



Performance Enhancement of Cognitive Radio Using Double Thresholds Eigenvalues Detection

Sinan M. Abdulsatar¹ Hadi T. Ziboon¹ Humam F. Majeed^{1*}

¹*University of Technology, Iraq*

* Corresponding author's Email: 31612@student.uotechnology.edu.iq

Abstract: An essential element and one of the challenging tasks in cognitive radio is spectrum sensing. In this paper, a new method to enhance the sensing is presented and implemented, in this scheme eigen-values are obtained from the sample covariance matrix of the signal that received at the secondary user's receivers. Random Matrix Theory (RMT) derives the expression of the thresholds required for effective sensing. Low signal to noise ratio cases have been overcome by the new method which bested the traditional energy detection method as well as the conventional eigenvalues based on single threshold. The simulation results based on randomly generated signals show that the proposed method exhibits a detection probability of (91.3%) when signal to noise ratio is (-19dB) while it's (78.5%) for classical eigenvalues method. The results also show that the samples' number that needed for reliable sensing is less than the energy detector and the conventional eigenvalues with single threshold method. An implementation of the the proposed method based on FPGA using myRIO-1900 kit is presented in this paper, the results obtained from the simulation and the hardware implementation are identical.

Keywords: Spectrum sensing, Cognitive radio, Eigenvalues, Double threshold, Covariance matrix.

1. Introduction

Because of the increasing need for higher data rates as a result of evolution of multimedia types, it becomes clear that current fixed frequency distribution schemes cannot meet the demands of an increasing number of higher data rate devices, as a result, innovative techniques are needed that can provide new ways to take advantage of available spectrum. The cognitive radio is created to be an attractive solution to the problem of spectral congestion by introducing an opportunistic use of frequency bands that are not greatly occupied by licensed users [1-4]. The localization and sensing of the frequency spectrum are two critical tasks in the modern warfare of electronic and cognitive radio, a radio frequency sensor can be used to implement these tasks for detecting signals and estimate their frequencies in the air. Cognitive radio is the concept of emerging wireless communications where the network or wireless node can sense its environment, especially the holes in the spectrum, and change the

transmission and receiving chains to communicate opportunistically, without interfering with licensed users[5]. By dynamically modifying the operating parameters, cognitive radio senses the spectrum, identifies the vacant ranges, and uses these available bands in an opportunistic manner, thus improving overall spectrum usage [6]. In licensed domains, wireless users who have a specific domain authorization to access the channel are known as licensed users or Primary Users (PUs), as long as they do not cause interference to the PUs cognitive radio user which also known as Secondary Users (SUs) are allowed to use and access the channel. In spite of that, there are several factors that causes an issue in the sensing for the cognitive users, one of that factors is the low signal-to-noise ratio may be very low at the receivers of the cognitive users. Fig. 1 below shows a classical cognitive cycle.

Over time different methods of spectrum sensing have been proposed and each with different operational requirements advantages and

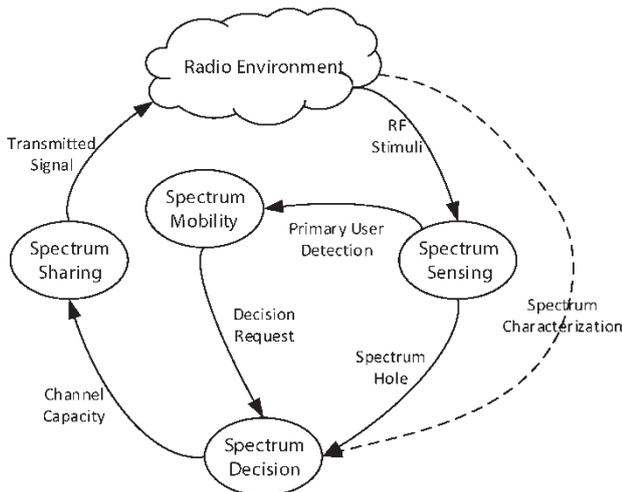


Figure. 1 Simplified cognitive cycle

disadvantages. As example of these methods, the matching filter is optimized, meaning that it increases the ratio of Signal to Noise Ratio (SNR) thus reducing detection time, but it needs to know the wavelength and the licensed user channels, in addition, it needs dedicated receiver circuits for each range considered for secondary access, making the complexity of the secondary receiver prohibitively high [7, 8]. Cyclostationary feature detection has the capability to distinguish between noise and licensed user signals, however it requires knowledge of periodic frequencies for primary users [9, 10]. The conventional energy detection is optimized to detect an independent signal distributed identical, however it depends on the knowledge of the precise noise power, but for most practical applications the signals are correlated and that lead to inaccurate estimate of the noise power leading to phenomenon known as the SNR wall which cause a high probability of false alarm [11-13].

The performance evaluation of cognitive spectrum sensing based on energy detector was presented by [14] another two sensing methods based on the principle components of the received signal at the secondary user is proposed in [15] the first suggested algorithm is based on the ratio of the principal component's maximum eigenvalue to principal component's minimum eigen value and compared it with a threshold and it achieved a P_d of 90% at SNR of -14dB, while the second method is based on the ratio of the average principal component's eigen value to principal component's minimum eigen value and it achieved a P_d of 80% at -12dB. The sample's number used in simulation for both methods is 100000. While when using the ratio of the maximum to minimum eigenvalue the method of [16] these methods achieved P_d of 85% at -19dB SNR when the $N_s = 10000$ and $P_f = 0.1$.

Spectrum sensing scheme based on the sample covariance matrix for the received noisy signal at the receiver of the secondary user, this scheme used the ratio of summation of all elements of the covariance matrix to summation of the diagonal elements for the same matrix and compared with with two thresholds, this method achieved a P_d of 95% at -16dB SNR with $N_s = 10000$ and the smoothing factor is 5 [17]. Another scheme by implement efficient disjoint and mutually spectrum sensing in a cognitive radio to minimize the probability of false alarms under constant detection probability achieved P_d of 86% where P_f is 0.1 [18].

To overcome deficiencies in energy detection, in this paper, two thresholds (Upper threshold and Lower threshold) based eigenvalues algorithm is suggested, the new scheme is depending on the eigenvalues characteristic of the statistical covariance matrix of the noisy signal that received at the Secondary Users (SUs). To decide whether the registered customer PU is operating or not, the proposed approach used as a comparison statistic the maximum percentage of its eigenvalue to the minimum eigenvalue. The expression for the detection thresholds needed for effective sensing is derived from the latest Random Matrix Theory (RMT) as for the ratios of the eigenvalues which will used as a test statistic. The proposed scheme exploits the relationship between signal samples to distinguish the PUs signal and the accompanied noise. Advance channel information, signalling and synchronization also not required by the suggested method.

The rest partitions of the paper are arranged as follows; Firstly, Section 2 examines several conventional sensing methods. Section 3 presented the proposed system of double thresholds to enhance spectrum sensing. The results of the simulation that show the effectiveness of the suggested method is detailed in section 4. Section 5 deals with FPGA implementation, of the maximum-minimum eigenvalues detection method and the proposed double threshold eigenvalue sensing methods. Finally the conclusions of this paper are presented in Section 6.

2. Sensing methods

This section presents traditional spectrum sensing schemes that ordinarily used like Maximum-Minimum Eigenvalues Detection (MMED) based on single threshold and the traditional Energy Detection (ED) [19]. The aims of this paper are to analyze, design, simulate and implement different methods of spectrum sensing schemes based on the Eigenvalues

and the sample covariance matrix of the received signal at the secondary user of a cognitive radio system.

2.1 Spectrum sensing system model

The licensed user PUs sensing states problem can be modelled as the problem of testing two major hypotheses [19-21].

$$\mathcal{H}_0: x(t) = n(t) \tag{1}$$

$$\mathcal{H}_1: x(t) = s(t) + n(t) \tag{2}$$

Where the sample of received signal at the secondary user's receiver is indicate by $x(t)$, $s(t)$ is a sample of the primary users' signal sent at an average of mean 0 and variance σ^2 , $n(t)$ represent the Additive White Gaussian Noise (AWGN) of the channel that the primary signal is transmitted over. Considering that the noise samples are independent and distributed identically with mean 0 and variance σ^2 .

The PUs is not present and the frequency band is not occupied is indicated by the first hypotheses (\mathcal{H}_0). While hypothesis (\mathcal{H}_1) indicates that the frequency band is occupied and the PUs is active. In spectrum sensing, the following possibilities are vital: the probability of an unoccupied frequency band is being detected as a busy band is known as the probability of false alarm P_f and it is categorized under the assumption of (\mathcal{H}_0). Probability of detection P_d is the one that indicates the discovery of the primary user PUs and the spectrum is not vacant and it is under hypothesis (\mathcal{H}_1). The probability that refers to occupied frequency band being detected as idle and not busy band is known as the probability of miss detection P_m which lead to interference between the PUs and the cognitive users SUs and it is under hypothesis (\mathcal{H}_1). To gain over a higher throughput for the cognitive users SUs and provide superior protection the P_m should be minimal as possible and for the P_f also should be low [22, 23]. The P_f and P_d are defined as follow:

$$P_f = Pr (T > Th; \mathcal{H}_0) \tag{3}$$

$$P_d = Pr (T > Th; \mathcal{H}_1) \tag{4}$$

Where Th is the threshold being used in the detection, while the test statistic for the sensing method is denoted (T).

2.2 Conventional energy detection

Due to its low computational and application complexity, energy detector-based approach, also known as radiometry or periodogram, is the most common way of sensing spectrum [24, 25]. The signal is detected by comparing the energy of detector output with a noise-dependent threshold.

For the traditional energy detection scheme the test statistic $T(x)$ that considered in the spectrum sensing is given as below.

$$T(x) = \frac{1}{N_s} \sum_{n=1}^{N_s} |x(n)|^2 \tag{5}$$

Where N_s : is the samples' number.

The threshold Th can be given in term of a nominated value of probability of false alarm P_f and Q-function as below.

$$Th = \sigma_\eta^2 \left(\sqrt{\frac{2}{N_s}} Q^{-1}(P_f) + 1 \right) \tag{6}$$

here $Q(x)$ is normal cumulative distribution function.

2.3 Conventional eigenvalue detection

In this method the sample covariance C_{xx} is evaluated for the received noisy signal at the secondary user:

$$C_{xx} = \begin{bmatrix} f_0 & f_1 & \dots & f_{L-1} \\ f_1 & f_0 & \dots & \cdot \\ \vdots & \vdots & \ddots & \vdots \\ f_{L-1} & \cdot & \dots & f_0 \end{bmatrix} \tag{7}$$

Where

$$f(i) = \frac{1}{N_s} \sum_{n=0}^{N_s-1} x(n)x(n-i)^* \tag{8}$$

for $i = 0, 1, 2, \dots, L-1$, where L refers to the smoothing factor and N_s is the number of samples. The test statistic for this scheme is evaluated from the average of maximum eigenvalue λ_{max} to the minimum eigenvalue λ_{min} and compared it to a threshold Th that calculate as given in [26].

$$Th = \frac{(\sqrt{N_s} + \sqrt{L})^2}{(\sqrt{N_s} - \sqrt{L})^2} \left(1 + \frac{(\sqrt{N_s} + \sqrt{L})^{-\frac{2}{3}}}{(N_s L)^{\frac{1}{6}}} F_1^{-1}(1 - P_f) \right) \tag{9}$$

3. The suggested double-threshold approach based on the measurement of eigenvalues

The sensing scheme that depends on one threshold stumbles almost in case of low SNR rate.

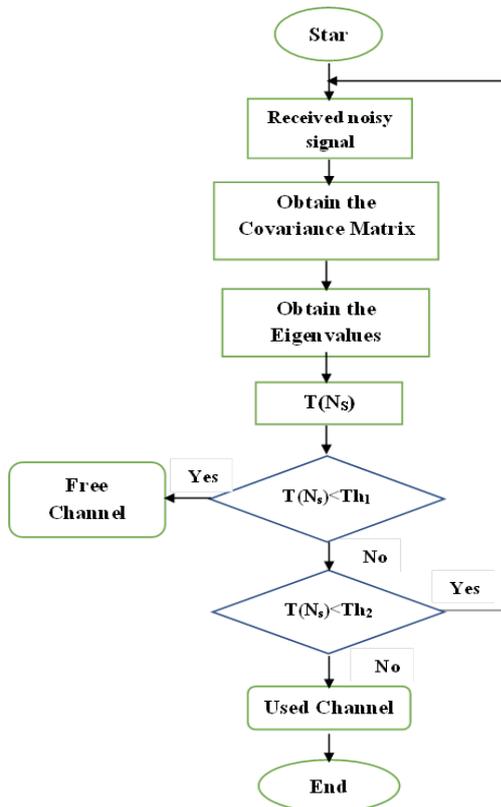


Figure. 2 Flowchart for the proposed scheme

The double threshold scheme based on the calculated eigenvalue of the sample covariance matrix of the received noisy signal at the receiver of the SU_s is used to beat this issue. Both of the threshold expression is derived and obtained from the latest random matrix theory. The statistical test here is evaluated in the same of the conventional eigenvalue detection as it is the ratio between the largest eigenvalue λ_{max} to the smallest one λ_{min} then it is compared to both thresholds to determine the busyness of the licensed band either it is free or not as the flowchart in Fig. 2.

$$T(N_s) = \frac{\lambda_{max}}{\lambda_{min}} \quad (10)$$

Where $T(N_s)$ is refer to the test statistic that used in this method.

As shown in the flow chart if the test statistic $T(N_s)$ is smaller than Th_1 then band is free and not busy and if it is larger than Th_2 then the band is occupied by the PU signal and the third case is the $T(N_s)$ to be between the two thresholds, in this case the scheme will re-sense the spectrum and check with the thresholds again.

$$Dicision = \begin{cases} \text{vacant band in case } (Th_1) > T(Ns) \\ \text{resensing in case } (Th_2) > T(Ns) > (Th_1) \\ \text{occupied band in case } (Th_2) < T(Ns) \end{cases}$$

Table 1. Tracy-Widom distribution function numerical table of order 1

$F_1(t)$	0.01	0.05	0.10	0.50	0.90	0.95	0.99
t	3.90	3.18	2.78	1.27	0.45	0.98	2.02

The probability of detection P_d and the probability of a false alarm P_f are the two factors that characterize cognitive radio performance well. Therefore, the threshold Th_2 is chosen so that P_f is a small value to ensure that the secondary user has a high throughput so it is the same as the conventional eigenvalue detection's threshold which evaluated in [19].

$$Th_2 = \frac{(\sqrt{N_s + \sqrt{L}})^2}{(\sqrt{N_s - \sqrt{L}})^2} \left(+ \frac{(\sqrt{N_s + \sqrt{L}})^{\frac{2}{3}}}{(N_s L)^{\frac{1}{6}}} F_1^{-1}(1 - P_f) \right) \quad (11)$$

Where F_1 denote the Tracy-Widom distribution function of the order 1. The calculation of this function is very difficult luckily, the function is evaluated through MATLAB codes and given in tables as in [27-29].

Table 1 shows some value for the function for specific point and can be used to obtain the inverse of the function F_1^{-1} . To offer a high degree of protection for the licensed user PU, the second threshold Th_1 is evaluated as Eq.12, P_m should be small value of P_f to ensure high probability of detection P_d [16]:

$$Th_1 = \frac{(\sqrt{N_s + \sqrt{L}})^2}{(\sqrt{N_s - \sqrt{L}})^2} \left(1 + \frac{(\sqrt{N_s + \sqrt{L}})^{\frac{2}{3}}}{(N_s L)^{\frac{1}{6}}} F_1^{-1}(P_m) \right) \quad (12)$$

The steps for the suggested scheme of the detection is as follows:

First step: The thresholds Th_2 , Th_1 are evaluated from the Eq. (11) and Eq. (12) after choosing the desired values of L , N_s , P_f and P_m .

Second step: Using auto-correlation the covariance matrix $C_{xx}(N_s)$ which is evaluated from the received noisy signal at the receiver of the SU.

Third step: The test statistic is evaluated from the ratio of the largest eigenvalue λ_{max} to the smallest one λ_{min} , $T(N_s) = \lambda_{max} / \lambda_{min}$.

Fourth step: make the decision from the cases:

$$\text{Count} = \begin{cases} \text{count} = 0 \text{ if } (Th_1) > T(Ns) \\ \text{go to the second step } (Th_2) > T(Ns) > (Th_1) \\ \text{count} = 1 \text{ if } (Th_2) < T(Ns) \end{cases}$$

Where count=0 mean the received signal is only noise and the PU is not active while count=1 that the PU signal is presented and the spectrum is occupied.

4. Simulation and discussion

The results of the simulation are presented to verify the effectiveness of proposed scheme Double Threshold based Eigenvalue Detection (DTED) compared to some existing methods such as Maximum-Minimum eigenvalues detection (MMED) and the traditional Energy Detection (ED). The Monte Carlo examinations that used in these simulations are 1000 and, for each realization a random noise AWGN with binary phase shift keying modulation's inputs were generated.

In Fig.3, the number of sample N_s that used here is 10000, and the smoothing factor that used here is $L=10$ and the calculations of the two-thresholds were obtained based on $P_m = 0.1$ and $P_f = 0.1$

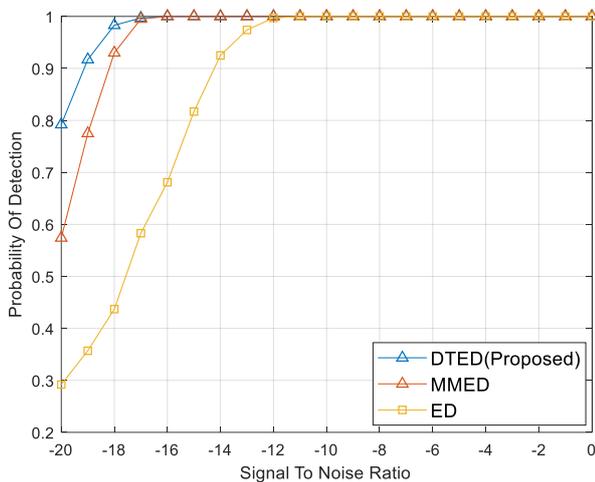


Figure. 3 Probability of detection P_d with $N_s=10000$, $L=10$

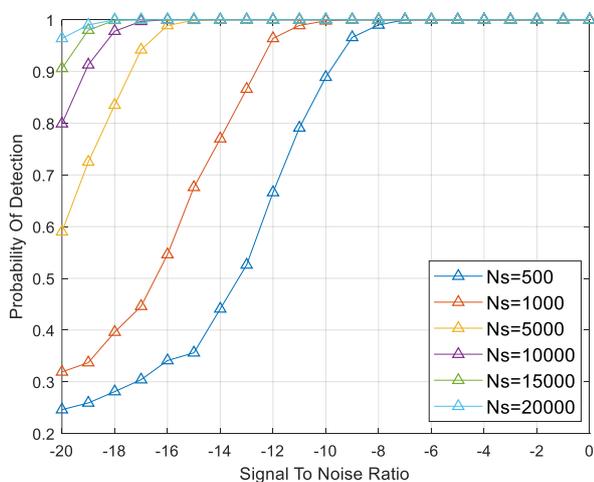


Figure. 4 Probability of detection P_d with different samples' numbers, $L=10$

Table. 2 The detection probability of for different samples' number at (SNR= -19dB)

N_s	500	1000	5000	10000	15000	20000
P_d	0.272	0.334	0.705	0.928	0.976	0.999

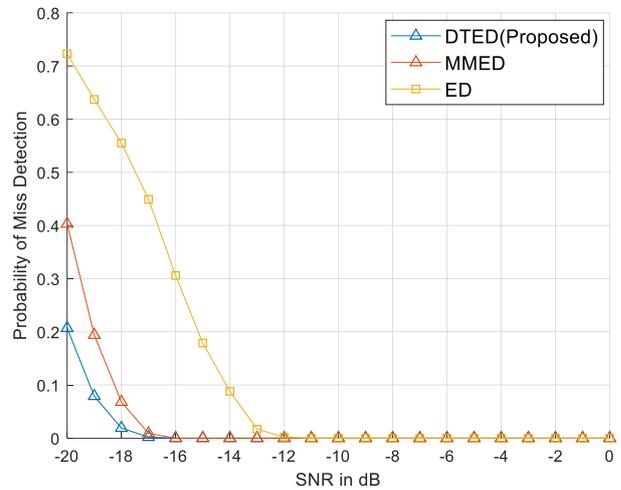


Figure. 5 Probability of miss detection P_m , $N_s=10000$, $L=10$

The simulation plot shows the probability of detection P_d with respect to SNR when the noise uncertainty is not taken in consideration, from Fig. 4, it is noticed that the suggested scheme can achieves a reliable probability of detection of 0.913 at SNR=-19dB while the ED and MMED methods achieved 0.338 and 0.785 respectively.

In Table 2 shows the variation of probability of detection P_d for the suggested scheme with the variation of number of samples N_s . It is observed from Fig.4 and Table 2 that the probability of detection P_d is increased as the number of samples N_s is increased.

Fig.5 shows that probability of miss detection P_m for suggested scheme is the lowest one in comparison with the other two methods, here P_m equal to 0.082 at SNR= -19dB while P_m for the ED and the MMED is 0.638 and 0.218, respectively.

Fig.6 shows the effect of taking different samples' number on the probability of miss detection P_m which we clearly observed that is the inverse of P_d and by increasing the N_s the P_m is decreasing.

The variation of the probability of miss detection P_m with N_s at -19dB is illustrated in Table 3.

In Fig.7, the curves of P_d for the DTED and the ED shows that the proposed scheme need fewer samples' number to achieve a dependable detection of 0.863 at SNR of -18dB than the ED method which get 0.310.

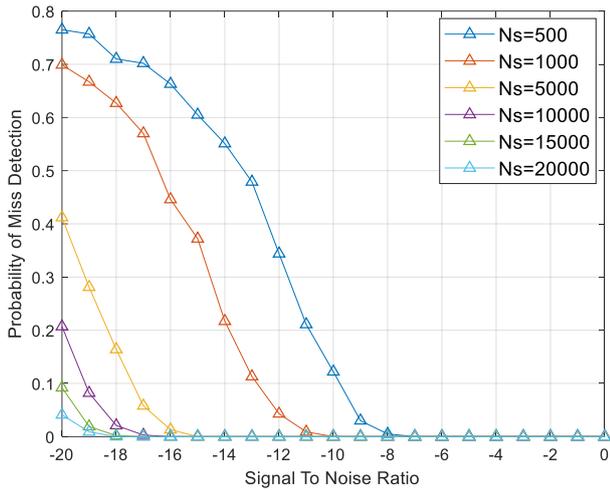


Figure. 6 Probability of miss detection P_m with different samples' numbers, $L=10$

Table 3. Probability of miss detection for different samples' number at (SNR= -19dB)

N_s	500	1000	5000	10000	15000	20000
P_m	0.794	0.697	0.424	0.197	0.093	0.025

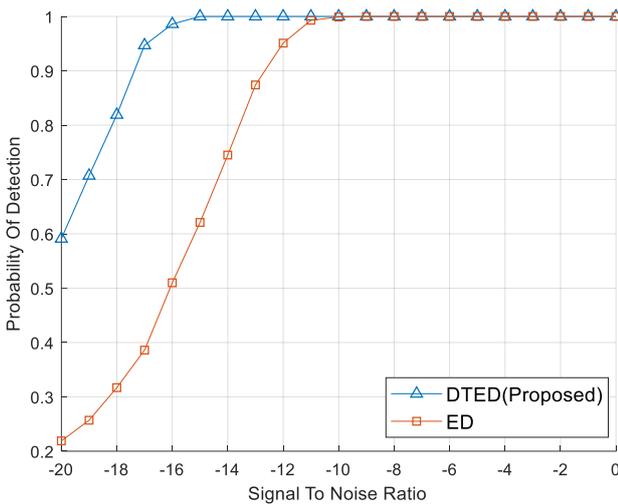


Figure. 7 Probability of detection P_d with $N_s=5000$, $L=10$

Table 4. The Detection Probability of for different SNR with $N_s=5000$

SNR (dB)		-20	-19	-18	-17	-16
P_d	DTED	0.551	0.701	0.863	0.934	0.993
	ED	0.228	0.256	0.310	0.400	0.464

Table 4 shows the result for the P_d for different SNR with N_s equal to 5000, from which, the P_d of the proposed DTED is larger than P_d of ED method for all values of SNR.

In Fig.8 the effect of the smoothing factor L variation is shown while N_s fixed, when L is increased the P_d is increased as well.

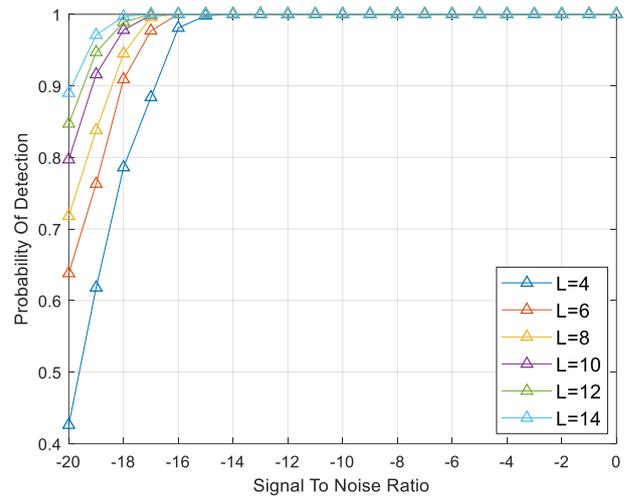


Figure. 8 Probability of detection P_d with different smoothing factor L values, $N_s=10000$

Table 5. The detection probability of for different smoothing factor L values at (SNR= -19dB)

L	4	6	8	10	12	14
P_d	0.618	0.763	0.838	0.916	0.947	0.971

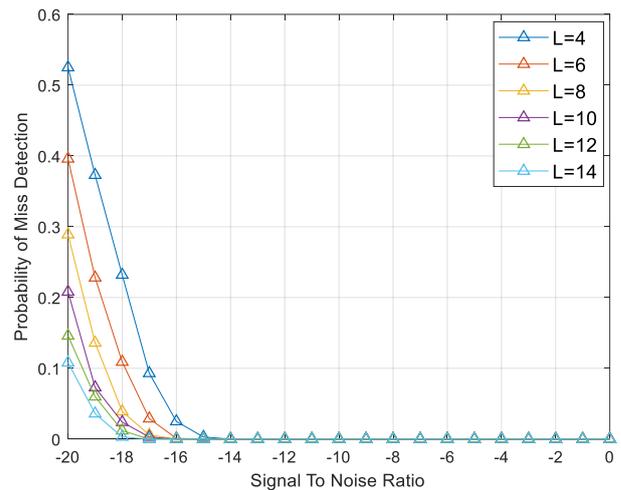


Figure. 9 Probability of miss detection P_m with different smoothing factor values L , $N_s=10000$

Table 6. Probability of miss detection with different smoothing factor L values at (SNR= -19dB)

L	4	6	8	10	12	14
P_m	0.373	0.228	0.136	0.073	0.060	0.036

Table 5 below illustrated the value of P_d with the corresponding value of L at $SNR=-19dB$. It is noted as L increased P_d increased too.

Fig.9 shows the relation between the probability of P_m with different L is revealed that by increasing the value of L lead to decrease the value of P_m .

Table 6 shows the results for the P_m for different L with SNR equal to -19dB, from which, the P_m decreased as the smoothing factor L increased.

5. Implementation and experimental results

This section deals with FPGA implementation, of the MMED method and the proposed double threshold eigenvalue sensing methods. The implementation for each system is done by Matlab. LabVIEW program is used to convert the Matlab code into a code that can be downloaded to the FPGA. The FPGA kit named Xilinx Z-7010. The implementation includes the extraction of the maximum and minimum eigenvalues for the covariance matrix that calculated for a received signal and shows the evaluation of the thresholds, form the comparison between the ratio of the eigenvalues and the thresholds output then the decision is made whether the output is signal or noise. The modulation type of the transmitted signal used in this implementation is Binary Phase Shift Keying (BPSK) and AWGN is added, the number of samples N_s used is 10000, the smoothing factor L is 10 for all tests, the probability of false alarm is taken as 0.1 and SNR used is -19dB. To test the effectiveness of this method, the analysis of the snapshot test is considered. The tests are taken in the case of presence of transmitted signal and when there only noise and the results shown in Table 7.

As observed from the Table 8, the two thresholds are fixed because the number of samples and the smoothing factor is fixed for all test, according to Eq.11 and Eq.12 the thresholds only affected by those two factors. For the first two test, the ratio of the eigenvalue is larger than threshold 2 so the spectrum is occupied and for the fourth test, the ratio is less than first threshold so the spectrum is vacant and the channel is free to use, but in the third test the ratio is between the two thresholds so the system here will re-sense the spectrum by forming a new covariance matrix and the operation will repeated.

As noticed from the Table 7, the value of the threshold does not change because the threshold depends only on the smoothing factor L and the number of samples N_s . In the case number four the input signal was only noise so the ratio of the eigenvalue is smaller than the threshold.

The first threshold calculation is based on probability of miss detection of 0.1, and the calculation of the second threshold is done by taking the probability of false alarm as 0.1.

Table 8 summarized the results when N_s is 10000 and the SNR = -19dB for DTED.

Table 9 shows the values of the two thresholds changed when the N_s changed and its' values decreased and that increased the probability of detection.

Table 7. Summary of snapshots for MMED

No.	Threshold Value	The ratio of the eigenvalue	The presence of signal
1	1.1383	1.25775	The spectrum is busy
2	1.1383	1.21885	The spectrum is busy
3	1.1383	1.20396	The spectrum is busy
4	1.1383	1.05991	The spectrum is vacant

Table 8. Summary of multiple Snapshots for DTED $N_s=10000$

No	Threshold Value	Threshold 2 Value	The ratio of the eigenvalue	The presence of signal
1	1.11383	1.1383	1.17968	The spectrum is busy
2	1.11383	1.1383	1.8841	The spectrum is busy
3	1.11383	1.1383	1.12835	Re-sense the spectrum
4	1.11383	1.1383	1.01315	The spectrum is vacant

Table 9. Summary of multiple Snapshots for DTED $N_s=15000$

No.	Threshold Value	Threshold 2 Value	The ratio of the eigenvalue	The presence of signal
1	1.09197	1.11156	1.20614	The spectrum is busy
2	1.09197	1.11156	1.19445	The spectrum is busy
3	1.09197	1.11156	1.17848	The spectrum is busy
4	1.09197	1.11156	1.01125	The spectrum is vacant

For the first three tests the ratio of the eigenvalue is larger than threshold 2 value so that lead to the occupation of the spectrum but in the fourth test only noise is used as input so the ratio is appeared smaller than the first threshold leading to free spectrum.

Fig.10 shows the hardware implementation connection between the host computer and FPGA myRIO-1900 through a Hi-Speed USB 2.0.

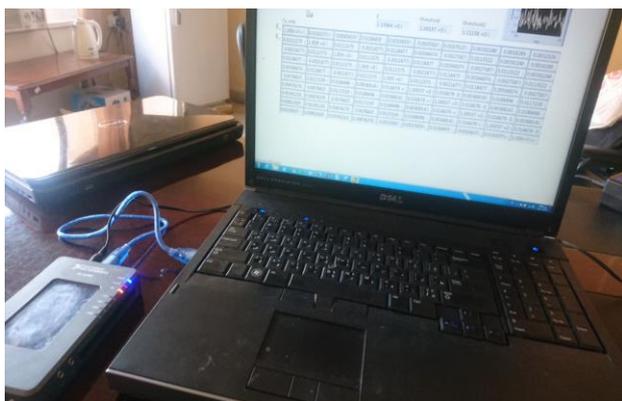


Figure. 10 The host computer and myRio-1900 kit

6. Conclusions

This paper shows the double thresholds based eigenvalues detection technique is work properly well, the thresholds have been derived using random matrix theories and the ratio of the eigen-values have been quantified from the sample covariance matrix that obtained from the received signal at the secondary user's receivers. The suggested algorithm works very well for various signal detection applications and under low SNR and can be used without knowledge of signal, channel and noise resources as opposed to the conventional energy detection technique involving previous noise information. The double threshold eigenvalue sensing method is performing better than Maximum-minimum eigenvalues detection and the conventional energy detector. This is clearly seen from the obtained results where the proposed method get a detection probability of 91.3% and the MMED get 78.5% while the ED get only 33.8% at signal to noise ratio of -19dB for all methods. Hardware implementation using FPGA of the proposed spectrum sensing method based on the eigenvalues of the covariance matrix with double threshold system have been done. The results obtained from the simulation and the hardware implementation is identical.

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