. Surprisingly however, the survey in [1] has shown that a significant fraction of the spectral bands which are allocated to the licensed users are unused at any given instant of time. In this context, cognitive radio [2], [3] has emerged as a key enabling technology for dynamic spectrum access that allows secondary/ unlicensed users to opportunistically access the unused radio spectrum allotted to the primary/ licensed users. Thus, spectrum sensing towards reliable detection of *spectral holes* or unused primary user bands is a key task in cognitive radio networks.

Several spectrum sensing techniques have been proposed in literature [4]. Among these, the energy detector [5], which has a simple structure, has gained a wide appeal for spectrum sensing in cognitive radio networks. It has been demonstrated in [6], that the energy detector can be derived as the simplification of the optimal estimator-correlator (EC) detector for non-coherent spectrum sensing scenarios with isotropic signal and noise covariance matrices. Further, it is known from works such as [6]–[8] that the performance of the EC deteriorates with covariance uncertainty. However, due to the limited resources at the secondary users, estimation error and the fading nature of the wireless channel, it is often difficult to obtain an accurate estimate of the signal covariance matrix.

Therefore, we propose robust detection schemes in order to mitigate the effect of the uncertainty in the estimated signal covariance matrix on spectrum sensing in practical wireless scenarios. Employing perturbation theory, we derive results to bound the distortion in the estimated covariance matrix. Based on these results, we develop the generalized likelihood ratio test (GLRT) detectors for robust estimator-correlator based non-coherent spectrum sensing and demonstrate that these can be formulated as appropriate optimization paradigms. The GLRT test statistic can be employed to formulate the robust test statistic detector (RTSD), which although simplistic, can be solved efficiently since it is convex. Further, the robust estimator-correlator detector (RECD) is also derived. Closed form expressions for the RTSD and RECD are derived employing the Karush-Kuhn-Tucker (KKT) conditions. Simulation results demonstrate a significant improvement in the primary user detection performance of the proposed detection schemes in comparison to the nominal covariance matrix estimate based uncertainty agnostic EC detector.

The rest of the paper is organized as follows. In section II we describe the system model for MIMO cognitive radio networks followed by the perturbation analysis. Next, in Section III we develop the optimization framework and derive closed form expressions for the proposed GLRT based RTSD and RECD schemes towards robust spectrum sensing. Simulation results and conclusion follow in sections IV and V respectively.

II. System Model

Consider a multiple-input multiple-output (MIMO) cognitive radio system with N_r receive antennas at the secondary user and N_t transmit antennas at the primary user base-station. Let the MIMO base-band system model between the primary user base-station and the secondary user, corresponding to the k^{th} symbol transmission, be represented as,

$$\mathbf{y}(k) = \underbrace{\mathbf{H}\mathbf{x}(k)}_{\mathbf{s}(k)} + \boldsymbol{\eta}(k),$$

where $\mathbf{y}(k)\in\mathbb{C}^{N_r\times 1}$, $\mathbf{x}(k)\in\mathbb{C}^{N_t\times 1}$ are the received and transmitted temporally independent and identically distributed (IID) zero-mean Gaussian signal vectors respectively, with the Gaussian signal covariance matrix $\mathbf{R}_s\in\mathbb{C}^{N_r\times N_r}$ defined as

A. Patel, B. Tripathi and A. K. Jagannatham are with the Department of Electrical Engineering, Indian Institute of Technology Kanpur, Kanpur, UP 208016, India (e-mail: adarsh@iitk.ac.in, bhishm@iitk.ac.in, adityaj@iitk.ac.in).

$\mathbf{R}_s= \mathrm{E}\{\mathbf{s}(k)\mathbf{s}^H(k)\}= \mathbf{H}\mathrm{E}\{\mathbf{x}(k)\mathbf{x}^H(k)\}\mathbf{H}^H$, similar to the works such as [4], [7]. The matrix $\mathbf{H}\in\mathbb{C}^{N_r\times N_t}$ is the MIMO channel matrix with each element $h_{r,t}$ denoting the channel coefficient between the t^{th} transmit antenna of the primary user base-station and the r^{th} receive antenna of the secondary user. The vector $\boldsymbol{\eta}(k)\in\mathbb{C}^{N_r\times 1}$ denotes the spatio-temporally white Gaussian noise with the known noise covariance $\mathbf{R}_\eta= \mathrm{E}\{\boldsymbol{\eta}(k)\boldsymbol{\eta}^H(k)\}=\sigma_\eta^2\mathbf{I}$. The primary user detection problem can be formulated as the binary hypothesis testing problem as,

$$\begin{aligned}\mathcal{H}_0 &:\mathbf{y}(k) = \boldsymbol{\eta}(k)\\ \mathcal{H}_1 &:\mathbf{y}(k) = \mathbf{s}(k) + \boldsymbol{\eta}(k),\end{aligned}$$

where the null hypothesis $\mathcal{H}_0$ denotes the absence of the primary user and the alternative hypothesis $\mathcal{H}_1$ denotes the presence of the primary user. The respective distributions of the observation vector $\mathbf{y}(k)$ described above are given as,

$$\begin{aligned}\mathcal{H}_0 &:\mathbf{y}(k) \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_\eta)\\ \mathcal{H}_1 &:\mathbf{y}(k) \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}),\end{aligned} \tag{1}$$

where the covariance matrix $\mathbf{R}$ is defined as $\mathbf{R} = \mathbf{R}_s + \mathbf{R}_\eta$. The optimal decision rule for the above primary user detection problem can be obtained using the likelihood ratio test (LRT). Let the columns of the matrix $\mathbf{Y}=[\mathbf{y}(1),\ldots,\mathbf{y}(K)]\in\mathbb{C}^{N_r\times K}$ denote the received signals corresponding to the K IID observed symbol vectors $\mathbf{y}(k)$, $1\leq k\leq K$. Hence, the joint LRT statistic for the scenario described above can be computed as,

$$\mathcal{L}(\mathbf{Y}) = \frac{p(\mathbf{Y};\mathcal{H}_1)}{p(\mathbf{Y};\mathcal{H}_0)} = \frac{\prod_{k=1}^{K} p(\mathbf{y}(k);\mathcal{H}_1)}{\prod_{k=1}^{K} p(\mathbf{y}(k);\mathcal{H}_0)},$$

where $p(\mathbf{y}(k);\mathcal{H}_0)$, $p(\mathbf{y}(k);\mathcal{H}_1)$ denote the marginal probability densities under hypotheses $\mathcal{H}_0, \mathcal{H}_1$ respectively of the k^{th} symbol $\mathbf{y}(k)$. Simplification of the above expression employing the distributions in (1), yields the test statistic as,

$$\begin{aligned}T(\mathbf{Y}) =&\log(\mathcal{L}(\mathbf{Y})) = K\log|\mathbf{R}_\eta|\\ &\underbrace{+\sum_{k=1}^{K}\mathbf{y}^H(k)\left[\mathbf{R}_\eta^{-1} - \mathbf{R}^{-1}\right]\mathbf{y}(k)}_{T_{EC}(\mathbf{Y})} - \underbrace{K\log|\mathbf{R}|}_{T_C},\end{aligned} \tag{2}$$

where $|\mathbf{R}|$ and $|\mathbf{R}_\eta|$ denote the determinants of the matrices $\mathbf{R}$ and $\mathbf{R}_\eta$ respectively. The component $T_{EC}(\mathbf{Y})$ of the test statistic $T(\mathbf{Y})$ constitutes the decision rule for the standard EC detector [5] with perfect knowledge of the covariance matrices $\mathbf{R}_s, \mathbf{R}_\eta$ and can be equivalently represented as,

$$T_{EC}(\mathbf{Y}) = \sum_{k=1}^{K}\mathbf{y}^H(k)\mathbf{R}_\eta^{-1}\mathbf{y}(k) - \sum_{k=1}^{K}\mathbf{y}^H(k)\mathbf{R}^{-1}\mathbf{y}(k). \tag{3}$$

The performance of the detector is critically dependent on the accuracy of the covariance estimates. However, in practical wireless scenarios, it is challenging to obtain an exact estimate of the signal covariance matrix due to the limited resources and processing capabilities available at the secondary users coupled with the time varying nature of the fading wireless channel. Frequently, in such scenarios, it is only possible to obtain a nominal estimate of the true signal covariance matrix which is unknown. Let γ_i, $1 \leq i \leq N_r$ be the eigenvalues of the true signal covariance matrix $\mathbf{R}_s = \mathbf{U}\boldsymbol{\Gamma}\mathbf{U}^H$ and similarly, $\hat{\gamma}_i$ be the eigenvalues of the estimated signal covariance matrix $\hat{\mathbf{R}}_s$, i.e. the diagonal matrices $\boldsymbol{\Gamma} = \mathcal{D}(\gamma_1,\ldots,\gamma_{N_r})$ and $\hat{\boldsymbol{\Gamma}} = \mathcal{D}(\hat{\gamma}_1,\ldots,\hat{\gamma}_{N_r})$ are the eigenvalue matrices corresponding to the true and estimated signal covariance matrices. Let the uncertainty in the eigenvalues $\hat{\gamma}_i$ of the estimated signal covariance matrix $\hat{\mathbf{R}}_s$ be modeled as,

$$\gamma_i = \hat{\gamma}_i + \triangle\gamma_i, \quad 1 \leq i \leq N_r,$$

where $\triangle\gamma_i$ denotes the perturbation with respect to γ_i, the true eigenvalue of $\mathbf{R}_s$. Let $\triangle\mathbf{R}$ denote the uncertainty in the covariance matrix, with $\|\triangle\mathbf{R}\| \leq \epsilon$, where ϵ denotes the uncertainty radius, similar to the model in works such as [9]. Let the matrix $\mathbf{U}=[\mathbf{u}_1,\ldots,\mathbf{u}_{N_r}]$, where $\mathbf{u}_i, 1 \leq i \leq N_r$ denotes the i^{th} column vector. The result below, derived using perturbation theory [10], describes an insightful property which characterizes the uncertainty bound for the eigenvalues of the true covariance matrix.

Lemma 1. *A first order bound for the perturbation in the eigenvalues of the true covariance matrix* $\mathbf{R}$ *is given as,*

$$\sum_{i=1}^{N_r}\triangle\gamma_i \leq \sqrt{N_r}\ \epsilon.$$

Proof. From the result for the perturbation of the eigenvalues in [10], we have $\triangle\gamma_i$, the perturbation in the eigenvalue $\hat{\gamma}_i$ of the estimated covariance matrix $\hat{\mathbf{R}}_s$ given as, $\triangle\gamma_i\approx\mathbf{u}_i^H\triangle\mathbf{R}\mathbf{u}_i$. Hence, the eigenvalue uncertainty radius can be bounded as,

$$\begin{aligned}\sum_{i=1}^{N_r}\triangle\gamma_i &\approx \operatorname{tr}\left(\sum_{i=1}^{N_r}\mathbf{u}_i^H\triangle\mathbf{R}\mathbf{u}_i\right)\\ &= \operatorname{tr}(\triangle\mathbf{R}\mathbf{I})\\ &\leq \sqrt{\|\triangle\mathbf{R}\|^2\|\mathbf{I}\|^2} = \epsilon\sqrt{N_r},\end{aligned}$$

where the last inequality follow from the Cauchy-Schwarz inequality for the matrix Frobenius norm. □

Based on the uncertainty model above, we propose a novel framework for detection in the next section.

III. Robust Detection with Covariance Uncertainty

From the uncertainty analysis presented above, it can be seen that the test statistic $T(\mathbf{Y})$ obtained in (2) varies with the uncertainty in the estimate of the true covariance matrix $\mathbf{R}$. Hence we formulate the RTSD and the RECD for primary user detection in cognitive radio scenarios that consider uncertainty in the signal covariance matrix.

A. Robust Test Statistic Detector (RTSD)

A simplistic GLRT based detector can be obtained by maximizing the EC test statistic in (3) for the given uncertainty radius. This can be readily seen to be equivalent to minimizing the term $\sum_{k=1}^{K}\mathbf{y}^H(k)\mathbf{R}^{-1}\mathbf{y}(k)$. Let the eigenvalue decomposition of the covariance matrix $\mathbf{R}$ be given as $\mathbf{R} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^H$, with the i^{th} eigenvalue λ_i of the diagonal matrix $\boldsymbol{\Lambda}$ given as

$\lambda_i = \gamma_i + \sigma_\eta^2$. Hence, the objective function for the above minimization problem can be equivalently formulated as,

$$\begin{aligned}\sum_{k=1}^{K}\mathbf{y}^H(k)\mathbf{R}^{-1}\mathbf{y}(k) &= \sum_{k=1}^{K}\mathbf{y}^H(k)\big(\mathbf{U}\mathbf{\Lambda}\mathbf{U}^H\big)^{-1}\mathbf{y}(k)\\ &= \sum_{k=1}^{K}\tilde{\mathbf{y}}^H(k)\mathbf{\Lambda}^{-1}\tilde{\mathbf{y}}(k)\\ &= \sum_{k=1}^{K}\left(\sum_{i=1}^{N_r}\frac{|\tilde{y}_i(k)|^2}{\lambda_i}\right),\end{aligned}$$

where $\tilde{y}_i(k), i{=}1,...,N_r$ are the elements of vector $\tilde{\mathbf{y}}(k){=}\mathbf{U}^H\mathbf{y}(k)$. Also note $\|\tilde{\mathbf{y}}\|^2{=}\|\mathbf{y}\|^2$ since $\mathbf{U}$ is a unitary matrix. Using the uncertainty model from Lemma 1 in above objective function, the optimization framework that yields the RTSD for primary user detection can be equivalently formulated as,

$$\begin{aligned}\underset{\triangle\lambda_i}{\text{minimize}} \quad & \sum_{i=1}^{N_r}\frac{\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}{\hat{\lambda}_i+\triangle\lambda_i}\\ \text{subject to} \quad & \sum_{i=1}^{N_r}\triangle\lambda_i \leq \epsilon\sqrt{N_r}.\end{aligned} \tag{4}$$

The above optimization problem can be easily seen to be convex and is readily solved employing the KKT conditions. Let $f^{\star}_{RTSD}$ denote the optimal value of the objective function for the optimization framework defined in (4). Hence, the test statistic (2) corresponding to RTSD for spectrum sensing in MIMO cognitive radio scenarios can be equivalently given as,

$$T_{RTSD} = \sum_{k=1}^{K}\mathbf{y}^H(k)\mathbf{R}_\eta^{-1}\mathbf{y}(k) - f^{\star}_{RTSD}. \tag{5}$$

We now derive a closed form expression for the above optimization framework by solving the Lagrangian objective function corresponding to the KKT conditions. Let the uncertainty $\triangle\lambda_i$ in the eigenvalue $\hat{\lambda}_i$ for $1{\leq}i{\leq}N_r$ be stacked as the uncertainty vector $\triangle\boldsymbol{\lambda}{=}[\triangle\lambda_1,\ldots,\triangle\lambda_{N_r}]$. The Lagrangian cost function $L(\triangle\boldsymbol{\lambda},\theta)$ for RTSD can be derived as,

$$L(\triangle\boldsymbol{\lambda},\theta) = \sum_{i=1}^{N_r}\frac{\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}{\hat{\lambda}_i+\triangle\lambda_i} + \theta\left(\sum_{i=1}^{N_r}\triangle\lambda_i - \epsilon\sqrt{N_r}\right),$$

where θ is the associated non-negative Lagrange multiplier. The KKT conditions [11] for the Lagrangian are given as,

$$\frac{\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}{(\hat{\lambda}_i+\triangle\lambda_i)^2} - \theta = 0, \quad \theta\left(\sum_{i=1}^{N_r}\triangle\lambda_i - \epsilon\sqrt{N_r}\right) = 0.$$

Solving the KKT conditions above, one can obtain the optimal value $\triangle\lambda_i^{\star}$ of the uncertainty $\triangle\lambda_i$ as,

$$\triangle\lambda_i^{\star} = -\hat{\lambda}_i + \sqrt{\frac{\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}{\theta}}, \tag{6}$$

where the Lagrange multiplier θ is given as,

$$\theta = \left(\frac{\sum_{i=1}^{N_r}\sqrt{\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}}{\epsilon\sqrt{N_r}+\sum_{i=1}^{N_r}\hat{\lambda}_i}\right)^2.$$

Next, we formulate the optimization framework to obtain the RECD for the primary user sensing problem.

B. Robust Estimator-correlator Detector (RECD)

The optimal GLRT based RECD for uncertainty aware non-coherent MIMO spectrum sensing can be derived as follows. The term $T_C = K\log|\mathbf{R}| = K\sum_{i=1}^{N_r}\log\lambda_i$ of the test statistic $T(\mathbf{Y})$ in (2) depends on the uncertainty in the signal covariance matrix. Hence, the optimization framework leading to the formulation of the optimal detection rule for the primary user detection problem with uncertainty in the signal covariance matrix is obtained by including T_C in the cost function of (4) and can be derived as,

$$\begin{aligned}\underset{\triangle\lambda_i}{\text{minimize}} \quad & K\sum_{i=1}^{N_r}\log\Big(\hat{\lambda}_i+\triangle\lambda_i\Big) + \sum_{i=1}^{N_r}\frac{\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}{\hat{\lambda}_i+\triangle\lambda_i}\\ \text{subject to} \quad & \sum_{i=1}^{N_r}\triangle\lambda_i \leq \epsilon\sqrt{N_r}\ .\end{aligned} \tag{7}$$

The above optimization problem is non-convex. Hence, the solution obtained from the KKT conditions yields a local optimum. The Lagrangian cost function can be formulated as,

$$\begin{aligned}L(\triangle\boldsymbol{\lambda},\mu) =& \sum_{i=1}^{N_r}\left(K\log\Big(\hat{\lambda}_i+\triangle\lambda_i\Big) + \frac{\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}{\hat{\lambda}_i+\triangle\lambda_i}\right)\\ &+\mu\left(\sum_{i=1}^{N_r}\triangle\lambda_i - \epsilon\sqrt{N_r}\right),\end{aligned}$$

where μ is the Lagrange multiplier. The KKT conditions [11] for the non-convex optimization problem in (7) are given as,

$$\begin{aligned}\frac{K}{\hat{\lambda}_i+\triangle\lambda_i} - \frac{\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}{(\hat{\lambda}_i+\triangle\lambda_i)^2} + \mu = 0,\\ \mu\left(\sum_{i=1}^{N_r}\triangle\lambda_i - \epsilon\sqrt{N_r}\right) = 0.\end{aligned}$$

The optimal value $\triangle\lambda_i^{\star}$ of the uncertainty $\triangle\lambda_i$ in the estimate of the eigenvalue $\hat{\lambda}_i$ can be obtained by solving the KKT conditions as,

$$\triangle\lambda_i^{\star} = -\hat{\lambda}_i + \frac{-K+\sqrt{K^2+4\mu\sum_{k=1}^{K}|\tilde{y}_i(k)|^2}}{2\mu},$$

where μ can be found using the bisection or trust region methods. Let $f^{\star}_{RECD}$ denote the optimal value of the objective function. Hence, from the optimization framework in (7), the test statistic in (2) can be equivalently formulated as,

$$T_{RECD} = \sum_{k=1}^{K}\mathbf{y}^H(k)\mathbf{R}_\eta^{-1}\mathbf{y}(k) - f^{\star}_{RECD}. \tag{8}$$

The above test statistic yields a robust decision rule for primary user detection in MIMO cognitive radio networks.

IV. Simulation Results

We consider a scenario with $N_t = 2$ transmit antennas at the primary user base-station and $N_r = 2$ receive antennas at the secondary user, i.e. a 2×2 MIMO system. We consider different levels of uncertainty ϵ with $\triangle\mathbf{R} = \epsilon\mathbf{G}$, where $\mathbf{G}$ is generated as the unit norm Wishart random matrix. We

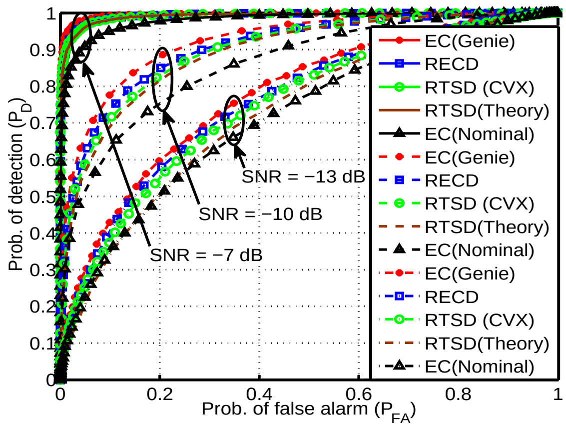

Fig. 1. Probability of detection vs. probability of false alarm comparison between the genie aided estimator-correlator (EC Genie), nominal estimate based estimator-correlator (EC Nominal), robust estimator-correlator (RECD), robust test statistic detector (RTSD) from the closed form solution (RTSD Theory) and CVX solver (RTSD CVX) for $N_r = 2$, $N_t = 2$ MIMO, $\epsilon = 0.5$ and $\mathbf{D}_1 = \mathcal{D}(1, 0.5)$.

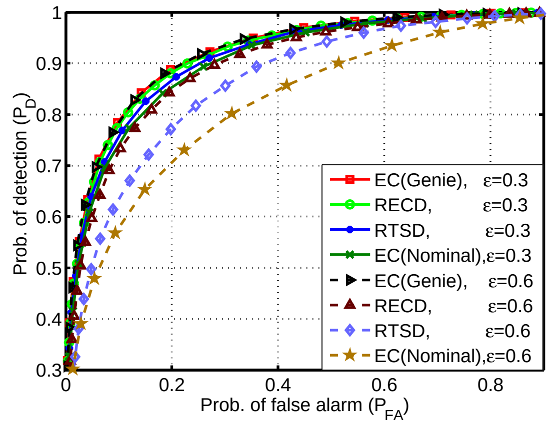

Fig. 2. Probability of detection vs. probability of false alarm comparison between the nominal estimate based estimator-correlator (EC Nominal), genie aided estimator-correlator (EC Genie), robust estimator-correlator (RECD) and robust test statistic detector (RTSD) for $N_r = 2$, $N_t = 2$ MIMO, SNR= -10dB, $\mathbf{D}_1 = \mathcal{D}(1, 0.5)$ and $\epsilon = 0.3, 0.6$.

consider the estimated covariance matrix $\hat{\mathbf{R}} = \mathbf{U}\hat{\mathbf{\Lambda}}\mathbf{U}^H$ with the diagonal matrix $\hat{\mathbf{\Lambda}} = \mathcal{D}(1, 0.5)$, i.e. $\hat{\lambda}_1 = 1, \hat{\lambda}_2 = 0.5$.

In Fig. 1. we plot the probability of detection (P_D) versus the probability of false alarm (P_{FA}) by varying the detection threshold in the range $(0, 1)$ at each SNR $\in \{-7, -10, -13\}$dB and compare the detection performance of the proposed RTSD in (5) and RECD in (8) with the uncertainty agnostic estimator-correlator detector (EC Nominal) (3) and the true covariance matrix based genie aided estimator-correlator (EC Genie) detector for spectrum sensing in MIMO cognitive radio networks. It can be observed that the proposed robust detectors significantly outperform the nominal estimate based estimator-correlator detector and are close to the performance of the true covariance matrix based genie aided estimator-correlator detector. It can also be observed that the proposed RECD has a performance edge over RTSD for spectrum sensing in MIMO cognitive radio scenarios with uncertainty in the estimated covariance matrix. However, the RTSD has low complexity and being convex in nature, it can be efficiently implemented in practical scenarios. Additionally, the performance of the closed form expression for RTSD derived in section III-A coincides with that obtained using the CVX solver for convex optimization problems [12].

In Fig. 2. we plot the probability of detection (P_D) versus the probability of false alarm (P_{FA}) for varying levels of uncertainty ϵ in the estimated covariance matrix for spectrum sensing and compare the detection performances of the proposed RTSD and RECD with the uncertainty agnostic estimator-correlator detector. It is evident from the simulations that as the uncertainty in the eigenvalues of the covariance matrix increases, the performance gap between the uncertainty agnostic estimator-correlator detector and the proposed robust detection schemes increases.

V. Conclusion

In this work we have proposed robust detection techniques for non-coherent spectrum sensing in MIMO cognitive radio scenarios. Towards this end, we have derived the uncertainty in the eigenvalues of the true signal covariance matrix employing results from perturbation theory. The proposed RTSD and RECD schemes significantly improve the primary user detection performance under CSI uncertainty. We further derived closed form expressions utilizing the KKT conditions for the GLRT based robust detection problems above. Simulation results demonstrate that the proposed robust detectors outperform the conventional uncertainty agnostic nominal CSI based estimator-correlator detector.

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