Performance Analysis of Multi-Antenna Hybrid Detectors and Optimization with Noise Variance Estimation

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***Abstract*—In this paper, a performance analysis of multi-antenna spectrum sensing techniques is carried out. Both well known algorithms, such as Energy Detector (ED) and eigenvalue based detectors, and an eigenvector based algorithm, are considered. With the idea of auxiliary noise variance estimation, the performance analysis is extended to the hybrid approaches of the considered detectors. Moreover, optimization for Hybrid ED under constant estimation plus detection time is performed. Performance results are evaluated in terms of Receiver Operating Characteristic (ROC) curves and performance curves, i.e., detection probability as a function of the Signal-to-Noise Ratio (SNR). It is concluded that the eigenvector based detector and its hybrid approach are able to approach the optimal Neyman-Pearson performance.**

Keywords–hybrid detector; largest eigenvector; noise estimation; spectrum sensing; cognitive radio.

I. INTRODUCTION

Spectrum sensing is the enabling unit of Secondary Users (SUs) in Cognitive Radio Networks (CRN) [1] for the accurate identification and exploitation of unused Primary User's (PU) spectrum in temporal and spatial domain. Precise identification of the spectrum holes is the major constraint for the establishment of Cognitive Radio, which ensures the dynamic exploitation of existing wireless spectrum. As an example, the Wireless Regional Area Network (WRAN) standard imposes stringent requirement on the probability of detection $(P_d) \geq 0.9$ with probability of false alarm $P_{Fa} \leq 0.1$ at Signal-to-Noise Ratio (SNR) $-20dB$ (for Digital TV band) [3].

In order to satisfy the constraint of high performance and considering the dependence of noise uncertainty and the implementation complexity under wireless fading channels, several detection algorithms are put forward in context of Cognitive Radio applications including Uniformly Most Powerful (UMP) test derived according to the Neyman-Pearson Lemma known as Neyman-Pearson (NP) test [2], Energy Detection (ED) [4], Match Filtering [5], Feature Detection Algorithms [6] proposed for individual SU and their cooperative counterpart for multiple SU sensing. A multidimensional CR receiver has been studied considering multiple receive dimensions at the CR receiver in the form of multiple antennas, over-sampled branches and cooperative nodes [7]–[10]. These methods are mostly based on the statistics of the eigenvalues of the received signal covariance matrix and use recent results from Random Matrix Theory (RMT).

In the last few years, Eigenvalue Based Detection (EBD) techniques received considerable attention in spectrum sensing literature with improved performance and less dependent on noise uncertainty [7]–[16]. Some of the popular EBD based techniques in present literature include Maximum Eigenvalue (ME) based [14], Eigenvalue Ratio Detector (ERD) [17], Signal Condition Number (SCN) based [10][12], Scaled Largest Eigenvalue (SLE) based [15][16], Akaike Information Criterion (AIC) [18], Minimum Description Length(MDL) [18]. Recently, more powerful techniques based on largest eigenvalue of the received covariance matrix, like Generalized Likelihood Root Test (GLRT) [20] and Roy's Largest Root Test (RLRT) [19] have been proposed and analyzed. Recently, a new algorithm known as EigenVEctor (EVE) test [21] has been introduced exploiting channel estimation parameter in the detection statistic whose performance is comparable with NP test.

Considering high performance detection algorithms like ED, RLRT and EVE test, the problem of unknown noise variance is crucial. In our previous work [21][22], the performance of hybrid approach of ED and Roy's Largest Root Test using estimated noise variance was carried out. It was suggested that, the optimum performance of ED and RLRT can be achieved even with the use of estimated noise variance by using a large number of slots for noise variance estimation.

In this work, we present a performance analysis of Roy's Largest Root Test (RLRT), Energy Detection (ED), EigenVEctor Test (EVE) and their hybrid approaches with noise variance estimation. Section II describes the system model and the NP test, which will be used as a benchmark. Section III illustrates the test statistics with known noise variance, while Section IV presents the hybrid approaches with estimated noise variance. Simulation results are presented in Section V, while in Section VI, some preliminary results of the optimization of Hybrid Energy Detection are presented. Finally, Section VII concludes the paper.

II. SYSTEM MODEL

Let us denote by K the number of antennas or cooperative sensors and by N the number of samples per sensing slot. We focus on a single source scenario, which is of interest for many detection problems in cognitive radio networks. The $K \times 1$ received vector at time n collects the baseband complex samples from the K antennas. The received samples are stored by the detector in the $K \times N$ matrix $\boldsymbol{Y}$.

Let us introduce the $1 \times N$ signal matrix $\boldsymbol{s} \triangleq [s_1 \cdots s_n \cdots s_N]$ and the $K \times N$ noise matrix $\boldsymbol{V} \triangleq [\boldsymbol{v}_1 \cdots \boldsymbol{v}_n \cdots \boldsymbol{v}_N]$ where,

- s_n is the transmitted complex signal sample at time n, modeled as Gaussian with zero mean and variance $\sigma_s^2 : s_n \sim \mathcal{N}_{\mathbb{C}}(0, \sigma_s^2)$

 ISBN: 978-1-61208-403-9

- $\boldsymbol{v}_n$ is a noise vector at time n, modeled as Gaussian with mean zero and variance σ_v^2 : $\boldsymbol{v}_n \sim \mathcal{N}_{\mathbb{C}}(\boldsymbol{0}_{K\times 1}, \sigma_v^2 \boldsymbol{I}_{K\times K})$

As all the signal samples s_n of $\boldsymbol{s}$ and the noise vectors $\boldsymbol{v}_n$ of $\boldsymbol{V}$ are assumed statistically independent, the detector must distinguish between Null and Alternate Hypothesis given by,

$$\boldsymbol{Y}|_{H_0} = \boldsymbol{V} \qquad \text{and} \qquad \boldsymbol{Y}|_{H_1} = \boldsymbol{h}\boldsymbol{s} + \boldsymbol{V}$$

where, $\boldsymbol{h}$ is the complex channel vector $\boldsymbol{h} = [h_1 \cdots h_K]^T$; assumed to be constant and memory-less during the sampling window.

Under $\mathcal{H}_1$, the average SNR at the receiver is defined as, $\rho \triangleq \frac{\mathcal{E}\|\boldsymbol{x}_n\|^2}{\mathcal{E}\|\boldsymbol{v}_n\|^2} = \frac{\sigma_s^2\|\boldsymbol{h}\|^2}{K\sigma_v^2}$ where, $||.||$ denotes the Euclidean norm and $\mathcal{E}$ the mean operator. The sample covariance matrix is given by $\boldsymbol{R} \triangleq \frac{1}{N}\boldsymbol{Y}\boldsymbol{Y}^H$ and $\lambda_1 \geq \cdots \geq \lambda_K$ its eigenvalues sorted in decreasing order.

The usual criterion for comparing two tests is to fix the false alarm rate P_{fa} and look for the test achieving the higher P_d. The Neyman Pearson (NP) lemma is known to provide the Uniformly Most Powerful (UMP) test, achieving the maximum possible P_d for any given value of P_{fa}. The NP criterion is applicable only when both both $\mathcal{H}_0$ and $\mathcal{H}_1$ are simple hypotheses. In our setting this is the case when both the noise level σ_v^2 and the channel vector $\boldsymbol{h}$ are a priori known. The NP test is given by the following likelihood ratio:

$$T_{NP} = \frac{p_1(\boldsymbol{Y}; \boldsymbol{h}, \sigma_s^2, \sigma_v^2)}{p_1(\boldsymbol{Y}; \sigma_v^2)} \tag{1}$$

and is known to be optimal, i.e., to achieve the maximum possible P_d for any given value of P_{fa}.

As an example, under the considered model, if the signal samples are independent Gaussian samples, the NP test is obtained by using:

$$\boldsymbol{p}_0(\boldsymbol{Y}; \sigma_v^2) = \frac{1}{(\pi\sigma_v^2)^{NK}} \exp\left(-\frac{N\boldsymbol{trR}}{\sigma_v^2}\right) \tag{2}$$

and

$$p_1(\boldsymbol{Y}; \boldsymbol{h}, \sigma_s^2, \sigma_v^2) = \frac{1}{(\pi^K det\boldsymbol{\Sigma})^N} \exp\left(-\boldsymbol{R}\boldsymbol{\Sigma}^{-1}\right) \tag{3}$$

where, $\boldsymbol{\Sigma} = \sigma_v^2 \mathbf{I}_k + \sigma_s^2 \boldsymbol{h}\boldsymbol{h}^H$

The NP test provides the best possible performance, but requires exact knowledge of both $\mathbf{h}$ and σ_v^2. For most practical applications, the knowledge of $\mathbf{h}$ and σ_v^2 is questionable.

III. Test statistics with known noise variance

To make the decision between $\mathcal{H}_0$ and $\mathcal{H}_1$, a test statistic compares a quantity T against a pre-defined threshold t: if $T > t$, $\mathcal{H}_1$ is selected, otherwise $\mathcal{H}_0$ is chosen. The test performance is evaluated by the false alarm probability and the detection probability, defined as:

$$P_d = \mathbb{P}(T > t|\mathcal{H}_1) \tag{4}$$
$$P_{fa} = \mathbb{P}(T > t|\mathcal{H}_0) \tag{5}$$

In practice, the decision threshold t is typically computed as a function of the target P_{fa}, to guarantee the Constant false Alarm rate (CFAR) property.

A. Roy's Largest Root Test (RLRT)

Using the information of the received signal matrix $\boldsymbol{Y}$ and assuming a perfect knowledge of the noise variance σ_v^2 and the channel parameter $\boldsymbol{h}$, test statistic for RLRT is given by

$$T_{RLRT} = \frac{\lambda_1}{\sigma_v^2}. \tag{6}$$

If $T_{RLRT} < t$ it decides in favor of Null Hypothesis $\mathcal{H}_0$ otherwise in favor of Alternate Hypothesis $\mathcal{H}_1$. The detection probability $P_d^{RLRT} > t|_{\mathcal{H}_1}$ and false alarm $P_{fa}^{RLRT} > t|_{\mathcal{H}_0}$ probabilities for this detector are well-known in the literature (e.g., [24]).

The optimality of RLRT in the class of semi-blind algorithms was pointed out in [25]. For a single emitting source, if the SNR is above the identifiability threshold given by $\rho > \rho_{Cric} = \frac{1}{\sqrt{KN}}$ [26], the signal is detectable by the largest eigenvalue λ_1 value. Starting from the NP test and using the asymptotic expansion of the hypergeometric function, it was shown in that, under known noise variance, distinguishing between $\mathcal{H}_0$ and $\mathcal{H}_1$ in the asymptotic regime ($N \to \infty$ with K fixed) depends to leading order only on λ_1.

B. Energy Detection (ED)

ED computes the average energy of the received signal matrix $\boldsymbol{Y}$ normalized by the noise variance σ_v^2 and compares it against a predefined threshold t_{ed}.

$$T_{ED} = \frac{1}{KN\sigma_v^2} \sum_{k=1}^{K}\sum_{n=1}^{N} |y_k(n)|^2. \tag{7}$$

If $T_{ED} < t_{ed}$ it decides in favor of Null Hypothesis $\mathcal{H}_0$ otherwise in favor of Alternate Hypothesis $\mathcal{H}_1$. The detection probability $P_d = Prob\{T_{ED} > t|_{H_1}\}$ and false alarm $P_{fa} = Prob\{T_{ED} > t|_{H_0}\}$ probabilities for this detector are well-known in the literature (e.g., [4]).

C. EigenVEctor Test (EVE)

The starting idea of the new test is that given a $\mathcal{H}_1$ slot, the eigenvector $\boldsymbol{e}_1$ associated to largest eigenvalue λ_1 provides an estimation of the channel vector $\boldsymbol{h}$.

Given S_{aux} signal slots available before the current sensing slot, we can construct a matrix of size $K \times (S_{aux} \cdot N)$ from all the samples and evaluate the eigenvector $\boldsymbol{e}_{aux}$ corresponding to largest eigenvalue. The proposed statistical test known as EVE test [10], which exploits the channel estimation parameter $\boldsymbol{e}_{aux}$ in its test statistic is defined as,

$$T_{EVE} = \frac{S_{aux}\left[\boldsymbol{e}_{aux}^H \boldsymbol{R}\,\boldsymbol{e}_{aux}\right] + \left[\boldsymbol{e}^H \boldsymbol{R}\,\boldsymbol{e}\right]}{\sigma_v^2(S_{aux}+1)} \tag{8}$$

Note that if $S_{aux} = 0$, the test reduces to

$$T_{EVE} = \frac{\boldsymbol{e}^H \boldsymbol{R}\,\boldsymbol{e}}{\sigma_v^2} = \frac{\|\boldsymbol{e}\|^2 \lambda_1}{\sigma_v^2} = \frac{\lambda_1}{\sigma_v^2} \tag{9}$$

and has the same statistical power of the RLRT.

 ISBN: 978-1-61208-403-9

IV. Hybrid test statistics

It is evident that the knowledge of the noise variance is imperative for the optimum performance of RLRT, ED and EVE tests. Unfortunately, the variation and the unpredictability of noise variance is unavoidable. Thus, the knowledge of the noise variance is one of the critical limitations of those tests for their ideal operation in low SNR. Under the considered scenario, noise variance can be estimated from S_{aux} auxiliary noise-only slots in which we are sure that the primary signal is absent.

Consider a sampling window of length M prior and adjacent to the detection window which contains noise-only samples for sure. Then the estimated noise variance from the noise-only samples using a Maximum Likelihood Estimation (MLE) can be written as,

$$\hat{\sigma}_v^2 = \frac{1}{KM} \sum_{k=1}^{K} \sum_{m=1}^{M} |v_{km}|^2 \tag{10}$$

If the noise variance is constant, the estimation can be averaged over S_{aux} successive noise-only slots and (10) can be modified by averaging over S_{aux} successive noise-only slots as,

$$\hat{\sigma}_v^2(S_{aux}) = \frac{1}{KS_{aux}M} \sum_{s=1}^{S_{aux}} \sum_{k=1}^{K} \sum_{m=1}^{M} |v_{km}|^2 \tag{11}$$

A. Hybrid RLRT (HRLRT)

Knowledge of the noise power is one of the critical limitation of RLRT for its operation in low SNR. Hybrid RLRT (HRLRT) [22] deals with the study of detection performance of the RLRT algorithm using noise variance estimated from S_{aux} auxiliary noise only slots where we are sure that the primary signal is absent. The test statistic of HRLRT can now be presented as,

$$T_{HRLRT} = \frac{\lambda_1}{\hat{\sigma}^2_{HRLRT}(S_{aux})} \tag{12}$$

where, $\hat{\sigma}^2_{HRLRT}(S_{aux})$ is the Maximum Likelihood Estimate of the true noise variance σ_v^2 given by (11).

Performance of HRLRT in terms of ROC parameters are derived and well justified in [22][23].

B. Hybrid ED (HED)

Hybrid ED (HED) [22] deals with the study of detection performance of the ED algorithm using noise variance estimated from S_{aux} auxiliary noise only slots where we are sure that the primary signal is absent. The test statistic of HED can be presented as,

$$T_{HED} = \frac{1}{KN\hat{\sigma}^2_{HED}(S_{aux})} \sum_{k=1}^{K} \sum_{n=1}^{N} |y_k(n)|^2 \tag{13}$$

where $\hat{\sigma}^2_{HED}(S_{aux})$ is computed as in (11) for HRLRT. The detection probability $P_d = Prob\{T_{HED} > t|_{H_1}\}$ and false alarm $P_{fa} = Prob\{T_{HED} > t|_{H_0}\}$ probabilities for this Hybrid ED can be referred in literature [22][23].

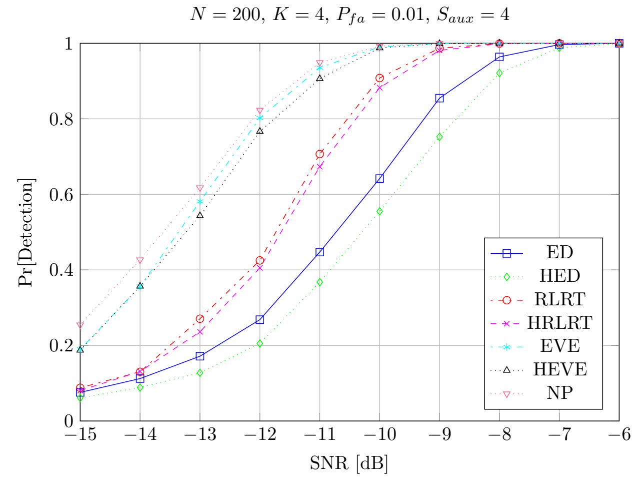

Figure 1. Performance curve, Pd vs. SNR, $K = 4$, $N = 200$

C. Hybrid EVE (HEVE)

If we apply the same hybrid approach for RLRT and ED of [22][23] to the new EVE test, we define a new Hybrid EigenVEctor (HEVE) test:

$$T_{HEVE} = \frac{S_{aux}\left[\boldsymbol{e}_{aux}^H \boldsymbol{R}\, \boldsymbol{e}_{aux}\right] + \left[\boldsymbol{e}^H \boldsymbol{R}\, \boldsymbol{e}\right]}{\hat{\sigma}^2_{HEVE}(S_{aux}) \cdot (S_{aux}+1)} \tag{14}$$

where $\hat{\sigma}^2_{HEVE}(S_{aux})$ is computed as in (11) for HRLRT and HED. In fact, we use in HEVE the same number of slots S_{aux} both to compute the eigenvector $\boldsymbol{e}_{aux}$ for channel estimation and to estimate the noise variance $\hat{\sigma}^2_{HEVE}(S_{aux})$. Similarly to (9) if $S_{aux} = 0$, the test reduces to $\lambda_1/\hat{\sigma}^2_{HEVE}(S_{aux})$, which has the same statistical power of HRLRT.

V. Simulation results

Results are shown in terms of Receiver Operating Characteristic (ROC) curves (P_d vs. P_{fa}) and performance curves, in which P_d is plotted against SNR, by fixing P_{fa}. All the tests described in Section III-IV have been simulated by using a Montecarlo approach with 10000 iterations for each SNR value. The primary signal has a Gaussian distribution and the typical Rayleigh flat fading channel scenario has been considered. In performance curves, P_{fa} is fixed to 10^{-2} while in ROC curves, SNR = -12 dB.

Figures 1 and 2 show respectively the performance and ROC curves of all the test statistics with 4 antennas, 200 samples per slot and 4 auxiliary slots. It can be noticed that EVE and HEVE are clearly capable to significantly reduce the gap with NP wrt RLRT. The gap between EVE and RLRT is 1 dB at $P_d = 0.9$. In general, the hybrid approaches HEVE, HRLRT and HED are very close in performance with their respective known-noise tests.

Figures 3 and 4 show how the number of slots affects the performance of these tests. The number of antennas is equal to 4, while we used 200 samples per slot. It is evident that there is an important gap between 2 and 4 auxiliary slots (especially for HEVE), while the curves with 4 and 6 auxiliary slots are almost overlapped.

Finally, we show 2 other performance curves. In Figure 5, the detection probability is plotted against the number of

 ISBN: 978-1-61208-403-9

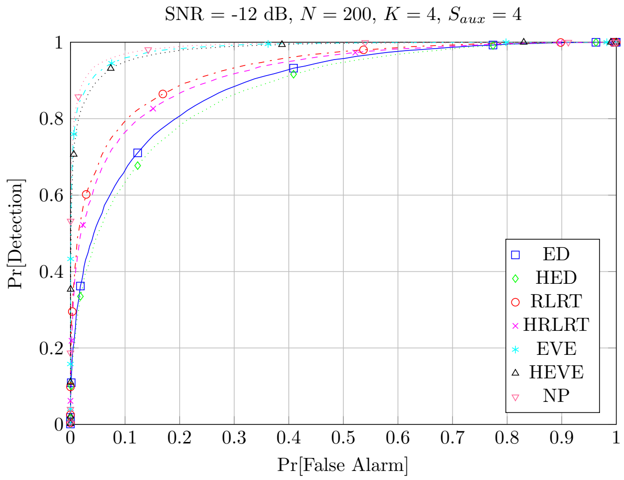

Figure 2. ROC curve, $K = 4$, $N = 200$

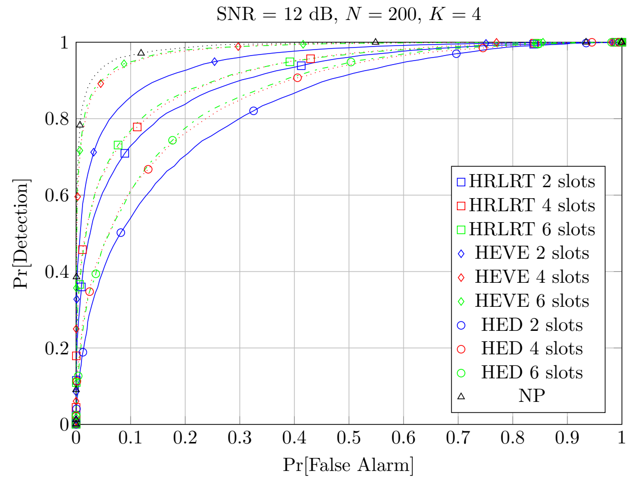

Figure 4. ROC curve, with 2, 4, 6 auxiliary slots

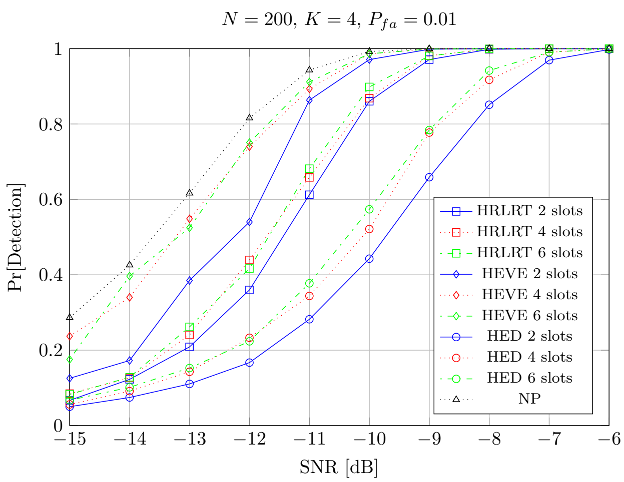

Figure 3. Performance curve, Pd vs. SNR, with 2, 4, 6 auxiliary slots

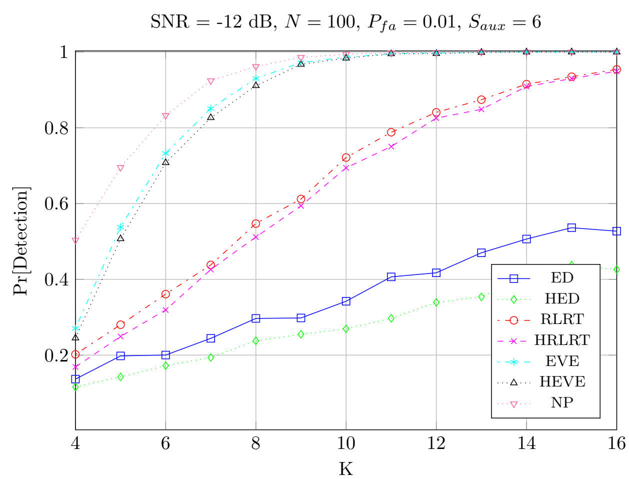

Figure 5. Performance curve, Pd vs. K, $N = 100$

antennas, with 100 samples per slot and 6 auxiliary slots, while in Figure 6, P_d is plotted against the number of samples, with 4 antennas and 6 auxiliary slots. NP and the EVE group tests require a much smaller number of antennas or sensors to reach $P_d \simeq 1$ wrt to all other tests.

VI. Optimization of Hybrid Energy Detection

In this section, we show some preliminary results on the optimization of Hybrid Energy Detection. Let us assume that the secondary user has a fixed time window for both noise estimation and detection, i.e., the number of samples that the SU can use for both noise estimation and signal detection is constant. For the sake of simplicity, the Maximum Likelihood expression of (10) will be considered for the optimization of HED described in IV-B. Considering K antennas, M samples are used for estimation and N samples for detection. Our fixed time constraint implies $M+N = c$ where c is a constant, hence our goal is to find the optimal M (and consequently optimal N) that gives the maximum detection probability.

In [22][23] the mathematical analysis of HED was performed, the false alarm and detection probability expressions are the starting point of our optimization task. The False Alarm Probability $P_{fa}^{(HED)}$ for number of sensors K, number of samples N, number of noise estimation samples M and threshold t is given by,

$$P_{fa}^{(HED)} = Q\left[\frac{t-1}{\sqrt{\frac{M+Nt^2}{KMN}}}\right] \tag{15}$$

Similarly, the Probability of Detection $P_D^{(HED)}$ in similar scenario is given by,

$$P_d^{(HED)} = Q\left[\frac{(t-1-\rho)}{\sqrt{\frac{t^2}{KM} + \frac{K\rho^2+2\rho+1}{KN}}}\right] \tag{16}$$

where ρ is the signal-to-noise ratio.

First of all, from (15) we find the threshold t expression

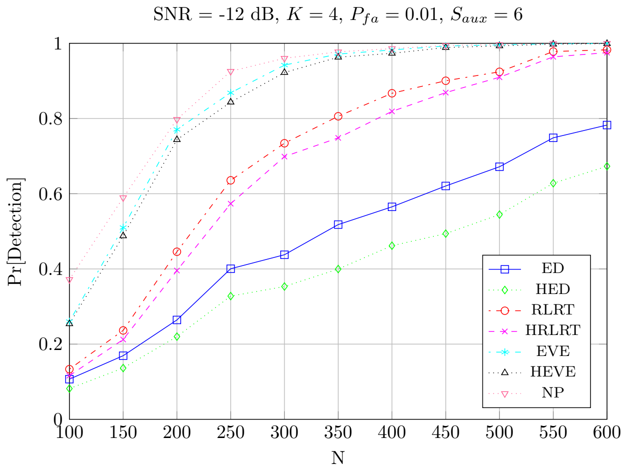

Figure 6. Performance curve, Pd vs. N, $K = 4$

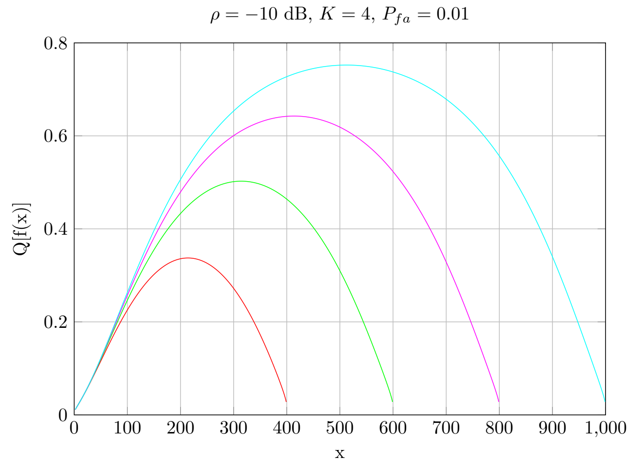

Figure 7. Probability of detection as a function of M given $M + N =$ const.

as a function of the P_{fa},

$$t = \frac{M\left(K + \epsilon\sqrt{\frac{KM+KN-\epsilon^2}{MN}}\right)}{KM - \epsilon^2} \tag{17}$$

where $\epsilon = Q^{-1}[P_{fa}]$. This is the only acceptable solution ($t > 1$) of a second degree equation. Unless KM is smaller than ϵ^2 (which is of no interest), this is always true.

By substituting (17) in (16) we obtain the following expression:

$$P_d = Q\left[\frac{\frac{M\left(K+\epsilon\sqrt{\frac{KM+KN-\epsilon^2}{MN}}\right)}{KM-\epsilon^2} - 1 - \rho}{\sqrt{\frac{M\left(K+\epsilon\sqrt{\frac{KM+KN-\epsilon^2}{MN}}\right)^2}{K(KM-\epsilon^2)^2} + \frac{K\rho^2+2\rho+1}{KN}}}\right] \tag{18}$$

Let us now use the following substitutions:

$$M = x \tag{19}$$
$$N = c - x \tag{20}$$

where $x \in \mathbb{N}$ and $c = M + N$.

We first rewrite the threshold expression in (17):

$$t = \frac{x(K + \epsilon\sqrt{\frac{Kc-\epsilon^2}{xc-x^2}})}{Kx - \epsilon^2} \tag{21}$$

Then, we rewrite the argument of the Q-function of (18):

$$f(x) = \frac{\frac{x\left(K+\epsilon\sqrt{\frac{Kc-\epsilon^2}{cx-x^2}}\right)}{Kx-\epsilon^2} - 1 - \rho}{\sqrt{\frac{x\left[K^2+\frac{\epsilon^2(Kc-\epsilon^2)}{cx-x^2}+2KQ\sqrt{\frac{Kc-\epsilon^2}{cx-x^2}}\right]}{K(K^2x^2+\epsilon^4-2\epsilon^2Kx)} + \frac{K\rho^2+2\rho+1}{Kc-Kx}}} \tag{22}$$

Figure 7 shows the probability of detection of HED as a function of M for different values of $M+N$, with 4 antennas, SNR equal to -10dB and P_{fa} equal to 10^{-2}. It is clear to see that, when c samples are available for both estimation and detection, the highest probability of detection occurs for:

$$M \approx N \approx \frac{M+N}{2} \tag{23}$$

Hence, given a time slot for spectrum sensing, the best performance occurs when estimation and detection slots are equally split.

VII. CONCLUSIONS

In this paper, some important classes of multi-antenna spectrum sensing algorithms have been considered. The hybrid approach of method based on the eigenvector of the covariance matrix has been introduced. Performance of the new hybrid test has been compared with the well-known RLRT end ED together with their hybrid approaches HRLRT and HED. It is shown that the EVE test and its hybrid approach are able to outperform RLRT, ED and they respective hybrid approaches, furthermore it can significantly reduce the gap with the NP test. Finally, given a fixed time slot or number of samples for HED, it is concluded that estimation and detection slots should be equally divided in order to achieve the optimal performance.

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 ISBN: 978-1-61208-403-9