# Proportional study of Eigen value Based Spectrum Sensing Techniques for Cognitive Radio Network

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***Abstract*: Cognitive radio, a solution for resolving spectrum insufficiency problem clashed in many countries, has been regarded as one of the most auspicious technologies for future wireless communications. The captious requirement in cognitive radio design is to ensure that the primary users are protected. One way to do so is called spectrum sensing. Due to various functional confinements such as noise power uncertainty, conventional sensing methods are difficult to achieve satisfied detection performance in low signal-to-noise ratio situation. Spectrum sensing is a fundamental component in a cognitive radio. The paper proposes new sensing methods based on the eigenvalues of the covariance matrix of signals received at the secondary users. In this two sensing algorithms are advisable, one is based on the ratio of the maximum eigenvalue to minimum eigenvalue and other is based on the ratio of the average eigenvalue to minimum eigenvalue. Exploring some latest random matrix theories (RMT), we specify the distributions of these ratios and derive the probabilities of false alarm and probabilities of detection for the projected algorithms. Also find the thresholds of the methods for a given probability of false alarm. The projected methods overcome the noise uncertainty problem, and can even perform better than the energy detection and Cyclostationary detection when the signals to be detected are highly correlated. The methods can be used for various signal detection utilization *without* requiring the knowledge of signal, channel and noise power.**

***Keywords*: *Cognitive Radio System, PU, SU, SNR, Cyclostationary, Detection Alarm, False Alarm.***

## I. INTRODUCTION

The exponential and unheralded growth in wireless communication demands additional bandwidth or efficient bandwidth utilization of limited spectra. Cognitive radio (CR) has come out as a leading technology because it can intelligently sense an soiled spectrum without creating any harmful interference to authorized users.

The Cognitive Radio technology will enable the user to find out which portion of the spectrum is available, detect the presence of primary user (spectrum sensing), select the available channel (spectrum management), coordinates the access to the channel with other users (spectrum sharing) and transmigrate to some other channel whenever the primary user is detected (spectrum mobility) [1].Cognitive Radio will modify the user to determine the presence of primary user, which portion of spectrum is available, in other words to detect the white spaces and it is called spectrum sensing, select the best available channel or to predicted how long the white spaces are available to use for unlicensed users also called spectrum management, to distribute the spectrum holes among the other secondary users which is called spectrum sharing and switch to other channel whenever primary user is sensed and this functionality of CR called spectrum mobility[2]. Among these function Spectrum Sensing is considered to be the one of the most important critical task to establish Cognitive Radio Networks.

The key objective behind spectrum sensing and detection is to maximize the probability of detection without the probability of false alarm while minimizing the complexity and time to sense/detect the radio. Cognitive Radio is defined by the information that it can adapt, according to the environment, by dynamic change its transmitting parameters, such as modulation, frequency, frame format, etc. [2]. The main challenges with CRs or secondary users (SUs) are that it should awareness the PU signal without any interference. This work focuses on the spectrum sensing techniques that are found on primary transmitter detection [3]. The basic and simple sensing techniques are Energy detection (ED) [4-7], Matched filter detection (MFD) [8-11], Cyclostationary feature detection (CFD) [12-14]. The focus of this work is on the study of another spectrum sensing detection methods namely Maximum eigenvalue to Minimum eigenvalue ratio detector (ERD) [15- 17] and one proposed modification in Maximum eigenvalue to Minimum eigenvalue ratio detector is Mean eigenvalue ratio detector (MERD). Comparative analysis has been carried out in terms of probability of false alarm Pf, probability of detection alarm $P_d$, and probability of miss detection $P_m$

The rest of the paper is organized as follows. Section II briefly describes the system model for all spectrum detection techniques under test. Simulation setup for performance analysis of the five spectrum sensing techniques with configuration of parameters is presented in Section III .Simulation results with comparative sensing performance is illustrated in Section IV. Finally conclusions are drawn in Section V.

## II. SYSTEM MODEL

In non-cooperative sensing we have to find the primary transmitters that are transmitting at any given time by using local measurements and local observations. The hypothesis for signal detection at time t can be described as [1].

$$x(n) = \begin{cases} w(n), & H_0 \\ s(n) + h(n) + w(n), & H_1 \end{cases} \quad (1)$$

Where,
x (n) =Signal received by CR user,
w (n) =Additive white Gaussian noise,
s (n) =PU Signal,
h (n) =Channel gain

$H_0$: corresponds to the absence of the signal and presence of only noise.
$H_1$: corresponds to the presence of both signal and noise.

Thus, for the two state hypothesis numbers of important cases are:-

**1)** $H_1$ turns out to be TRUE in case of presence of primary user i.e. P ($H_1$ / $H_1$) is known as Probability of Detection ($P_d$).

**2)** $H_0$ turns out to be TRUE in case of presence of primary user i.e. P ($H_0$ / $H_1$) is known as Probability of Missed-Detection ($P_m$).

**3)** $H_1$ turns out to be TRUE in case of absence of primary user i.e. P ($H_1$ / $H_0$) is known as Probability of False Alarm ($P_f$).

### *1. Maximum Eigenvalue to Minimum Eigenvalue Ratio Detector*

Energy detection does not need any primary information of the signal to be detected and is robust to unknown dispersive channel. However, energy detection distrusts on the knowledge of accurate noise power, and inaccurate estimation of the noise power leads to SNR wall and high probability of false alarm [20-22]. Thus energy detection is vulnerable to the noise uncertainty. Finally, while energy detection is best for detecting independent and identically distributed (ijd) signal, it is not best for detecting correlated signal, which is the case for most practical applications.

To overcome the shortcomings of energy detection, we use new methods based on the eigenvalue of the covariance matrix of the received signal [27]. It is shown that the ratio of the maximum or average eigenvalue to the minimum eigenvalue can be used to detect the presence of the signal. Based on some latest random matrix theories (RMT) [16-18], we quantify the distributions of these ratios and find the detection thresholds for the detection algorithms. The probability of false alarm and probability of detection are also derived by using the RMT. The method overcome the noise uncertainty problem and can even perform better than energy detection when the signals to be detected are highly correlated. The methods can be used for various signal detection applications without knowledge of the signal, the channel and noise power. Furthermore, different from matched filtering, the methods do not require accurate synchronization. Simulations based on randomly generated signals, wireless micro-phone signals and captured digital television (DTV) signals are carried out to verify the effectiveness of the methods. It is shown that the ratio of the maximum eigenvalue to the minimum eigenvalue can be used to detect the signal existence. Based on some latest random matrix theories (RMT), we can quantize the ratio and find the threshold. The probability of false alarm is also found by using the RMT. The method overcomes the noise uncertainty difficulty while keeps the advantages of the energy detection.

Assume that we are interested in the frequency band with central frequency and bandwidth W. We sample the received signal at a sampling rate higher than the Nyquist rate. Assume that there are M≥1 receivers (antennas). The received discrete signal at receiver is denoted by xi (n) (I = 1, 2…., M). There are two hypotheses $H_0$: there exists only noise (no signal); (2) hypothesis $H_1$: there exist both noise and signal. At hypothesis $H_0$, the received signal at receiver i is

$$xi(n) = \sum_{j=1}^{P} \sum_{k=0}^{Nij} hij(k)sj(n-k) + \eta i(n), \quad (2)$$

Where, $s_j$(n) (j = 1, 2,…, P ) are P≥1 source signals, $h_{ij}$(k) is the channel response from source signal j to receiver i, $N_{iji}$ s the order of channel $h_{ij}$(k), and $\eta_i$(n)is the noise samples. Based on the received signals with little or no information on the source signals, channel responses and noise power, a sensing algorithm should make a decision on the existence of signals. Let $P_d$ be the probability of detection, which is at hypothesis H1, the probability of the algorithm having detected signal. Let $P_{fa}$ be the probability of false alarm that is at Ho, the probability of the algorithm having detected the signal. Obviously, for a good detection algorithm, $P_d$ should be high and $P_{fa}$ should be low. The requirements of $P_d$ and $P_{fa}$ depend on the applications.

Maximum Minimum Eigenvalue Detection

Letting $N_j$ = max ($N_{ij}$), zero padding $h_{ij}$ (k) if necessary, and defining

$$x(n) = [x_1(n), x_2(n) \ldots\ldots, x_M(n)]T \quad (3)$$

$$h_i(n) = \left[h_{1j}(n), h_{2j}(n) \ldots\ldots. h_{Mj}(n)\right]T \quad (4)$$

$$\eta(n) = [\eta_1(n), \eta_2(n), \ldots\ldots. \eta_M(n)]\, T \quad (5)$$

We can express (3) into vector form as

$$x(n) = \sum_{j=1}^{P} \sum_{k=0}^{Nj} hj(k)sj(n-k) + \eta(n), \;\; n = 0,1 \ldots$$

Considering L consecutive outputs and defining

$$\hat{x}(n) = [x^T(n), x^T(n-1), \ldots\ldots. x^T(n-L)+1]T \quad (6)$$

$$\hat{\eta}(n) = [\eta^T(n), \eta^T(n-1), \ldots\ldots. \eta^T(n-L+1)]T \quad (7)$$

$\hat{s}(n) = [s_1(n), \ldots . s_1(n-1) \ldots . s_1(n-N_1-L+$
*1.. spn.....s1n−Np−L+1T* (8)

We get

$$\hat{x}(n) = \mathbb{H}\hat{s}(n) + \hat{\eta}(n) \quad (9)$$

The following assumption for statistical properties of transmitted symbols and channel noise are assumed
(A1) Noise is white.
(A2) Noise and transmitted signal are correlated.
Let R (Ns) be the sample covariance matrix of the received signal, that is,

$$\mathrm{R(Ns)} = 1/\mathrm{Ns} \sum_{n=L}^{L-1+Ns} x^n x^{+(n)}, \quad (10)$$

Where, Ns is the number of collected samples. If Ns is large, based on the assumption, we can verify that

$$R(N_s) = \ddot{H}R_s\ddot{H}^{+} + \sigma 2\eta\, I^{ML} \quad (11)$$

Where, Rs is statically covariance matrix of the input signal. $R_s = E(\hat{s}(n))\sigma 2\eta$ is the variance of the noise, and $I^{ML}$ is the identity matrix of order ML

Let $\lambda_{max}$ and $\lambda_{min}$ be the maximum and minimum eigenvalue of R and $\rho_{max}$ and $\rho_{min}$ are the maximum and minimum eigen values of $\ddot{H}R_s\,\ddot{H}^{+}$.Then $\lambda_{max} = \rho_{max} + \sigma 2Ŋ$ and $\lambda_{min} = \rho_{min} + \sigma 2Ŋ$ , $\rho_{max} = \rho_{min}$ if and only if $\ddot{H}R_s\,\ddot{H}^{+} = \delta I^{ML}$, δ is positive number. In practice, when signal present, it is very unlikely that $\ddot{H}R_s\,\ddot{H}^{+} = \delta\, I^{ML}$. Hence if there is no signal $\lambda_{max}/\lambda_{min} = 1$; otherwise, $\lambda_{max}/\lambda_{min} > 1$. The ratio of $\lambda_{max}/\lambda_{min}$ can used to detect the presence of signal.

Maximum Minimum Eigenvalue Detection steps
Step1. Compute

$$\mathrm{R(Ns)} = 1/\mathrm{Ns} \sum_{n=L}^{L-1+Ns} x^n x^{+(n)}, \quad (12)$$

Step2: Obtain the maximum and minimum eigenvalues of the matrix R (Ns) that is $\lambda_{max}$ and $\lambda_{min}$.
Step3: Decision: if $\lambda_{max} \geq \lambda\gamma\rho_{max}$, signal exist ("yes" decision); otherwise, signal does not exist ("No" decision), where $\lambda \geq 1$is a threshold.

*2. Mean Eigenvalue to Minimum Eigenvalue Ratio Detector*

The novel modification in method of spectrum sensing based on eigenvalue, maximum eigenvalue to minimum eigenvalue ratio detector [27] as discussed in previous section is proposed.

It is shown that the ratio of the mean eigenvalue to the minimum eigenvalue (MERD) can be used to detect the presence of the signal. Based on some latest random matrix theories (RMT), we compute the distributions of these ratios and find the detection thresholds for the proposed detection algorithms. Using Random matrix theory the probability of false alarm and probability of detection are also derived. The methods overcome the noise uncertainty problem and even perform better than energy detection when the signals to be detected are highly correlated. With-out knowledge of the signal, channel and noise power this method can be used for various signal detection application. Moreover, different from matched filtering, the proposed methods do not require accurate synchronization. Thus simulations based on randomly generated signals are carried out to verify the effectiveness of the proposed methods. It is shown that the ratio of the mean eigenvalue to the minimum eigenvalue can be used to detect the signal existence. Based on some latest random matrix theories (RMT), we can quantize the ratio and find the threshold. The probability of false alarm is also found by using the RMT.

The proposed Mean eigenvalue ratio detector (MERD) method overcome the disadvantage of maximum eigenvalue to minimum eigenvalue ratio detector and perform better for probability of false detection ($P_{fa}$) than all the remaining methods, also overcome noise level variation difficulty, and also have the advantages of maximum eigenvalue to minimum eigenvalue ratio detector & energy detection method. The proposed method is useful for detection of signal without prior knowledge of signals, channels and noise power.

Mean Eigenvalue Ratio Detection (MERD) steps
Step1. Compute

$$\mathrm{R(Ns)} = 1/\mathrm{Ns} \sum_{n=L}^{L-1+Ns} x^n x^{+(n)} \quad , \quad (13)$$

Step2: Obtain the mean and minimum eigenvalue of the matrix R (Ns) that is $\lambda_{mean}$ and $\lambda_{min}$.
Step3: Decision: If $\lambda_{mean}$ / $\lambda_{min}$, > Threshold, then signal exist ("$H_1$" decision)
Otherwise,
$\lambda_{mean}$ / $\lambda_{min}$, < Threshold, then signal does not exist ("$H_0$" decision)

## III. SIMULATION RESULTS

- Probability of Detection Alarm -

Figure 1 shows the probability of PU detection alarm (Pd) with respect to SNR. The probability of detection alarm should be as much as possible with respect to SNR. Figure 1 shows that eigenvalue detection is detecting PU signal at low SNR as compare to detection techniques

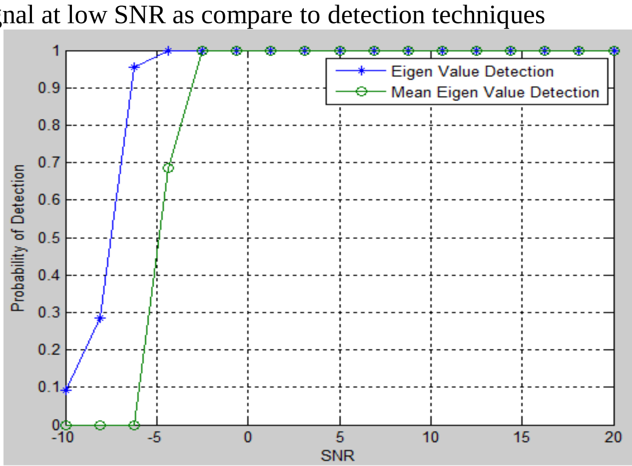


Figure 1: Probability of Detection vs. SNR for all Detection Methods

- Probability of Miss Detection

Figure 2 depicts the probability of miss detection (Pm) with respect SNR. Probability of miss detection should be as small as possible with respect to SNR. Figure 2 shows eigenvalue detection is superior to other techniques.

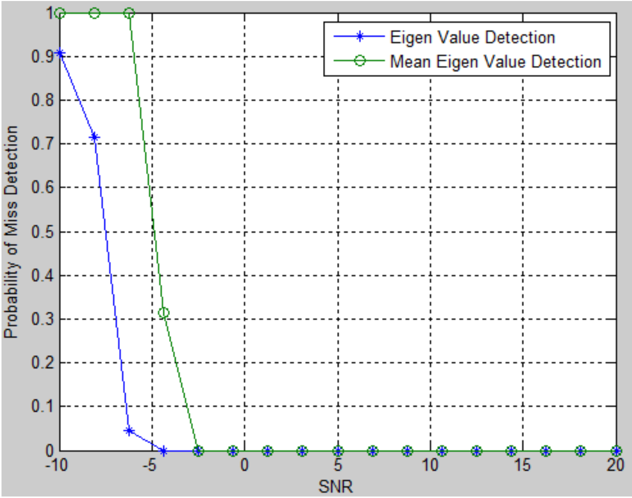


Figure 2: Probability of Miss Detection vs. SNR for all Detection Methods

- Probability of False Alarm

In Figure 3 the comparison of two spectrum sensing techniques in terms of the probability of false alarm detection (Pf) with respect to SNR is plotted. The probability of false alarm should as minimum as possible with respect to SNR. It is observed that probability of false alarm for mean eigenvalue detection is better than other techniques.

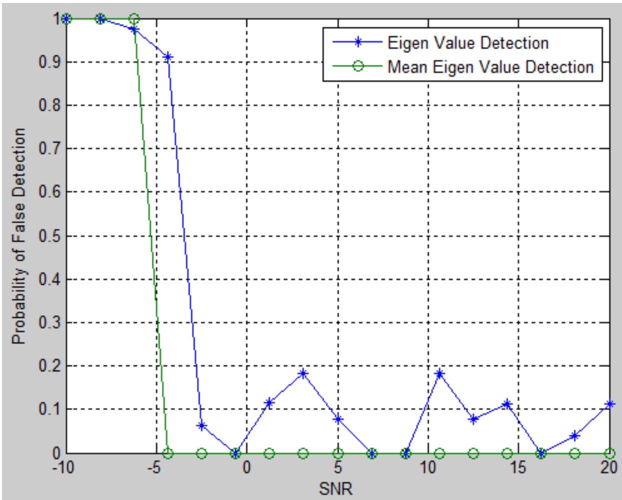


Figure 3: Probability of False Detection vs. SNR for all Detection Methods

## IV. Conclusion

In this paper, the performance of eigenvalue spectrum sensing techniques is assessed and presented through Probability of Detection ($P_d$), Probability of Miss Detection ($P_m$), and Probability of False ($P_f$) Detection for multiple SNR values.

Maximum eigenvalue to Minimum eigenvalue ratio detector methods overcome noise level variation difficulty, and also have the advantages of energy detection method. The Maximum eigenvalue to Minimum eigenvalue ratio detector method perform better for Probability of detection, but its performance is poor for probability of false detection, and this is biggest limitation of Maximum eigenvalue to Minimum eigenvalue ratio detector because due to false detection the interference may be occurs between primary user and secondary user.

The mean eigenvalue ratio detector has very low probability of false detection means it overcome the limitation of Maximum eigenvalue to Minimum eigenvalue ratio detector, probability of detection is high, and also have the advantages of Maximum eigenvalue to Minimum eigenvalue ratio and energy detection method. Finally, with simulation results shows that proposed mean eigenvalue ratio detector performs better than maximum to minimum eigenvalue detection technique.

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