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Minimum Eigenvalue Detection for Spectrum Sensing in Cognitive Radio

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ABSTRACT

Spectrum sensing is a key task for cognitive radio. Our motivation is to increase the probability of detection for spectrum sensing in cognitive radio. In this paper, we proposed a new semi blind method which is based on minimum Eigenvalue of a covariance matrix. The ratio of the minimum eigenvalue to noise power is used as the test statistic. The method does not need channel and signal information as prior knowledge. Eigenvalue based algorithm perform better than energy detection for correlated signal. Our proposed method is better than the maximum eigenvalue and energy detection for correlated signal. We perform Simulation which is based on digital TV signal. In all tests, our method performs better than maximum eigenvalue detection and energy detection.

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1. INTRODUCTION

The Advanced radio technology with emerging applications in current static and non-overlapped Industrial, Scientific and Medical (ISM) spectrum band leads in spectrum scarcity. Hence, available spectrum should be efficiently managed to provide higher data rate, which is difficult with current static spectrum allocation. According to Federal Communication Commission (FCC), larger amount of unused spectrum is available in licensed spectrum which is not effectively used due to non-uniform spectral demand in time, frequency and space. This reveals that inadequate spectrum management policies is the main subject for spectrum scarcity. To overcome this, the FCC approved to allow existing unlicensed radio services in the licensed TVWS (TV white space) through Cognitive radio. CR users share temporary licensed unused spectrum opportunistically without interrupting legitimate user's communication through software defined radio. Since, cognitive radio works on secondary basis, it should vacate current communicating channel whenever primary user is active in current spectrum band to avoid interference [1-3]. One of the examples of Cognitive radio is IEEE 802.22 wireless regional area network that spectrum reuse concept in UHF/VHF bands [4].

Many spectrum sensing methods have been proposed namely Energy detection [5], cyclostationary detection [5], the matched filtering [5], likelihood ratio test (LRT) [5], covariance based sensing [5] and wavelet-based sensing [5]. Every method has its own advantages and disadvantages. For example, energy detection is the most commonly used because it does not require any information about the signal and have low complexity. The basic drawback with energy detection is optimal for independent and identically distributed (i.i.d) signals, but not for correlated signals [5]. Matched filter [5] should know about knowledge of the signal and different matched filter is required for different signal. Cyclostationary detection has much higher complexity and requires knowledge of the cyclic frequencies [5]. On the other side eigenvalue based spectrum sensing is much better than existing sensing algorithms because it do not need any information of signal and Channel. Furthermore, it doesn't require synchronization [6-11].

Eigenvalue spectrum sensing algorithms can be divided into two types namely noise power based eigenvalue and eigenvalue without noise power. There have been several existing algorithms which do not require noise power. These are maximum-minimum-eigenvalue (MME) [6-8], Energy with minimum eigenvalue (EME) [8], maximum-eigenvalues-trace (MET) [9], arithmetic mean-geometric-mean (AM-GM) [9], maximum-eigenvalue-geometric-mean (ME-GM) [10], contra-harmonic-mean-minimum-eigenvalue (CHM) [11], maximum-eigenvalue-harmonic mean (ME-HM) [11] and maximum-eigenvalue-contra-harmonic-mean-p (ME-CHM-p) [11]. On the other hand, noise power based maximum eigenvalue (MAX) detection [12] has better performance compared with eigenvalue without noise power. In this paper, authors proposed Minimum eigenvalue (MIN) algorithm which is based on covariance matrix. The ratio of minimum eigenvalue to noise power is used as the test statistic. The proposed method has a higher probability of detection at low SNR compared with Maximum eigenvalue.

The rest of the paper is organized as follows. Section.2 briefly explains about system model and background information. In Section 3, the minimum eigenvalue-based sensing algorithm is proposed and Simulation results and discussion are presented in Section 4 and finally conclusion in Section 5.

2. SYSTEM MODEL

Consider a system in which a receiver/detector with an antenna is connected to signal processing unit to process the signal. Also note that the antenna is able to send the received signal to it is processing unit. For signal detection, we use hypothesis testing. Hypothesis testing is a method in which we claim the presence of signal. There are two hypothesis namely H_0 or null hypothesis and H_1 or alternate hypothesis. H_0 is the representation for signal does not present or only noise is present and H_1 is the representation for signal and noise both are present at same time. The received signal at the antenna is given by

$$H_0 : x(n) = \eta(n) \tag{1}$$

$$H_1 : x(n) = s(n) + \eta(n) \quad n = 1, \ldots, N \tag{2}$$

Where $s(n)$ is the received source signal samples passed through a wireless channel consisting of multipath fading, path loss and time dispersion effects at antenna/receiver and $\eta(n)$ is the received noise at antenna/receiver. The received source signal can be written as

$$s(n) = \sum_{k=1}^{N_p} \sum_{l=0}^{q_k} h_k(l)\tilde{s}_k(n-l) \tag{3}$$

Where N_p is the number primary signal, $\tilde{s}_k(n)$ transmitted primary signal from primary user or antenna k^{th}, $h_k(l)$ denotes the propagation channel coefficient from the k^{th} primary user or antenna to the receiver/antenna and q_k is the channel order for h_k.

Two probabilities are of interest for channel sensing: probability of detection and probability of false alarm. Probability of false alarmP_{fa} defines at the hypothesis H_0 and probability detection P_d, which claims the presence of the primary user signal defines at the hypothesis H_1.

3. MINIMUM EIGEN VALUE DETECTION

$$\mathbf{X}=\begin{bmatrix} x(N) & 0 & 0 & \cdots & \cdots & 0 \\ x(N-1) & x(N-1) & 0 & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & x(N-L+1) \\ \vdots & \vdots & \vdots & \vdots & \vdots & x(N-L) \\ \vdots & \vdots & \vdots & \vdots & \vdots & x(N-L-1) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x(1) & x(1) & x(1) & \cdots & \cdots & x(1) \end{bmatrix}^{T}_{N\ X\ L} \quad (4)$$

In the first step, we need to build a matrix **X** with N number of signal samples received from the antenna /receiver by L (smoothing factor) time stacking the signal sample, then we find sample covariance matrix of matrix **X.** Our last step is to find the minimum eigenvalue. The matrix X can be representedasshown in (4). Also note that, to reduce the complexity of the algorithm we need to set the value of L as smallas possible.

3.1. Sample Covariance Matrix

A sample covariancematrix is a matrix whose elements in the i, j position is the covariance between the i^{th} and j^{th} elements of a random vector. Each element of the vector is a scalar random variable with a finite number of observed samples. The sample covariance matrix of the received signal can calculate by using the following formula.

$$\mathbf{R_x}=\frac{1}{N}(\mathbf{XX}^T) \quad (5)$$

3.2. Eigenvalue

Eigenvalues are scalar values called lambda (λ) of a square matrix A, if there is a nontrivial solution of a vector x called eigenvector such that: (A -λI) x=0 Or (A- λI) =0. The idea of eigenvalues is used in signal detection is to find the noise in signal samples by finding the correlation between samples. As we know that (ideally) noise samples are uncorrelated with each other. When there is no signal, the received signal covariance matrix become identity matrix multiply by noise power ($\sigma^2 I$) which results all eigenvalues of this matrix become same as noise power.

3.3. Maximum Eigenvalues Verses Minimum Eigenvalues

Practically, the maximum eigenvalues fluctuate more rapidly as compared minimum eigenvalues at particular SNR level, or in other words, at particular SNR level, variance of maximum eigenvalues comparatively greater than variance minimum eigenvalues This results more minimum eigenvalues fall above to its threshold value as compared to maximum eigenvalues. This is a fundamental reason which maximizes the probability of detection of minimum eigenvalues relative to maximum eigenvalues.

3.4. Algorithm

Step 1. Calculate the sample covariance matrix of the received signal.

Step 2. Obtain the minimum eigenvalue $\lambda_{\min}(N)$ of the sample covariance matrix.

Step 3. Decision: if $\frac{\lambda_{\min}(N)}{\sigma^2} > \gamma$ then signal is present otherwise, signal is absent.

Here γ is a threshold and σ^2 noise power.

3.5. Theoretical Verification

Let consider $\mathbf{R_s}$ is the signal covariance matrix and $\sigma_\eta^2\mathbf{I}$ is a noise covariance matrix. At receiver/antenna the received signal covariance matrix $\mathbf{R_x}$ is as follows [6-12].

$$\mathbf{R}_{\mathbf{x},(L\ X\ L)}=\mathbf{R}_{\mathbf{s},(L\ X\ L)}+\sigma_\eta^2\mathbf{I}_L \quad (6)$$

Above equation represents when the signal is present the received signal covariance matrix $\mathbf{R}_x$ is the sum of signalcovariance matrix $\mathbf{R}_s$ and noise covariance matrix $\sigma_\eta^2\mathbf{I}$. Note that practically, to reduce the complexity of the algorithm we chose a small value of **L**. At this case, if there is signal the minimum eigenvalue of received signals covariance matrix is greater than noise power $\boldsymbol{\lambda}_{min}(\mathbf{R}_x) > \sigma_\eta^2$. We can represent eigenvalues of a received signal covariance matrix as follows [6-12].

$$\boldsymbol{\lambda}_n(\mathbf{R}_x) = \overline{\boldsymbol{\lambda}}_n(\mathbf{R}_s) + \sigma_\eta^2 \qquad (7)$$

Where λ and $\overline{\lambda}$ are the eigenvalues of received covariance matrix $\mathbf{R}_x$ and signal covariance matrix $\mathbf{R}_s$ respectively. Surely, if the signal is present $\boldsymbol{\lambda}_{\min}(\mathbf{R}_x) = \overline{\boldsymbol{\lambda}}_{\min}(\mathbf{R}_s) + \sigma_\eta^2$ which results $\frac{\lambda_{\min}}{\sigma_\eta^2} > \gamma$. On the other side, when signal is not present, the signal covariance matrix $\mathbf{R}_s = 0$ is equal to zero, this result the minimum eigenvalue $\boldsymbol{\lambda}_{\min}(\mathbf{R}_x) = \sigma_\eta^2$. Hence, signal can also be detected by checking the ratio $\frac{\lambda_{\min}}{\sigma_\eta^2}$, if the ratio is greaterthen threshold, signal is present otherwise, signal is absent. Where γ is threshold (theoretically $\gamma=1$).

3.6. Complexity

The algorithm runs in two parts. Part1: calculation of the covariance matrix. Part 2: the eigenvalue decomposition of the covariance matrix. For the first part, the complexity of a calculating covariance matrix is $O(L^2N)$ and for second part, complexity of calculating eigenvalue is $O(L^3)$. The total complexity (multiplications and additions, respectively) is therefore as follows:

$$O(L^2N) + O(L^3) \qquad (8)$$

4. SIMULATION AND DISCUSSION

In this section, we will discuss the effect of sample length, smoothing factor, ROC and present the probability of detection with different SNR levels. Also noted that the eigenvalue distribution of $\mathbf{R}_x$ is very complicated [13-16]. This makes theoretical determination of threshold very difficult. However, we set a threshold by using simulation, the method to find threshold isat first generate white Gaussian noise as the input (no signal). In Second step obtained minimum eigenvalues of noise samples and sort these eigenvalues in descendingorder. Lastly take i^{th} eigenvalues as a threshold to meet $p_{fa} \leq 0.1$ requirement. Value of i can be calculate by $\frac{n_s}{p_{fa}}$.Where n_s is number of iterations and p_{fa} i.e. probability of false alarm.

Our all tests for the algorithms are based on the captured ATSC DTV signals, these signals are collected at Washington D.C USA. The location of the receiver is 48.41 miles away from the DTV station [17]. The sampling rate of the vestigial sideband (VSB) DTV signal is 10.762 MHz [18] on the other side the sampling rate at the receiver is two times higher than the transmit rate.

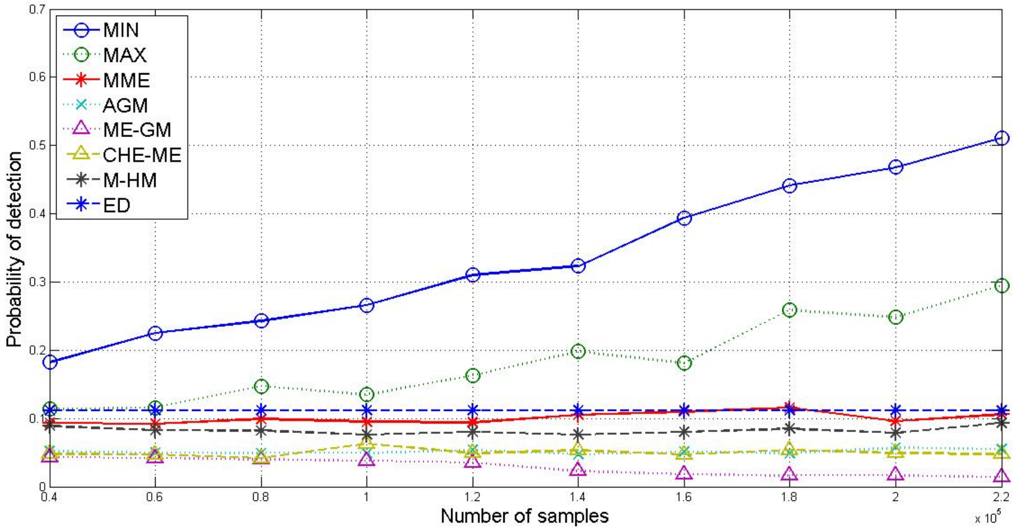

Figure 1. Probability of detection for DTV Signal SNR=-27, L=16.

In Figure 1, we test the impact of the number of samples. The SNR is fixed at -27dB and vary the number of samples from 40000 to 220000. It is seen that the $P_d$of the Minimum eigenvalue algorithm increases more rapidly as compared with blindeigenvaluealgorithm with the numbers of samples, while the energy detection almost have no changed. In Figure 2, we test the impact of the smoothing factor. We fix the SNR at -27 dB, *N*= 100000 and vary the smoothing factor *L* from 4 to 16. It is seen that the probability of detection of all algorithms slightly decreases with increase of *L*, but the probability of detection of minimum eigenvalue iscomparativelygreater than the existing eigenvalue detectionalgorithms.

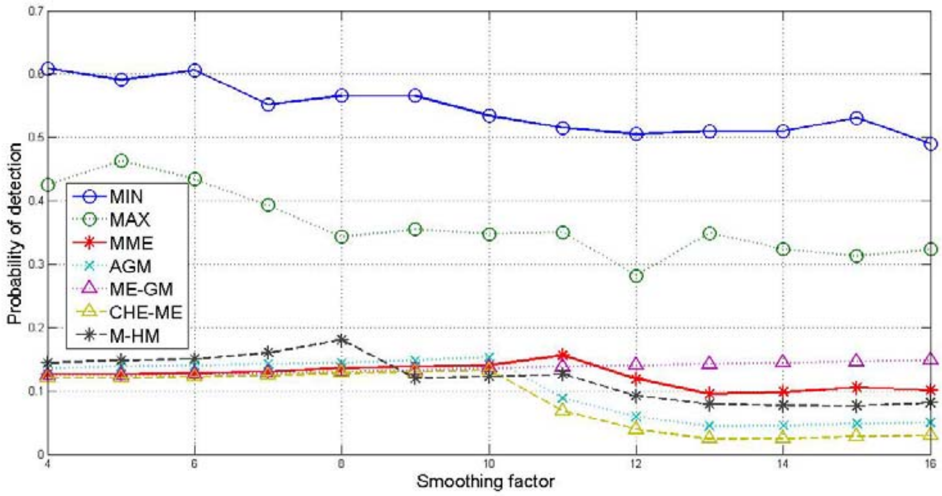

Figure 2. Impact of smoothing factor for DTV Signal SNR=-27, N=100000.

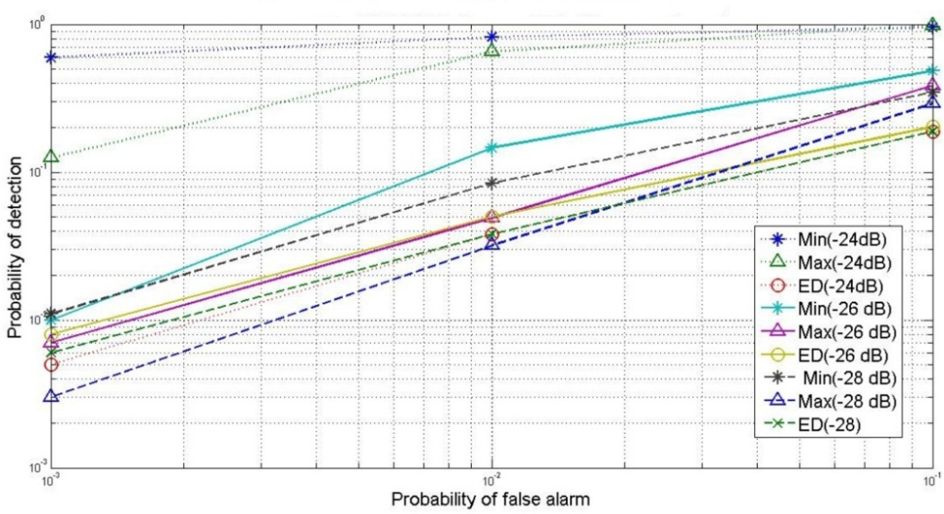

Figure 3. Receiver operating curve for DTV Signal L=16, N=100000.

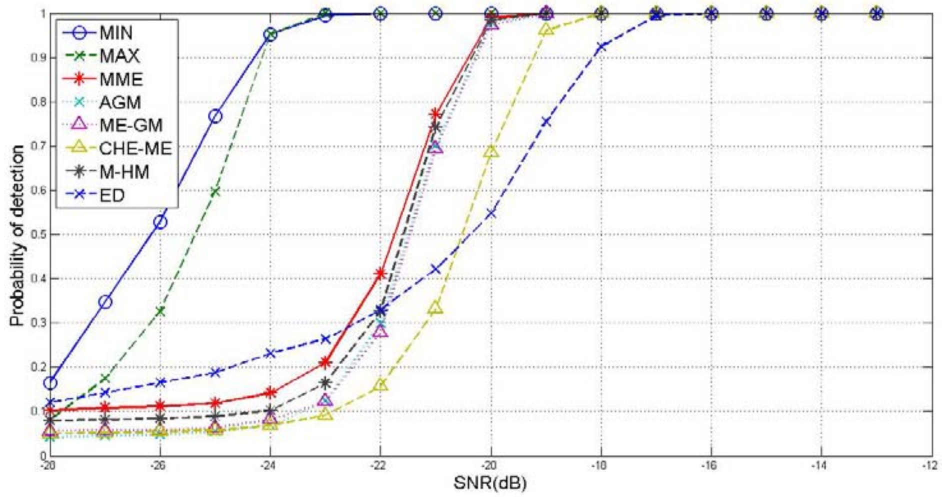

Figure 4. Probability of detection for DTV Signal L=16, N=100000

In Figure 3, the Receiver Operating Characteristics (ROC) curve is shown where the sample size is N= 100000, L=16 and SNR=-24, -26, -28. We slightly adjust the thresholds to keep all the methods having the same values. For the energy detection, the threshold is based on the predicted noise power and theoretical formula is very inaccurate to obtain the target P_{fa}. The graph shows that minimum eigenvalue is the best among all the methods. Figure 4, gives the probability for DTV signal. We setsmoothing factor L=16, wwhite noises are added to obtain the various SNR levels where the samples size is N=100000. This result shows that the detection probability of minimum eigenvalue detection algorithm performs better thantraditionaleigenvalues and energy detectionalgorithms.

5. CONCLUSION

In this paper, we propose a new eigenvalue spectrum sensing algorithm based on covariance matrix. The ratio of the minimum eigenvalue to noise power is used as test statistic the method need only noise power. The proposed method is better than maximum eigenvalue detection and the energy detection for correlated signals**.** Our method can be used for various signal detection applications without knowledge of signal and the channel.

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