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# An Adaptive Covariance Matrix Based on Combined Fully Blind Self Adapted Method for Cognitive Radio Spectrum Sensing

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**Abstract**
The main aim of this paper is to analysis and simulate existing methods such as energy detection, Maximum–Minimum Eigen value detectors (MME), MME with blind two stage detector and compare with the proposed adaptive covariance threshold method. This comparison is being made keeping in mind the complexity and accurateness in the terms of the sensing receiver operating characteristics curve. The influence of signal bandwidth of signal in comparison to the bandwidth of observation is done for every detector. As of the MME detector, the ratio between the bandwidth of the signal and the bandwidth of the observation is observed to be 0.5 when the reasonable values are used. The performance of the adaptive covariance threshold with combined full blind self-adapted detector are simulated on Matlab. The proposed method of detector shows a superior performance values when compared to three individual detectors. The performance metrics of proposed method are performed better than other three individual detector.

**Keywords** Cognitive radio · Spectrum sensing · Maximum–minimum Eigen value detectors · Low SNR environment

## 1 Introduction

There has been an immense amount of development and expansion in the arena of wireless services nowadays. With its increasing popularity, comes the increase in demand for higher bandwidths that can fulfill the need for soaring data rates, therefore, creating a situation of spectrum scarcity [1]. In such a situation, there is a dearth of adequate radio spectrum that can easily manage the ever-increasing mobile data traffic. Many studies have also found out that several of the radio spectrums are also being under-utilized by the existing systems [2–4]. So the problem that is being faced is that, on one hand, there is inadequate radio spectrum that can manage all the wireless services while on

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the other hand, the existing systems are not properly utilizing the available radio spectrums. This has led to the introduction of a radio system based on the DSA (dynamic spectrum access) that is being one of the important attributes of CR (cognitive radio) system. Here, a radio enabled device can alter its transmission accepting parameters to adjust according to the prevalent or upcoming changes in the radio environment [5].

The foremost challenge that DSA faces is regarding detection of free of the spectrum-hole use. Such a spectrum hole can easily be detected with the help of either sensing of spectrum technique, geolocation database, else with signals of beacon [6]. With the aid of sensing of the spectrum, one can easily measure the signal inside a band and can also find out whether a signal is present or absent [7]. Spectrum sensing can be classified into 2 categories namely non-blind and blind. In the non-blind kind of sense, that device which is actually doing the sensing have an idea about some of the features of the licensed user i.e. the PU [8–10]. The PU signals can be sometimes totally unknown or might be computationally expensive so cannot be restored. In the blind sensing method, the PU signal features are absent and that is what is needed to detect the signals [11].

The other method used for detection is the ED (energy detection) method. In this method, the signal energy that is received is compared and assessed with the noise energy. ED can be categorized as both blind as well as non-blind. It is blind considering the required amount of knowledge regarding signals and it is non- blind given the fact that for ED noise energy is still needed to be identified [12–15].

This paper presented an energy detection and MME (maximum–minimum Eigenvalue) has been introduced such as is known as the two-stage combined detector. The 2EMC is modeled on the multistage spectrum sensing technique where both accuracy and complications are compromised [16–18].

## 2 Literature Review

The main driving force behind adopting a multistage detector is there to utilize of all the benefits of each of the detectors basing on the signals obtained by each of them. The main advantage of this detector is primarily the SNR, whose higher values make the initial stages simpler. However, when the SNR gives lower rates, the simplicity compromises the sensing accuracy.

It has been observed that the accuracy of detection of signal varies with changing sampling rate. The DFT filter bank utilized to adjustments the sampling rate depending on the expected SNR of every detector [19]. The ED uses this as the foremost detection stage and cyclo-stationary as the 2nd stage if nothing is identified during the 1st stage [20]. In case of the recommended algorithm, if the signal absence is declared in the first stage only then SNR is calculated and the second stage is based on that, or else the calculations of the first stage are taken into consideration [20, 21]. The two-stage detector differs from the proposed algorithm in the sense that SNR based estimation is carried out firstly and then the cyclo-stationary or energy identification is done depending on the SNR based estimations [22]. While in a 2-stage fuzzy, the method of detection of logic is commenced. In the 1st stage, there are individual detections carried out by various CR's by means of the different methods for detection. The 2nd stage combines the sensing results obtained from the 1st stage and uses fuzzy logics to estimate the presence or lack of a signal [23].

Algorithms detecting multistage spectrums are classified into three categories. The first one is a sequential multistage spectrum, in which there is a serious connection between the different detection stages.

The energy detection is implemented in the 1st phase, and a covariance absolute value (CAV) detector is utilized in the 2nd stage if energy detection estimate signal absence [24].

In the 1st-stage ED is utilized to kind the channels established on SNR values and cyclo-stationary detection is utilized for low SNRs in the channels [25–27].

Each of the stages can be performed or skipped based on the outcome obtained from the previous phases. The 2nd phase is the parallel kind of detection wherein different detectors are utilized at the same time to continue with the detection and then the final decision is taken based on the combination of all these parallel kind of decisions. The 3rd category is where parallel or sequential kind detection is used along with SNR based estimation. Sequential multistage sensing faces computational complexities that are dependent on the SNR; the advantage is when a high SNR estimation is received. Alternatively, the parallel kind of sensing takes the similar time irrespective of the SNR and takes its decision basing on the contributions from every stage. This study paper focuses on sequential multistage sensing technique.

## 3 Motivation and Contribution

This paper lists the points that have not been addressed by authors to the best of their knowledge regarding sequential sensing. The various points are as follows:

1. Development of a full blind multistage detection based on adaptive covariance threshold method. It has been observed that several multistage detectors have a blind stage but none of the have adaptive covariance threshold method. The proposal laid by this paper regarding the full blindness of adaptive covariance threshold detectors is as follows:

    (a) Using MME and 2EMC in the second stage detection in two different cases.
    (b) Making use of noise detection wherein noise estimation is done by MME, 2EMC.
    (c) Proposed method compared with their existing method respectively.

2. The previous studies do not lay much emphasis on the impact of other parameters apart from SNR. This study paper analyses on how both of the bandwidth of signal and the bandwidth of observation are important and the impact on the performance of the ED, MME as well as the 2EMC.
3. The combined kind of detector on the existing methods have been proposed through this paper is well tested with the help of simulation matrix and mathematical equation proof [28].

## 4 Spectrum Sensing Methods and Methodology

Here, presented the system model with some of the theoretical features, which is utilized through the paper.

### 4.1 System Model

In our findings, we used a received signal x(n) of SU users. Here the cognitive receiver's general discrete signal is shown as:

$$\begin{aligned} H_0 &: x(n) = \eta(n) \\ n &= 0, 1, \ldots, N - 1 \end{aligned} \tag{1}$$

$$H_1 : x(n) = s(n) + \eta(n) \tag{2}$$

Here s(n) and x(n) represents the primary signal of PU and received signal of SU respectively; (n) denotes the background noise; N denotes the size of the sample. Here the noise is assumed to be AWGN or Gaussian white noise that has a variance $\sigma_0^2$ and () could be a stochastic signal that represents channel features including multipath and fading. The samples of primary signal s(n) can be demonstrated as a Gaussian random process with $\sigma_s^2$ variance. Therefore, the signal to noise ratio (SNR) is

$$SNR = \sigma_s^2 / \sigma_0^2. \tag{3}$$

The problem of spectrum sensing is said to be the binary hypotheses. Here $H_0$ represents the absence of the signal that is primary. To accomplish the higher protection to PU, $P_d$ should be high, whereas $P_f$ should be as small as possible to maximize the throughput of SU. Figure 1 demonstrations of the sequential multistage model for spectrum sensing.

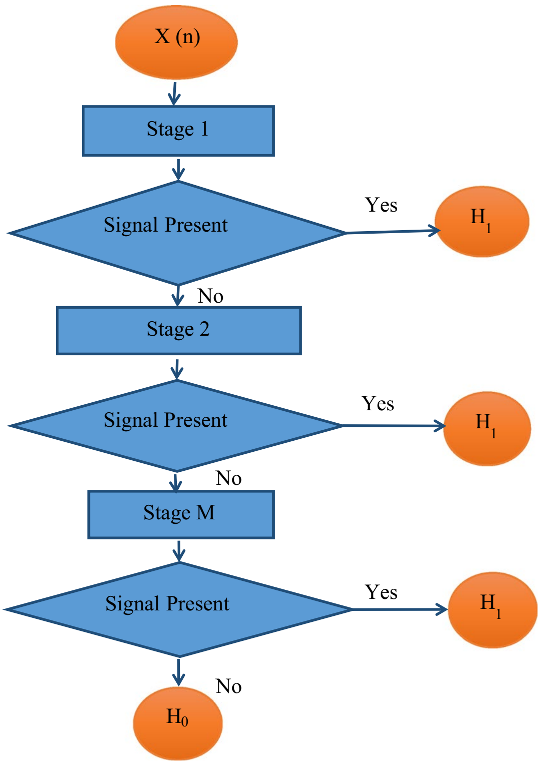


**Fig. 1** Sequential multistage model for spectrum sensing

The probability of false alarm Pfa and probability of detection $p_d$ is formulated as

$$\left.\begin{aligned} \mathrm{Pfa} &= \Pr\left(H_1 | H_0\right) \\ p_{\mathrm{d}} &= \Pr\left(H_1 | H_0\right) \end{aligned}\right\} \tag{4}$$

## 4.2 Detection Methodology

### 4.2.1 Energy Detector

The samples of signal have being squared up and then added up to evaluate the energy of signal in the ED. Let's say, the energy of signal is estimated from the given values of N that is received signal.

Later, $x_j$ and $s_j$ represent the received-signal with noise signal respectively. Following the estimation of the energy signal is consequently contrasted against the components of the energy related to noise-only in the spotting band. Therefore, the below stated conclusion is stated as:

$$X \rightarrow \begin{cases} \left(\sum_{j=1}^{M} \left|x_j\right|^2\right) < \rho, & H_0 \\ otherwise, & H_1 \end{cases} \tag{5}$$

where $\rho$ is the detection threshold. The outcome of the ED is in the form of Chi square distribution, than may be estimated as being Gaussian distributed assuming that the $N \rightarrow \infty$ [26, 29], stay on the estimation, the Pd versus Pfa of the ED. The Pfa for the ED $p_f^E$ achieved by

$$P_f^E = Q\left(\frac{\rho - N\sigma_z^2}{2\sqrt{2\sigma_z^2}}\right) \tag{6}$$

Here Q(·) is the Q function demonstrating the cumulative distribution function (CDF) of a Gaussian random process as well as $\sigma_z^2$(noise variance).

$$\rho = \sqrt{2N}\sigma_z^2 Q^{-1}\left(P_f^E\right) + N\sigma_z^2 \tag{7}$$

Here $Q^{-1}(\cdot)$ representing inverse function of Q.

After calculating the ρ from Eq. (7), based on the $\rho$ value calculate the probability of detection ($p_d^E$) using the following formula:

$$p_d^E = Q\left(\frac{\rho - N(\gamma + 1)\sigma_z^2}{2\sqrt{2N}(\gamma + 1)\sigma_z^2}\right) \tag{8}$$

As for the ED complexity, the multiplication operations of N are needed to square up the samples received, as well as (N−1) summations are required in summing them up altogether. Thus, the complexity of the ED, $C^E$ is achieved as

$$C^E = O(N) \tag{9}$$

### 4.2.2 Maximum–Minimum Eigenvalue Detector

The Eigenvalues distribution of the covariance matrix is offered an interactive process of research in the theory of random matrix [30; 31]. In general, the theory of random matrix and in particular, the distribution of covariance matrix Eigenvalue, are broadly utilized to solve the problems related to wireless-communication [32].

Many techniques have been established based on the eigenvalues and eigenvectors of the received signal covariance matrix for spectrum sensing. In addition to MME methods include the signal energy with minimum and maximum eigenvalue for generalized likelihood ratio test. Elaborated elucidations of the procedures are incorporated. This segment of this research paper offers one of these techniques of eigenvalue-based detection, such as, MME, that is established within [17] and [18]. The first step to compute the MME is a sample covariance matrix (SCM) $\hat{R}_x$ as

$$\hat{R}_x = \frac{1}{N} X X^H \tag{10}$$

With $(\cdot)^H$ representing the Hermitian. From Eq. (10) $\hat{R}_x$, is calculating and here L eigenvalues indicated $\lambda_1, \lambda_2 \ldots \lambda_L$, where $\lambda_1 > \lambda_2 > \ldots > \lambda_L$, are achieved. Subsequently, a detection threshold $(\Lambda)$ is measured as:

$$\Lambda = \left( \frac{\sqrt{N} + \sqrt{L}}{\sqrt{N} - \sqrt{L}} \right)^2 \left( 1 - \frac{\left(\sqrt{N} + \sqrt{L}\right)^{-\frac{2}{3}}}{(NL)^{\frac{1}{6}}} F_1^{-1}\left(1 - p_f^M\right) \right) \tag{11}$$

where Pfa for MME is $(\left(P_f^M\right)$, and $F_1^{-1}(\cdot)$ represented the inverse Tracy–Widom distribution order 1.

$$X \rightarrow \begin{cases} \left(\frac{\lambda_L}{\lambda_L}\right) \leq \Lambda, \ H_0 \\ otherwise, \ \ H_1 \end{cases} \tag{12}$$

As follow the Ref. [18], the $p_d$ values for MME is indicating $P_d^M$ and the computation is very complex. So make the process easier empirical formula is found in [18].

The bandwidth of the signal is one of the important factors which influence the accuracy of sensing of the MME [33]. We have first introduced the following terms and the notations. The bandwidth observed happens to be the bandwidth of the elements as the recipient captured and is designated to be B. The occupation bandwidth observed when comprises of the mixture of the signal as well as noise, whereas the other part of the bandwidth observed consists of the components being noise. The ratio of the occupation bandwidth to the designated by $\beta = (b/B)$. In the blind sensing, the underlying assumption is that $\beta$ is unidentified and isn't computed; thus, the detection is being done individually, but is affected by $\beta$ [33]. For the Gaussian form of signals, at $\beta = 1$, the signal as well as the noise, summed up on top of one another. As a result, the resulting outcome of this summation of the variance $(\sigma_s^2 + \sigma_s^2)$ [34]. Thus, the null hypothesis $H_0$ will be stated when no signal is there else when a Gaussian signal exists there engaging the whole observation bandwidth.

In the 2 cases, the detection probability is at its minimum, that is, 0000, the false alarm probability. Consequently, the MME detection probability is found to be a concave function relating to β. As of [33], the below relations are being proven:

$$\underset{\beta}{argmin}\left(p_d^M\right) = [0, 1] \tag{13}$$

$$\underset{\beta}{argmix}\left(p_d^M\right) = 0.5 \tag{14}$$

As affirmed in [18], to the MME computational complexity context, the governing two MME procedures are erecting the SCM, in (13), as well as attaining the L Eigen values of the SCM by decomposition of singular value. To determine the SCM (since its Toeplitz Matrix [18]), evaluating the 1st row only that is required. It needs N number of multiplications as well as (N − 1) summations. Thus, evaluating the 1st row of the SCM has the complication of O(N). The 2nd procedure of carrying out decomposition of singular value has the complexity of O ($L^3$) [35]. Coalescing of the two procedures would have outcome of a MME complexity $C^M$ as

$$C^M = O(N) + O\left(L^3\right) \tag{15}$$

#### 4.2.3 Maximum–Minimum Eigenvalue with Combined Detector Solution

Generally, MME surpasses ED as of the detection probability. This benefit of MME over ED with regard to the detection probability is traded off against the complexity of sensing. As given in (9) and (15) equations, the MME executes the sensing at an order of ($L^3$) extra operations contrasted with the ED.

The detection probability of a 2-staged detector is devised in [21] as well as [22]. From the detection process flow in the sensing of sequential multistage spectrum, the detection probability relationship in [21] and [22] is designated pd(γ) and may be universalized for a detector of M-stage as

$$p_d\gamma = p_d^1(\gamma) + \sum_{i=2}^{M}\left(p_d^i(\gamma)\prod_{j=2}^{i-1}\left(1 - p_d^j(\gamma)\right)\right) \tag{16}$$

Likewise, the false alarm probability for a 2-staged detector is establish to be within [21] and [22] as well as universalized for a detector of M-stage. Designate this universalized false alarm probability as $p_f$, that is

$$p_f = p_f^1 + \sum_{i=2}^{M}\left(p_f^i(\gamma)\prod_{j=1}^{i-1}\left(1 - p_f^j\right)\right) \tag{17}$$

In context to the prior shown contrast, if a completely blind detector is intended for, then we require to make a decision about which detector to use and when. How so ever, completely blind will depict that the detector doesn't know the received SNR range to be expected, the occupation bandwidth values, and moreover, the noise energy within the interest band. Thus, a detector that obtains benefit from each of the detectors having no prior information of the conditions of the signal received is required. A 2-staged

ED–MME combined detector has been built up in this research paper that is elucidated in a detailed manner later. Henceforward, the combined detector thus developed is known as 2EMC that stands for 2-staged EMM combined detector. Figure 2 representing the system model diagram of the 2EMC.

From Eq. (17), the pfa for the 2EMC denoted $p_f^C$ is obtained as

$$p_f^C = p_f^E + \left(1 - p_f^E\right)p_f^M = p_f^E + p_f^M - p_f^E \cdot p_f^M \tag{18}$$

As in Eq. (18), if a specific Pfa is represent for the ED below the limit of pfa is fixed for the 2EMC, consequently the MME Pfa is found as

$$p_f^M = \frac{p_f^C - p_f^E}{1 - p_f^E} \tag{19a}$$

As in Eq. (19a), there are the combinations of $p_f^M$ and $p_f^M$ in infinite number to attain a particular value of $p_f^C$. If the $p_f^E$ value happens to be too elevated, consequently the ED would be capable to spot signals of weaker manner and would be utilized more. The complexity of the 2EMC on the whole would be diminished. It would craft the MME less proficient since the false alarm probability would be too low, and it would not be able to spotting signals with less values of SNR. Whereas, for too low $p_f^E$ values, the stage of ED needs high value of SNR to be capable of detecting, and mostly, it will entrust the decision over to the MME, which makes the ED less useful and consequently 2EMC further complex. To solve this problem, a halfway solution with equivalent Pfa

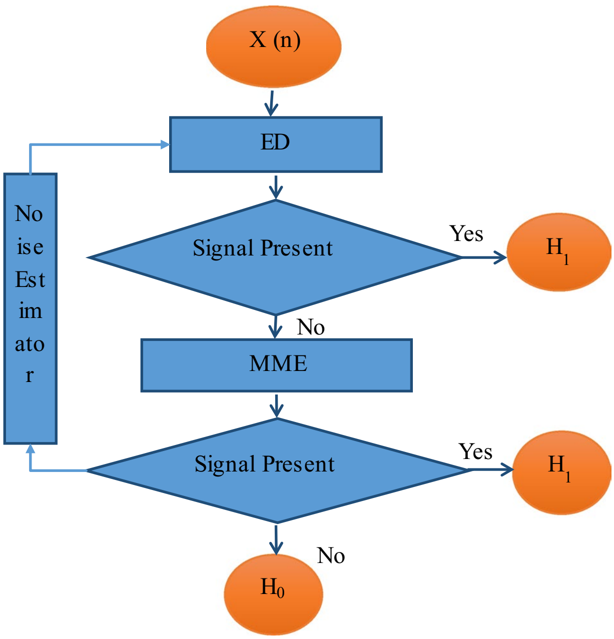


**Fig. 2** The model of the 2EMC detector

of the ED and MME both are put into this method. Therefore, with the solution (18), the Pfa for both the stages are ascertained to be

$$p_f^E = p_f^M = 1 - \sqrt{1 - p_f^C} \tag{19b}$$

Based on (15), the $p_d$ of the 2EMC indicated as $p_d^C$ is related to $p_D^E and p_d^M$ as

$$p_d^C = p_d^E + \left(1 - p_d^E\right)p_d^M = p_d^E + p_d^M - p_d^E \cdot p_d^M \tag{20}$$

## 4.3 Proposed Adaptive Covariance threshold Detection Method

Now the proposed Adaptive Covariance threshold-based detection (ACTD) scheme can be summarized as:

- Select the L (smoothing factor) and $N_s$ (number of samples).
- Obtain the sample covariance matrix of the received signal by SU using Eqs. (4–5) from energy detection phase.
- Measure the test statistics using Eqs. (21) and (22):

$$T_1(N_s) = \frac{1}{L\sum_{n=1}^{L}\sum_{m=1}^{L}\left|r_{nm}\left(N_s\right)\right|} \tag{21}$$

$$T_2(N_s) = \frac{1}{L\sum_{m=1}^{L}\left|r_{nm}\left(N_s\right)\right|} \tag{22}$$

where $r_{nm}$ ($N_s$) is f the sample covariance matrix Rs ($N_s$).

- Achieved the complete correlation strength ($\gamma_L$) between the sequential L samples in Eq. (23), considering 30 sensing interval i.e. N = 30$N_s$.is defined as:

$$\gamma_L = \frac{\left(T_1\left(N_s\right) - T_2\left(N_s\right)\right)}{SNR\sigma_\eta^2} \tag{23}$$

where N represents total no. of samples including previous sensing intervals making $N \gg N_s$

- Compute the best decision threshold $Y^*$ for indicated spectrum deployment ratio in Eq. (24).

$$Y^* = \left[\frac{\left((L-1)\sqrt{\frac{2}{N_s\pi}} - \frac{2\gamma_L SNR}{(SNR+1)}\right)}{In\left[\frac{1-\alpha}{\alpha}\frac{\left(1+(L-1)\sqrt{\frac{2}{N_s\pi}}\right)}{1+\frac{\gamma_L SNR}{(SNR+1)}}\right]\frac{4}{N_s}}\right].$$

$$\left[-1\left(\left(1+\frac{(L-1)\sqrt{\frac{2}{N_s\pi}}-\frac{2\gamma_L SNR}{(SNR+1)}+2}{(L-1)\sqrt{\frac{2}{N_s\pi}}-\frac{2\gamma_L SNR}{(SNR+1)}+2}\right)\cdot In\left[\frac{1-\alpha}{\alpha}\frac{\left(1+(L-1)\sqrt{\frac{2}{N_s\pi}}\right)}{1+\frac{\gamma_L SNR}{(SNR+1)}}\right]\frac{4}{N_s}\right)^{0.5}\right] \tag{23}$$

$$\lim_{N_s\to\infty} E\left(T_1(N_s)-T_2(N_s)\right)=\frac{2\sigma_s^2}{L}\sum_{l=1}^{L-1}(L-1)\left|\alpha_l\right| \tag{24}$$

where $\alpha_1$ represents the correlation between signal samples. Figure 3 shown the systematic diagram of the proposed work. It can be noted that, under hypothesis $H_1$, the overall correlation between the sequential L samples can be obtained from the off-diagonal fundamentals of the sample covariance conditions $R_x$ ($N_s$) and $T_2$ (Ns) it can be written that:

- Achieve the test statistic.

$$T(N_s)=\frac{T_1(N_s)}{T_2(N_s)} \tag{25}$$

- Takings the sensing conclusion as:

$$D=\begin{cases}1 & T(N_s)>\gamma^*\\ 0 & T(N_s)\geq\gamma^*\end{cases} \tag{26}$$

where the decision D = 0 designates when the PU is absent,where decision D = 1 means that primary user is active.

## 5 Simulation and Numerical Results

This paper present the simulation of Energy-Detection (ED), ED with Maximum–Minimum Eigenvalue (MME), ED-MME with combine detector (2EMC) and Noise estimation with MME Spectrum Sensing Methods. All these methods are proposed based on the Covariance based Adaptive threshold detection (ACTD). The results presented in this paper demonstrate the performance of the proposed Adaptive Covariance threshold-based detection (ACTD) approach. The existing approach are compared with the proposed covariance (ACTD) based spectrum sensing schemes. The method of spectrum sensing are proposed and compare to each other respectively such as ED with ED-ACTD, ED-MME with MME-ACTD, 2EMC with 2EMC-ACTD and last on NMSE with NMSE-ACTD based spectrum sensing scheme are also simulated and compare the performance to each other respectively.

In our experiments, we proposed to solve two probabilities that are concerned with detection which is $P_d$ and false alarm as represented by $P_f$.

Here, $P_d$ is concerned with the algorithm probability that accurately detects if primary signals are present or not under $H_1$ hypothesis. $P_f$ relates to the false algorithm relating to the declaration of the primary signal. During the transmission mode of the PU, the SU has to leave the band. This results in false alarm low probability resulting in higher reusability of bands that are unoccupied. Similarly, if the probability detection is high then, PUs is detector better (Table 1).

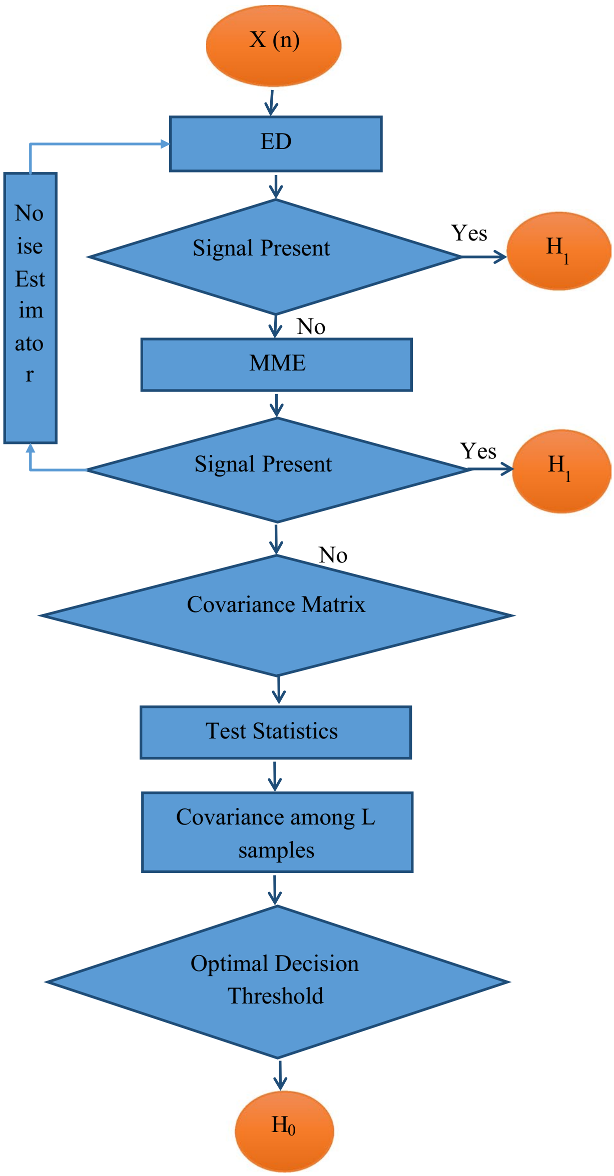


**Fig. 3** The model of the proposed detector

In the experiment, the number of samples ($N$)is a sensing interval, which is vary from 1000 to 5000, the parameter $L$ is taken as 5, 20 and 50.

Various simulations scenarios on the different SNR approaches were done. $H_0$ hypothesis is kept as constant independent of the size of the sample. The ratio of the false alarm is kept as invariant. The size of sample could have an influence on the probability of detection in hypothesis $H_1$.

**Table 1** Simulation parameter

| Parameters | Values |
|---|---|
| Operating System | Windows |
| Matlab version | 2015b |
| L | 5, 20, 50 |
| N | 5000, 1000 |
| SNR_dB | − 20, − 14, − 12, − 10, − 8 |
| B | 0.5:0.05:1 |
| Algorithm | ED, ED–ACTD, MME, MME–ACTD, 2EMC, 2EMC–ACTD and noise estimation |

When the performance of ED, MME and 2EMC are concerned without applied adaptive covariance threshold method, they are evaluated based single test statics *T* (*Y*) and threshold by considering the probabilities of false alarm and detection. It is denoted by using *Pd* and *Pf*.

Experiments of Monte Carlo are done for about 5000 runs *L* = 1000. The detection performance curves versus false alarm probability of energy detection and proposed energy detection with covariance threshold with different SNR (dB) in Figs. 4 and 5 respectively, where the primary and the binary phase shift keying BPSK signal is modulated with frequency carrier of *fc* = 40 kHz. Here the sampling frequency *fs* = 100 kHz and the sampling time is *t* = 5 ms.

It is seen that the performance is different based on the SNR values but as SNR value increases in the simulation with respect SNR probability of detection increased respectively. The performance of energy detection with covariance threshold method versus Pfa based on the SNR (dB) variation having higher values of $P_f$ as compared to the

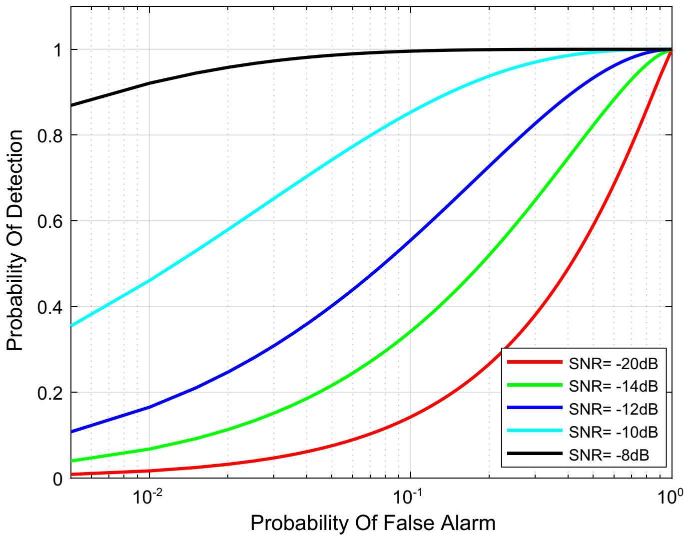


**Fig. 4** Detection performance versus false alarm probability of ED and ED-ACTD with different SNR (dB) and sample Size (N = 5000)

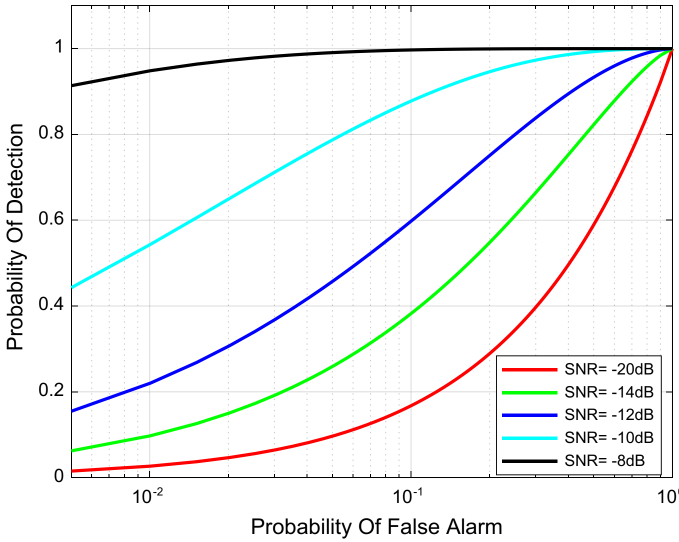


**Fig. 5** Detection performance versus false alarm probability of ED and ED-ACTD with different SNR (dB) and sample Size (N = 5000)

existing energy detection method. The performance of ED is deeply degraded at low probability of false alarm and high SNR.

As shown in the Figs. 4 and 5, the simulated energy detection with ACTD performance higher at the value of SNR is − 6 dB.

Figures 6 and 7, shows the performance curves of detection. Here the MME and MME-ACTD performance is calculated for different level of SNR where SNR is (− 20, − 14, − 12, − 10 and − 8) as concerned with the constant probability of false alarm. The method of MME-ACTD is better than the method of MME.

The detection performance comparison curves versus false alarm probability of 2EMC on the basics of the SNR (dB) in Figs. 8 and 9. It is seen that the performance is changing based on the SNR (dB) but the false alarm is constant. As we can conclude the detection probability is decreasing as SNR (dB) value is increasing but 2EMC–ACTD have higher efficiency as compare to the 2EMC and MME.

Moreover, for a variation in SNR, the detection probability performance is higher at (− 8 & 10 dB) and worst performance at (− 20 & 14 dB) SNR. As compare to above two method low SNR region is not acceptable.

The main indication of the 2EMC method of spectrum sensing is to implement a probability detection ($p_d$) over the high value of SNR and later on move to low SNR values where probability detection is very complex. In this algorithm first energy detection performed, if yes then assumed SNR value is high and signal presence. If not, then SNR value is low and signal is signal not existence, only noise is received.

After that 2nd phase start of detection using MME algorithms, here probability for lower SNR are achieved highly with the high complexity.

Figures 10 and 11 shows estimated noise versus β with N = 5000, 1000 and L = 5, 10, 50. For the various value of β assumptions, energy detection or MME outperform to each other, based on the different value of β. Consequently, the 2EMC algorithm shown improvement over the every detector where as the β values is unfamiliar.

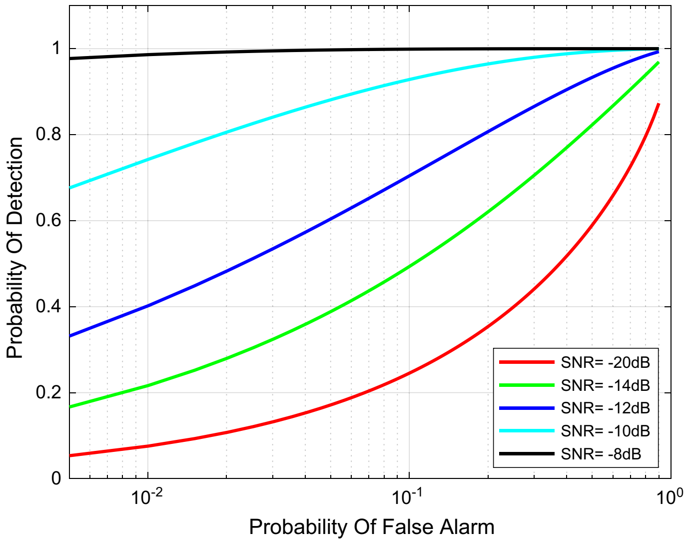


**Fig. 6** Detection performance versus false alarm probability of MME and MME-ACTD with different SNR (dB) and sample Size (N = 5000)

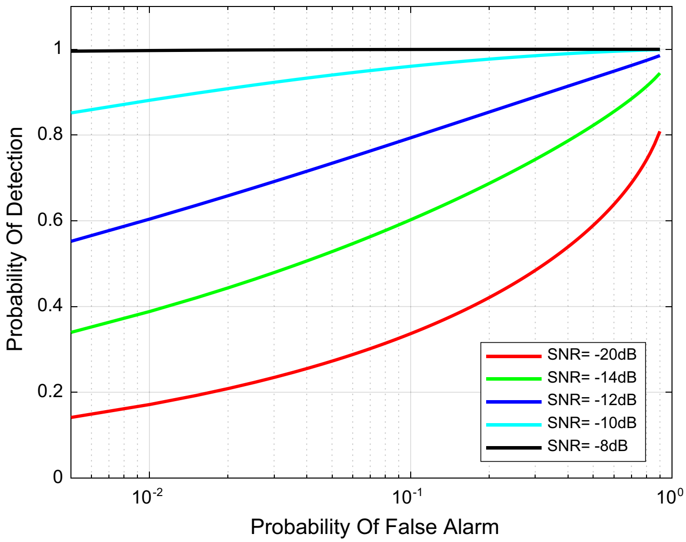


**Fig. 7** Detection performance versus false alarm probability of MME and MME-ACTD with different SNR (dB) and sample Size (N = 5000)

The Figs. 10 and 11 is generated based on SNR of − 8 dB, N = 5000, $p_f^C = 0.1$ and L = 5, 20. As shown in below figure, detection values is low at low values of β. So here performance is checked on the variation of the β values. At the intermediate range of the vales MME perform recovering than the energy detections and at high values energy detection perform better than MME.

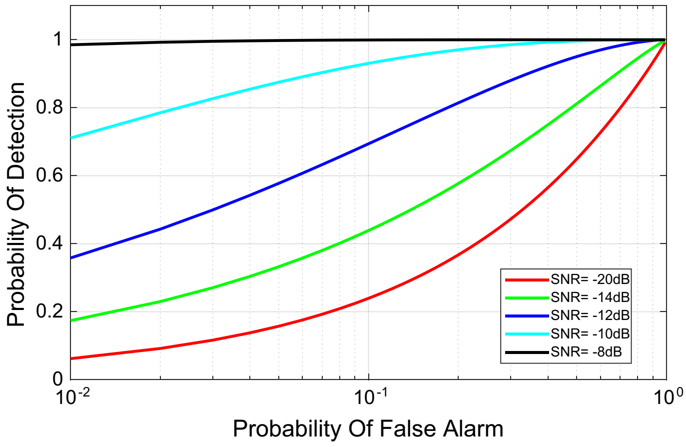


**Fig. 8** Detection performance versus false alarm probability of 2EMC and 2EMC–ACTD with different SNR (dB) and sample Size (N = 5000)

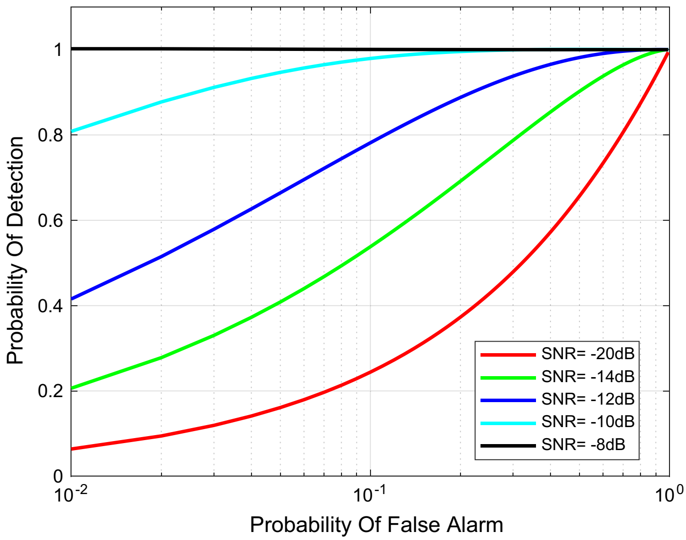


**Fig. 9** Detection performance versus false alarm probability of 2EMC and 2EMC-ACTDwith different SNR (dB) and sample Size (N = 5000)

## 6 Conclusion

In this experiment we proved that the scheme that we proposed based on the adaptive covariance threshold matrix taking the help of experiments of Monte Carlo. Here we also showed that the existing algorithm with adaptive covariance threshold matrix would be highly efficient as compared to the existing published algorithms based on the single threshold. As compared to them a −20 dB till −8 dB improvements was observed respectively.

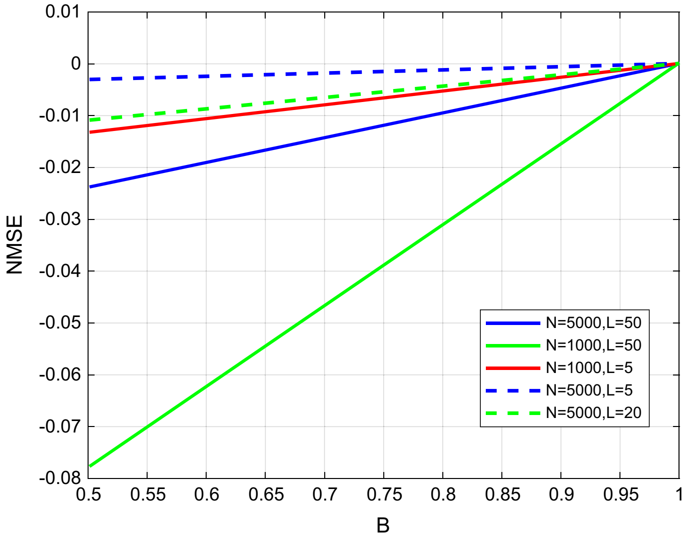


**Fig. 10** Estimated noise versus different value of β of NMSE using various values of N and L

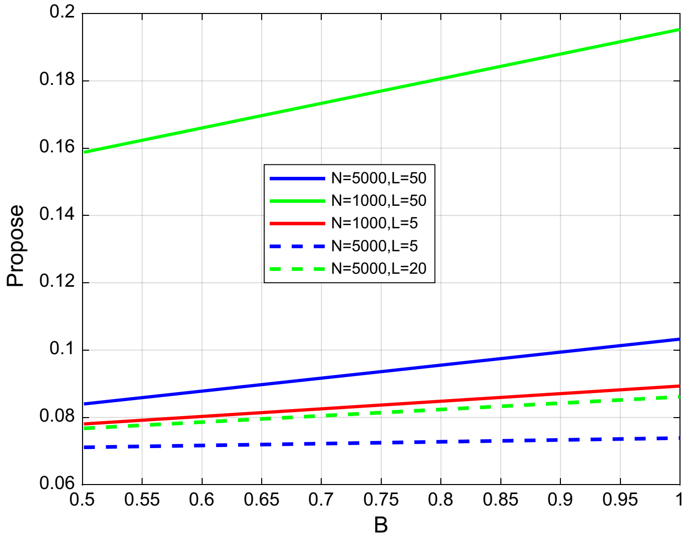


**Fig. 11** Estimated noise versus different value of β of NMSE-ACTD using various values of N and L

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