TRIBHUVAN UNIVERSITY

INSTITUTE OF ENGINEERING

PULCHOWK CAMPUS

THESIS NUMBER : 070/MSI/610

"COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIOS : PERFORMANCE EVALUATION FOR HETEROGENEOUS COOPERATING NODES"

BY:

RAJENDRA SHRESTHA

A THESIS

SUBMITTED TO DEPARTMENT OF ELECTRONICS AND COMPUTER ENGINEERING IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN INFORMATION AND COMMUNICATION ENGINEERING

DEPARTMENT OF ELECTRONICS AND COMPUTER ENGINEERING

LALITPUR, NEPAL

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UNDER THE SUPERVISION OF

Dr. NANDA BIKRAM ADHIKARI

DEPARTMENT OF ELECTRONICS AND COMPUTER ENGINEERING

LALITPUR, NEPAL

NOVEMBER, 2015

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LALITPUR, NEPAL

The undersigned certify that they have read and recommended to the Department of Electronics and Computer Engineering for acceptance, a thesis report entitled **"Cooperative Spectrum Sensing in Cognitive Radios: Performance Evaluation for Heterogeneous Cooperating Nodes"**, submitted by Rajendra Shrestha in partial fulfillment of the requirement for the award of the degree of Master of Science in Information and Communication Engineering.

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DEPARTMENT ACCEPTANCE

The thesis entitled **"Cooperative Spectrum Sensing in Cognitive Radios: Performance Evaluation for Heterogeneous Cooperating Nodes"**, submitted by **Rajendra Shrestha** in partial fulfillment of the requirement for the award of the degree of "**Master of Science in Information and Communication Engineering**" has been accepted as a bonafide record of work independently carried out by him in the department.

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ABSTRACT

The rapid growth in wireless communications has contributed to a huge demand on the deployment of new wireless services .Cognitive Radio (CR) is the promising solution of underutilized licensed spectrum. Thus the two most popular research areas when it comes to CR are spectrum sensing and interference management and resource allocation. Spectrum sensing is the ability to find available frequencies/timeslots to transmit in.

The detection of PUs in practical wireless channels with a single CR sensor is challenging due to several issues such as the hidden node problem, path loss, shadowing, multipath fading, and receiver noise/interference uncertainty. In this context, Cooperative Spectrum Sensing (CSS) is considered a promising technique in order to enhance the overall sensing efficiency. Existing CSS methods mostly focus on homogeneous cooperating nodes considering identical node capabilities, equal number of antennas, equal sampling rate and identical Signal to Noise Ratio (SNR). However, in practice, nodes with different capabilities can be deployed at different stages and are very much likely to be heterogeneous in terms of the aforementioned features. In this context, CSS technique for the heterogeneous nodes with different capabilities on the basis of different sensing techniques i.e. energy detection based spectrum sensing technique and eigen value based spectrum sensing technique was analysed. The performance of this CSS technique was evaluated by the use of Receiver Operating Characteristics (ROC) and complementary Receiver Operating Characteristics (ROC) curves over additive white Gaussian noise (AWGN) channel.

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LIST OF ABBREVIATIONS

AWGN	Additive White Gaussian Noise
BPF	Bandpass Filter
CR	Cognitive Radio
CSS	Cooperative Spectrum Sensing
ED	Energy Detector
FCC	Federal Communication Commission
ME	Maximum Eigenvalue
PD	Probability of Detection
PFA	Probability of False Alarm
PM	Probability of Missed detection
PU	Primary User
ROC	Receiver Operating Characteristics
SCN	Signal Condition Number
SLE	Scaled Largest Eigenvalue
SU	Secondary User

CHAPTER ONE

INTRODUCTION

1.1 Background

The rapid growth in wireless communications has contributed to a huge demand on the deployment of new wireless services in both the licensed and unlicensed frequency spectrum. As we know that the natural frequency spectrum is scared resource, the efficient use of it can only accommodate the spectrum demand of increase in wireless devices and applications. However, recent studies show that the fixed spectrum assignment policy enforced today results in poor spectrum utilization. Therefore for efficient utilization of the spectrum band, Federal Communication Commission (FCC) allowed secondary (unlicensed) users to utilize the licensed band without interfering the primary (licensed) users when it is not in use by primary user named it as Cognitive Radio.

A Cognitive radio is a system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets [1].

The Functions of Cognitive Radio are [1]-[2], [5] :

i. Spectrum sensing and Analyzing**:** Determine which portion of the spectrum is available and detect the presence of licensed users when a user operates in a licensed band.
ii. Spectrum management and Handoff**:** It selects the best available channel (frequency) for communication.
iii. Spectrum sharing and Allocation: It coordinates fair spectrum access to this channel with other users.
iv. Spectrum mobility: Vacate the channel when a licensed user is detected while still maintaining seamless communication requirements during the transition to a better piece of spectrum.

A major challenge in cognitive radio is that the secondary users need to detect the presence of primary users in a licensed spectrum and quit the frequency band as quickly as possible if the corresponding primary radio emerges in order to avoid interference to primary users. This technique is called spectrum sensing. A number of methods have been proposed for identifying spectrum opportunities in a scanned frequency band. Typically, spectrum sensing is grouped within three main detection approaches [1], [2] :

1. Transmitter based detection methods
    i. Energy Detection Technique
    ii. Cyclostationary Feature Detection Technique
    iii. Matched Filter Technique
2. Cooperative detection methods
    i. Decentralized Uncoordinated Technique
    ii. Centralized Coordinated Technique
    iii. Decentralized Coordinated Technique
3. Interference based method.
    i. Primary Receiver Detection Technique
    ii. Interference Temperature Management Technique

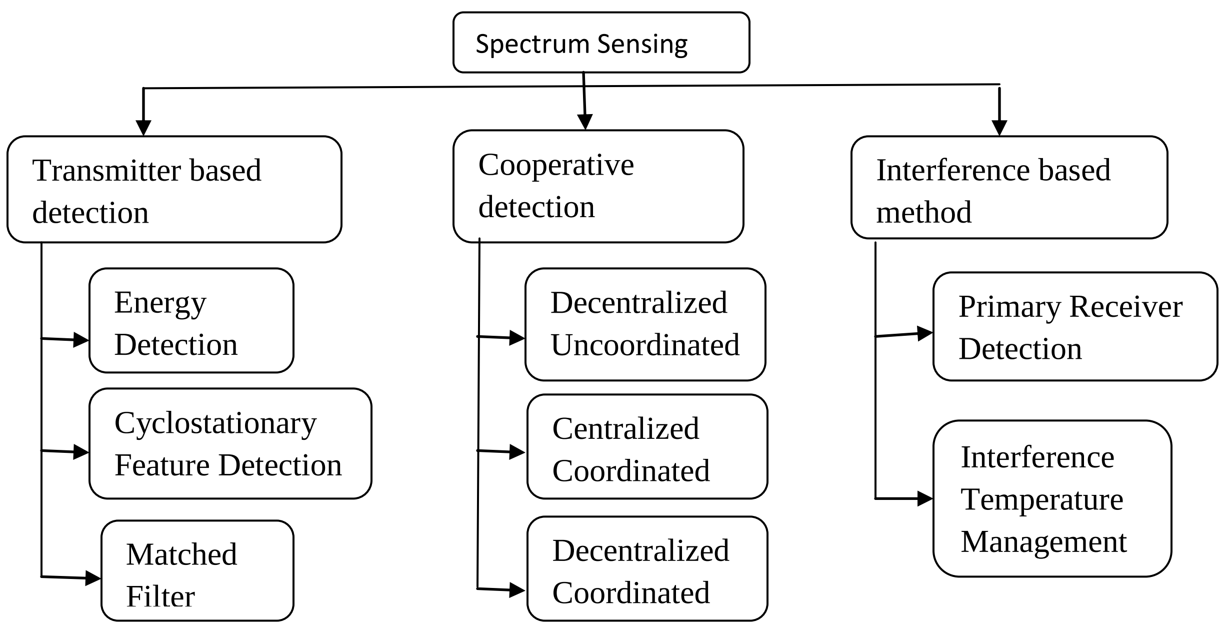

Figure 1.1 : Spectrum Sensing Methods

1.2 Problem Definition

As stated the major challenge in cognitive radio is that the secondary users need to detect the presence of primary users in a licensed spectrum and quit the frequency band as quickly as possible if the corresponding primary radio emerges in order to avoid interference to primary users. But in case of failure in the performance of spectrum sensing implies a missed opportunity for secondary users to utilize the whitespace of the spectrum, thereby causing harmful interference to the primary user. The detection of active Primary Users (PUs) in practical wireless channels with a single Cognitive Radio (CR) sensor is challenging due to several issues such as the hidden node problem, path loss, shadowing, multipath fading, and receiver noise/interference uncertainty. In this context, Cooperative Spectrum Sensing (CSS) is considered a promising technique in order to enhance the overall sensing efficiency. Existing CSS mostly focus on homogeneous cooperating nodes considering identical node capabilities, equal number of antennas, equal sampling rate and identical Signal to Noise Ratio (SNR). However, in practice, nodes with different capabilities can be deployed at different stages and are very much likely to be heterogeneous in terms of the aforementioned features.

The problem considered in this project is to ascertain the performance of a detection scheme that quickly scans a spectrum band to decide on the availability of a primary user. This system will not involve prior knowledge of the primary user signaling scheme and channel information between users. The performance of secondary user (SU) using the energy of a received signal and eigen value of the matrix formed by the received signal to determine presence of a primary user for the heteregeneous cooperative nodes is to be investigated.

1.3 Objectives

The main objectives of the project can be listed as follows:

i. To study and analyze the different Cooperative Spectrum Sensing techniques for homogeneous and heterogeneous Sensor nodes.

ii. To study and investigate the combination of multiple decision statistics in the heterogeneous environment in cooperative nodes.

1.4 Report Organization

The thesis report is developed into five chapters, each of which focuses on one different aspect of the thesis. The thesis states the various algorithms and techniques used in research, evaluates the performance and performs the analysis.

Chapter one includes a basic introduction of the thesis. It includes a basic problem that is stated in the problem definition. The objectives of this thesis are also shown in this chapter.

Chapter two includes literature review of the thesis. It includes the existing works that have been carried out in this field.

Chapter three includes methodology used in the thesis. Different system models for different spectrum sensing techniques are prepared. The detail explanation of each model is made. So, this section includes schematic diagram and program carried out in the thesis. The program illustrates the flow-diagram and algorithm.

Chapter four includes simulation result and analysis. This section contains the overall output of the thesis. The output can be modeled on graphical form and tabular form.

Chapter five includes conclusion. This section includes discussions and conclusion of the thesis.

CHAPTER TWO

LITERATURE REVIEW

A number of methods have been proposed for identifying spectrum opportunities in a scanned frequency band. Typically, spectrum sensing is grouped within three main detection approaches [1]-[2].

i. Transmitter based detection methods,
ii. Cooperative detection methods and
iii. Interference based method.

Transmitter detection methods consists of matched fillter, cyclostationary and energy detection [1]. These techniques are further classified as coherent, semi-coherent or non-coherent; that is, either having complete, partial or no prior knowledge of the transmitter respectively.

2.1 Energy detection

Energy detection is a non-coherent detection method that detects the primary signal based on the sensed energy. Due to its simplicity and no requirement on a priori knowledge of PU signals, energy detection is the most popular sensing technique in cooperative sensing.

A model for detection of energy in deterministic signals under AWGN in the time domain consisting of passing the received signal y(t) through an ideal bandpass fillter (BPF) with a center frequency fo and bandwidth W, with transfer function [1],[2],[9];

$$H(f) = \frac{2}{\sqrt{N\mathrm{o}}}\ , \qquad |f - f\mathrm{o}| \leq W$$

$$= 0, \qquad |f - f\mathrm{o}| > W\ , \qquad (2.1)$$

where N is the one-sided noise power spectral density which normalizes if found convenient to compute the false-alarm and detection probabilities using the related transfer function. From these, the signal is then squared and integrated over an interval T, to produce a test statistic, V, compared to a threshold. The receiver makes a decision on the target signal, based on the condition that the threshold is exceeded.

While comparing the existing Spectrum Sensing techniques, it can be noted that the ED technique is simple to implement but is susceptible to noise variance uncertainty [1],[9]. This drawback can be addressed by using blind eigenvalue-based techniques such as

MME or Signal Condition Number (SCN), Scaled Largest Eigenvalue (SLE), John's Detection (JD) method, Spherical Test (ST) detector, etc [3].

2.2 Eigenvalue-based detection

In this approach, different eigenvalue properties of the received signal's covariance matrix can be exploited to perform sensing. Several eigenvalue-based sensing and SNR estimation techniques have been proposed in the literature exploiting the properties of Wishart random matrices[3]. For implementing this technique, the receiving node has to collect the received samples in the K x N matrix form with K being the receive dimension. This receive dimension can be either the number of fractional sampled branches, multiple antennas or the cooperating nodes. The main advantage of the eigenvalue-based approach in practical scenarios is that it does not require any prior nformation about the PU's signal and the channel. After collecting N samples using different receive dimension K, the received $K \times N$ data matrix **Y** is represented as

$$\mathbf{Y} = \begin{bmatrix} y_1(1) & y_1(2) & \dots & y_1(N) \\ y_2(1) & y_2(2) & \dots & y_2(N) \\ \vdots & \vdots & \ddots & \vdots \\ y_k(1) & y_k(2) & \dots & y_k(N) \end{bmatrix}. \qquad (2.2)$$

Mathematically, the primary user detection problem is a hypothesis test between two hypotheses. Hypothesis 0 (**H0**) denotes the absence of the primary user and hypothesis 1 (**H1**) denotes the presence of the primary user. If we assume no fading in the temporal domain, i.e. the channel stays constant during the sensing time, the two hypotheses can be represented as [3]:

$$\begin{aligned} &H0 : y_{k,n} = n_{k,n} \\ &H1 : y_{k,n} = \sum_{i=1}^{P} h_k(i)\, s_n(i) + n_{k,n} \quad , \qquad (2.3) \end{aligned}$$

where $k = 1, \dots, K$ and $n = 1, \dots, N$. Here $n_{k,n}$ is the complex Gaussian noise with zero mean and variance σ^2 , P denotes the number of simultaneously transmitting primary users. The receive covariance matrix $\mathbf{R_x}$ is defined as $\mathbf{R_x} = \mathbf{YY^H}$, where H denotes the Hermitian conjugate operator. By using different eigenvalue properties of R such as Maximum Eigenvalue (ME), Signal Condition Number (SCN), Scaled Largest Eigenvalue (SLE), etc., the presence or absence of the PU signal can be decided.

2.3 Cooperative sensing method

The cooperation of CR users for spectrum sensing can be modeled by different approaches. The modeling in cooperative sensing is primarily concerned with how CR users cooperate to perform spectrum sensing and achieve the optimal detection performance. Thus, Cooperative Spectrum Sensing (CSS), in which several nodes cooperate with each other in order to enhance the overall sensing performance, has been considered as a promising approach [6]-[8].

The cooperation can be among the CRs or external sensors that can be deployed to build a CSS network. In the former case, the cooperation can be implemented in the following ways [7]:

2.3.1 Decentralized Uncoordinated Techniques

The cognitive users in the network don't have any kind of cooperation which means that each CR user will independently detect the channel, and if a CR user detects the primary user it would vacate the channel without informing the other users.

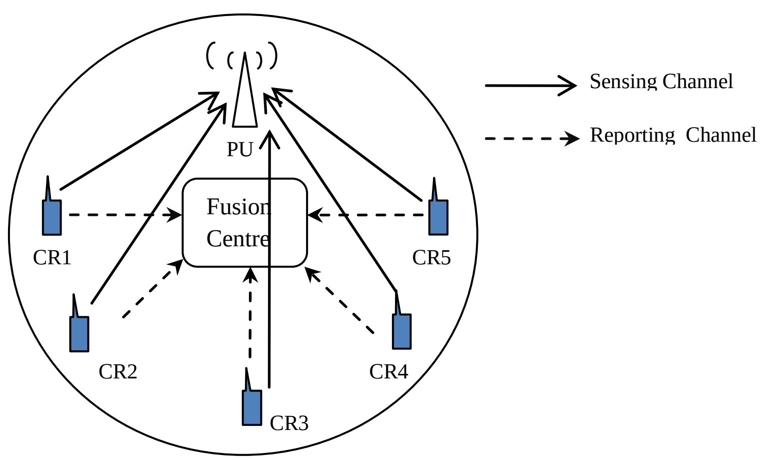

Figure 2.1 : Decentralized Uncoordinated Techniques

2.3.2 Centralized Coordinated Techniques

In such networks, an infrastructure deployment is assumed for the CR users. One CR that detects the presence of a primary transmitter or receiver, informs a CR controller which can be a wired immobile device or another CR user.

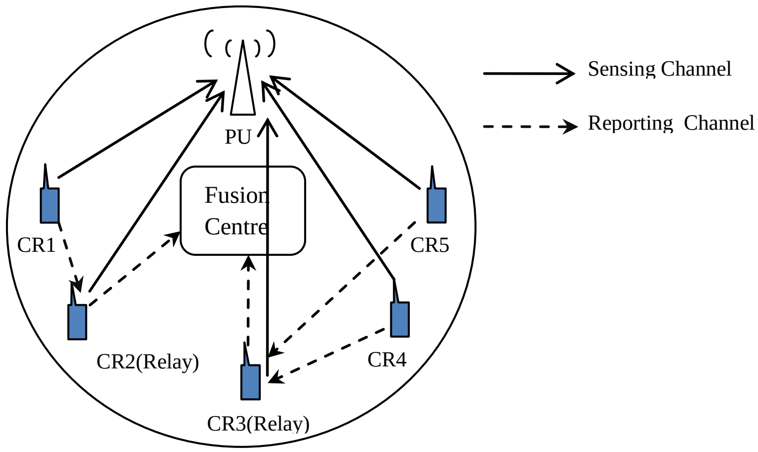

Figure 2.2 : Centralized Coordinate Techniques

2.3.3 Decentralized Coordinated Techniques

This type of coordination implies building up a network of cognitive radios without having the need of a controller. Various algorithms have been proposed for the decentralized techniques among which are the gossiping algorithms or clustering schemes, where cognitive users gather to clusters, auto coordinating themselves.

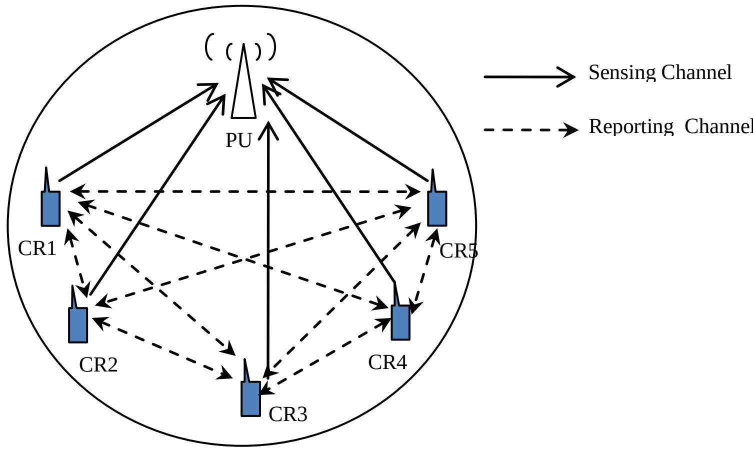

Figure 2.3 : Decentralized Coordinated Techniques

2.4 Homogeneous and heterogeneous cooperative nodes

A CR network can be classified as homogeneous and heterogeneous cooperating nodes on the basis of the properties of the sensor nodes .

1. If the sensor nodes are assumed to have identical capabilities, equal number of antennas, equal sampling rate, and identical received Signal to Noise Ratio(SNR) for cooperating nodes then it can be termed as homogeneous Cooperative Nodes.
2. If the sensor nodes are assumed to have different capabilities that can deployed at different stages and are heterogeneous in terms of different features like number of antennas, sampling rate, and received Signal to Noise Ratio(SNR) for cooperating nodes then it can be termed as heterogeneous Cooperative Node.

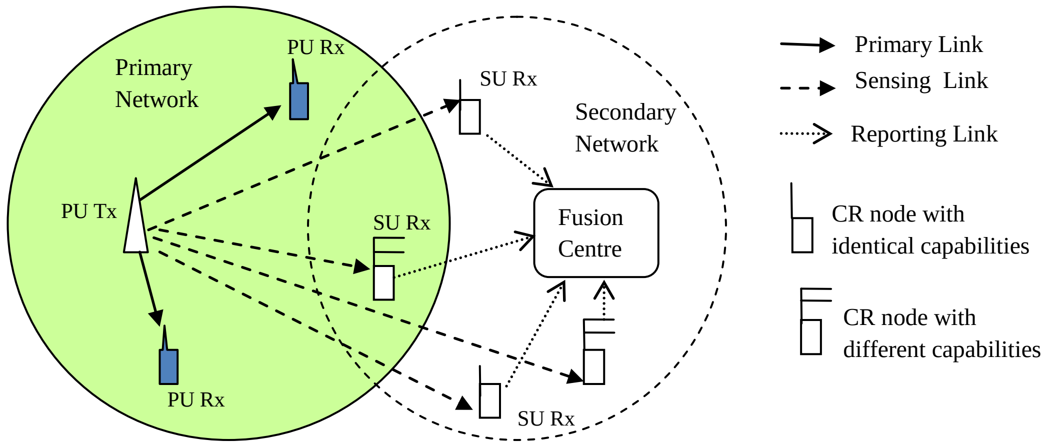

Figure 2.4 : Schematic Diagram Showing Heterogeneous Cooperating Nodes

Most of the existing CSS literature considers a CR network with homogeneous sensor nodes and assumes identical capabilities, equal number of antennas, equal sampling rate and identical received Signal to Noise Ratio (SNR) for all the cooperating nodes[1], [2], [7].

However, in practice, the nodes with different capabilities can be deployed at different stages and are very much likely to be heterogeneous in terms of the sensor nodes features like number of antennas, sampling rate, and received Signal to Noise Ratio(SNR), etc. In this context, it's an important challenge to investigate suitable CSS techniques which can provide better sensing performance in heterogeneous environments. Further, most of the existing decision and data fusion techniques in the CSS context use a single type of detector (ED in many cases) as local and CSS mechanisms. However, in heterogeneous environments, different nodes can employ separate decision statistics since they may have different capabilities. The issue of data fusion considering different decision statistics for CSS has not been addressed and analysed n the literature. To address the above issues, the combination of ED and eigenvaluebased decision statistics in order to achieve reliable sensing in heterogeneous environments is to be investigated that is addressed in this research.

CHAPTER THREE

METHODOLOGY

3.1 System Model

3.1.1 System model for energy detection technique for spectrum sensing

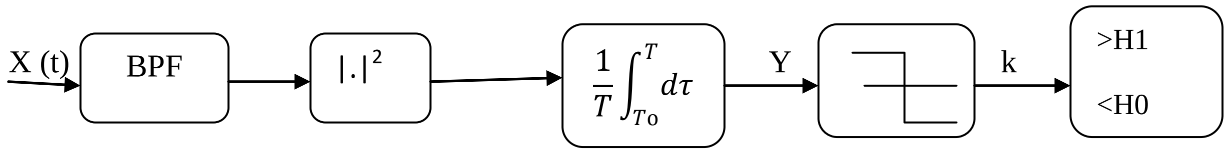

Figure 3.1: Block diagram of Energy Detector for spectrum sensing

In implementing an energy detector, the received signal x(t) is filtered by a band pass filter (BPF), followed by a square law device. The band pass filter serves to reduce the noise bandwidth. Hence, noise at the input to the squaring device has a band-limited, at spectral density. The output of the integrator is the energy of the input to the squaring device over the time interval T. Next, the output signal from the integrator (the decision statistic), Y , is compared with a threshold, to decide whether a primary (licensed) user is present or not.

For the decision hypothesis test is implemented as follows:

$$x(t) \;= n(t), \qquad H\text{o}$$
$$= h * s(t) + n(t), \qquad H1\,, \qquad (3.1)$$

where,

H0 implies an absence of the signal,

H1 denotes presence of the signal,

x(t) is the sample to be analyzed at each instant t,

n(t) is additive noise; assumed to be white Gaussian noise (AWGN)(with samples having zero-mean and variance σ^2),

h is the complex channel gain between the primary signal transmitter and the detector.

s(t) is the transmitted signal to be detected.

For the evaluation of the detection performance, the probabilities of detection (Pd) and false alarm (Pf) are defined as

Pd = P{decision = H1|H1} = P{Y > λ | H1} (3.2)

Pf = P{decision = H1|H0} = P{Y > λ | H0} . (3.3) where Y is the decision statistic and λ is the decision threshold. The value of λ is set depending on the requirements of detection performance. Based on these definitions, the probability of a miss or miss detection is defined as Pm = 1 − Pd = P{decision = H0|H1}.

3.1.1.1 Energy detection over AWGN channel

The additive white Gaussian noise (AWGN) is a channel model where the only impairment to communication is noise; with a constant spectral density. With this model, noise possesses zero mean, and is assumed to be white over the band- width of consideration; i.e. samples of the noise process are uncorrelated. These model does not account for channel impairments (hence it is considered a non- fading model). It produces insight to the behaviour of a system before any other phenomenon is conceived.

In AWGN channel probabilities of detection and false detection are represented as [1],[9]

$$P_f = Q\left(\frac{\lambda-\mu_0}{\sigma_0}\right) \qquad (3.4)$$

and

$$P_d = Q\left(\frac{\lambda-\mu_1}{\sigma_1}\right) \quad , \qquad (3.5)$$

where Q denote complementary error function which can be expressed by

$$Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{(-y^2/2)}\,dy \quad , \qquad (3.6)$$

where

$\mu_0=\sigma_n^2$

$\sigma_0=\frac{\sigma_n^2}{\sqrt{N}}$

$\mu_0= \sigma_0^2*(\gamma+1)^2$

$\sigma_1= \sigma_0*\sqrt{(2*\gamma+1)}$,

where γ is SNR .

Therefore the expression for the probability of false Alarm and Probability of Detection is given as:

$$\lambda(\text{threshold}) =\frac{Q^{-1}(Pf)}{\sqrt{N}} + 1 \qquad (3.7)$$

and,

P_d (Probability of detection) $= Q\left(\frac{\lambda-(\gamma+1)\sqrt{N}}{\sqrt{2}(\gamma+1)}\right)$. (3.8)

3.1.2 System model for eigenvalue based detection

Consider a primary signal detection problem with *K* collaborating sensors. These sensors may be, for example, *K* receive antennas in one secondary terminal or *K* collaborating secondary devices each with a single antenna, or any combination of these. We assume periodical sensing, where each sensor periodically collects *N* samples during a sensing time. This collaborative sensing scenario is more relevant if the *K* sensors are in one device, i.e. for multi-antenna assisted spectrum sensing. For multiple collaborating devices, communication to the fusion center by sensors of different locations becomes a problem even for a small sample size *N* [3], [4].

The received $K \times N$ data matrix **Y** is represented as

$$\mathbf{Y} = \begin{bmatrix} y_1(1) & y_1(2) & \dots & y_1(N) \\ y_2(1) & y_2(2) & \dots & y_2(N) \\ \vdots & \vdots & \ddots & \vdots \\ y_k(1) & y_k(2) & \dots & y_k(N) \end{bmatrix}. \quad (3.9)$$

Mathematically, the primary user detection problem is a hypothesis test between two hypotheses. Hypothesis 0 (**H0**) denotes the absence of the primary user and hypothesis 1 (**H1**) denotes the presence of the primary user. If we assume no fading in the temporal domain, i.e. the channel stays constant during the sensing time, the two hypotheses can be represented as [3]:

$$\mathrm{H0} : y_{k,n} = n_{k,n}$$

$$\mathrm{H1} : y_{k,n} = \sum_{i=1}^{P} h_k(i)\, s_n(i) + n_{k,n} , \quad (3.10)$$

where $k = 1, \dots, K$ and $n = 1, \dots, N$. Here $n_{k,n}$ is the complex Gaussian noise with zero mean and variance σ^2 , *P* denotes the number of simultaneously transmitting primary users. The receive covariance matrix $\mathbf{R_x}$ is defined as $\mathbf{R_x} = \mathbf{YY^H}$, where *H* denotes the Hermitian conjugate operator. By using different eigenvalue properties of R such as Maximum Eigenvalue (ME), Signal Condition Number (SCN), Scaled Largest Eigenvalue (SLE), etc., the presence or absence of the PU signal can be decided.

3.1.2.1 Probability of False Alarm and Threshold Values

Let the eigenvalues of Rx and HRsH† be $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_{ML}$ and $\rho_1 \geq \rho_2 \geq \cdots \geq \rho_{ML}$, respectively. Obviously, $\lambda_n = \rho_n + \sigma_\eta^2$. When there is no signal, we have be $\lambda_1 = \lambda_2 = \cdots = \lambda_{ML} = \sigma_\eta^2$. Hence $\frac{\lambda_1}{\lambda_{ML}} = 1$. When there is a signal, if $\rho_1 > \rho_{ML}$, we have $\frac{\lambda_1}{\lambda_{ML}} > 1$. Hence, we can detect if signal exists by checking the ratio $\frac{\lambda_1}{\lambda_{ML}}$. This is the mathematical ground for the MME. Obviously , $\rho_1 = \rho_{ML}$ if and only if HRsH† =λI_{ML}, where λis a positive number.

Assume that the noise is real. Let A(N) =$\frac{N}{\sigma_\eta^2}$ R_η(N)

$$\mu = (\sqrt{N-1} + \sqrt{M})^2 \qquad (3.11)$$

$$v = \left(\sqrt{N-1} + \sqrt{M}\right)\left(\frac{1}{\sqrt{N-1}} + \frac{1}{\sqrt{M}} \right)^{1/3}. \qquad (3.12)$$

Assume that

$$\lim_{N\to\infty} \frac{M}{N} = y(0 < y < 1)$$

then, $\frac{\lambda_{max}\,(A(N))-\mu}{v}$ converges (with probability one) to the Tracy-Widom distribution of order 1 .

Bai and Yin found the limit of the smallest eigenvalue as described in the following theorem.

Theorem 2. Assume that $\lim_{N\to\infty} \frac{M}{N} = y(0 < y < 1)$.

Then $\lim_{N\to\infty} \lambda_{min} = \sigma_\eta^2 (1 - \sqrt{y})^2$ (with probability one).

Based on the theorems, when N is large, the largest and smallest eigenvalues of R_η(N) tend to deterministic values $\frac{\sigma_\eta^2}{N}(\sqrt{N} + \sqrt{M})^2$ and $\frac{\sigma_\eta^2}{N}(\sqrt{N} - \sqrt{M})^2$ respectively, that is, they are centered at the values, respectively, and have variances tend to zeros. Furthermore, Theorem 1 gives the distribution of the largest eigenvalue for large N.

The Tracy-Widom distributions were found by Tracy and Widom as the limiting law of the largest eigenvalue of certain random matrices . Let F1 be the cumulative distribution function (CDF) (sometimes simply called distribution function) of the Tracy-Widom distribution of order 1. There is no closed form expression for the distribution function. The distribution function is defined as

$$F1(t) = exp(-\frac{1}{2}\int_t^{\infty}(q(u) + (u-t)q^2(u))du) \qquad (3.13)$$

where q(u) is the solution of the nonlinear Painlev´e II differential equation

$$q''(u) = uq(u) + 2q^3(u). \qquad (3.14)$$

It is generally difficult to evaluate it. Fortunately, there have been tables for the functions and Matlab codes to compute it . Table 1 gives the values of F1 at some points. It can also be used to compute the inverse F_1^{-1} at certain points. For example, F_1^{-1} (0.9) = 0.45, F_1^{-1} (0.95) = 0.98.

Table 1: Numerical table for the Tracy-Widom distribution of order 1

t	-3.9	-3.18	-2.78	-1.91	-1.27	-0.59	0.45	0.98	2.02
$F_1(t)$	0.01	0.05	0.1	0.3	0.5	0.7	0.9	0.95	0.99

Using the theories, we are ready to analyze the algorithms. The probability of false alarm of the MME detection is

$$\begin{aligned} P_{fa} &= P(\lambda_{max} > \gamma_1\lambda_{min}) \\ &= P(\frac{\sigma_\eta^2}{N}\lambda_{max}(A(N)) > \gamma_1\lambda_{min}) \\ &\approx P(\lambda_{max}(A(N)) > \gamma_1(\sqrt{N} - \sqrt{M})^2) \\ &= P\,(\frac{\lambda_{max}\,(A(N))-\mu}{v} > \frac{\gamma_1(\sqrt{N}-\sqrt{M})^2-\mu}{v}) \\ &= 1 - F_1(\frac{\gamma_1(\sqrt{N}-\sqrt{M})^2-\mu}{v}) \qquad (3.15) \end{aligned}$$

This leads to

$$F_1\left(\frac{\gamma_1\left(\sqrt{N} - \sqrt{M}\right)^2 - \mu}{v}\right) = 1 - P_{fa}$$

or, equivalently,

$$\left(\frac{\gamma_1\left(\sqrt{N}-\sqrt{M}\right)^2-\mu}{v}\right) = F_1^{-1}(1-P_{fa}) \;\; .$$

From the definitions of μ and v, we finally obtain the threshold

$$\gamma_1 = \frac{(\sqrt{N}+\sqrt{M})^2}{(\sqrt{N}-\sqrt{M})^2}\left(1+\frac{(\sqrt{N}+\sqrt{M})^{-2/3}}{(\sqrt{NM})^{1/6}}F_1^{-1}(1-P_{fa})\right) . \qquad (3.16)$$

Unlike energy detection, here the threshold is not related to noise power. The threshold can be pre-computed based only on N, P_{fa}, irrespective of signal and noise.

3.1.2.2 Probability of detection

When there is a signal, the sample covariance matrix $R_x(N)$ is no longer a Wishart matrix. Up to now, the distributions of its eigenvalues are unknown. Hence, it is very difficult (mathematically intractable) to obtain a precisely closed form formula for the Pd. So the approximation of it is done with some empirical formulae. Since N is usually very large, we have the approximation

$R_x(N) = HRsH^\dagger + R_\eta(N)$

Note that $R_\eta(N)$ approximates to $\sigma_\eta^2 I_{ML}$. Hence, we have

$$\lambda_{max}\left(R_x(N)\right) \approx \rho_1 + \lambda_{max}\left(R_\eta(N)\right). \qquad (3.17)$$

$$\lambda_{min}\left(R_x(N)\right) \approx \rho_{Ml} + \sigma_\eta^2 \quad . \qquad (3.18)$$

For the MME method,the P_d is

$$P_d = P(\lambda_{max}\left(R_x(N)\right) > \gamma_1\lambda_{min}\left(R_x(N)\right) \qquad (3.19)$$

$$\approx P(\lambda_{max}\left(R_x(N)\right) > \gamma_1\left(\rho_{ML}+\sigma_\eta^2\right) - \rho_1)$$

$$= 1 - F_1\left(\frac{\gamma_1 N + N(\gamma_1\rho_{ML}-\rho_1)/\sigma_\eta^2 - \mu}{v}\right) . \qquad (3.20)$$

From the formula, the P_d is related to the number of samples N, and the maximum and minimum eigenvalues of the signal covariance matrix (including channel effect).

3.1.3 System model for cooperative spectrum sensing

To deal the problem that arise during spectrum sensing like fading, shadowing and noise uncertainty multiple CRs can be organized in order to perform spectrum sensing cooperatively.

In general cooperative spectrum sensing consists of the following steps both for the homogeneous and heterogeneous cooperating nodes:

i. Every CR independently performs measurements for its local spectrum sensing and then makes a binary decision to check on whether the PU is present or not.

ii. These binary decisions by all CR are forwarded to a common receiver which is a base station (BS) in a cellular network or an access point (AP) in a wireless LAN.

iii. Those binary decisions are combined by a common receiver and a final decision is made in order to infer the absence or presence of the PU in the observed band.

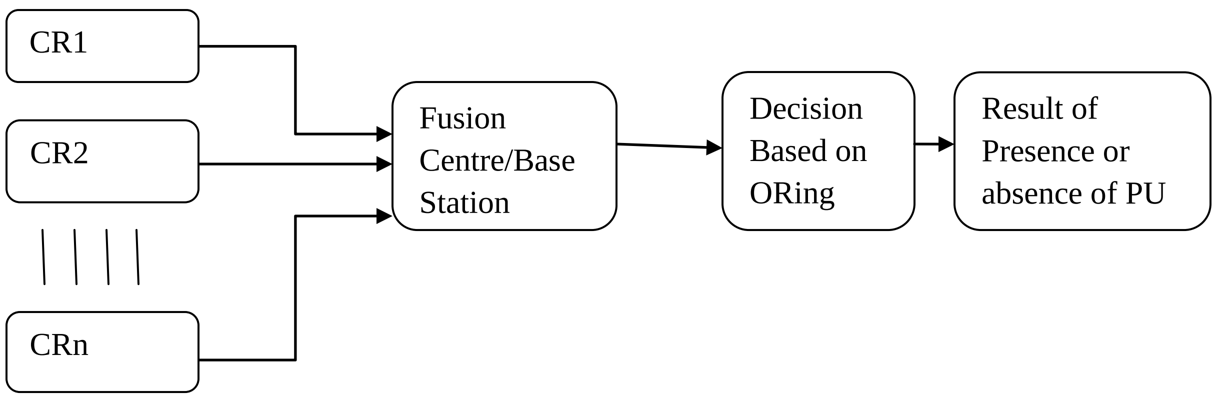

Figure 3.2 : Block diagram of Cooperative System

Hence for the homogeneous cooperating nodes only the binary decisions based on any spectrum sensing techniques either the ED technique or Eigen value based technique, these decisions are combined in the Fusion centre to infer the presence or absence of the PU in the observed band. Similarly, for the heterogeneous cooperating nodes the decision of the presence or absence of PU is done calculating the joint features from all the cooperating nodes. So, all features from each of the cooperating nodes are transfered to the Fusion Centre for the decision.

Let *N* denote the number of users sensing the PU. Each CR user makes its own decision regarding whether the primary user present or not, and forwards the binary decision (1 or

0) to fusion center (FC) for data fusion. The PU is located far away from all CRs. All the CR users receive the primary signal with same local mean signal power, i.e. all CRs form a cluster with distance between any two CRs negligible compared to the distance from the PU to a CR. For simplicity we have assumed that the noise, fading statistics and average SNR are the same for each CR user. We consider that the channels between CRs and FC are ideal channels (noiseless). Assuming independent decisions, the fusion problem where *k* out of *N* CR users are needed for decision can be described by binomial distribution based on Bernoulli trials where each trial represents the decision process of each CR user. With a hard decision counting rule, the fusion center implements an *n*–out-of-*M* rule that decides on the signal present hypothesis whenever at least *k* out of the *N* CR user decisions indicate 1 H . Assuming uncorrelated decisions, the probability of detection at the fusion center is given by

$$P_d = \sum_{l=k}^{N} \binom{N}{l} {P_{d,i}}^{l} (1 - P_{d,i})^{N-l} \qquad (3.21)$$

$$P_f = \sum_{l=k}^{N} \binom{N}{l} {P_{f,i}}^{l} (1 - P_{f,i})^{N-l} \ . \qquad (3.22)$$

3.1.3.1 Data Fusion for Cooperative Nodes

In cooperative sensing, data fusion is a process of combining local sensing data for hypothesis testing, which is also an element of cooperative sensing. In general, the sensing results reported to the FC or shared with neighboring users can be combined in three different ways in [7] :

(i) Soft Combining: CR users can transmit the entire local sensing samples or the complete local test statistics for soft decision.

(ii) Quantized Soft Combining: CR users can quantize the local sensing results and send only the quantized data for soft combining to alleviate control channel communication overhead.

(iii) Hard Combining: CR users make a local decision and transmit the one bit decision for hard combining.

Obviously, using soft combining at the FC can achieve the best detection performance among all three at the cost of control channel overhead while the quantized soft combining and hard combining require much less control channel bandwidth with possibly degraded performance due to the loss of information from quantization. This thesis focus on the fusion rules for decision fusion when the hard combining is used.

3.1.3.2 Hard combining and decision fusions for Cooperative Nodes

When binary local decisions are reported to the FC, it is convenient to apply linear fusion rules to obtain the cooperative decision. The commonly used fusion rules are:

i. AND-Rule : In this rule, if all of the local decisions sent to the decision maker are one, the final decision made by the decision maker is one. Cooperative detection performance with this fusion rule can be evaluated by setting $k = N$ in eq. (3.21).

The cooperative probability of detection using AND rule is

$P_{d,AND}$ =Pr{Fusiondeccision=1|H1}= $\prod_{i=1}^{N} P_{d,i}$. (3.23)

The cooperative probability of false alarm using AND rule is

$P_{f,AND}$ =Pr{Fusiondeccision=1|H0}= $\prod_{i=1}^{N} P_{f,i}$. (3.24)

The cooperative probability of misdetection using hard decision AND rule is

$P_{Pm,AND}$ = 1- ($P_{d,AND}$)

= 1- ($\prod_{i=1}^{N} P_{d,i}$). (3.25)

ii. OR-Rule : In this rule, if any one of the local decisions sent to the decision maker is a logical one, the final decision made by the decision maker is one. Cooperative detection performance with this fusion rule can be evaluated by setting k=1 in eq. (3.21).

The cooperative probability of detection using OR rule is

$P_{d,OR}$ =Pr{Fusiondeccision=1|H1}=1 - $\prod_{i=1}^{N}(1 - P_{d,i})$. (3.26)

The cooperative probability of false alarm using OR rule is

$P_{f,OR}$ =Pr{Fusiondeccision=1|H0}=1 - $\prod_{i=1}^{N}(1 - P_{f,i})$. (3.27)

The cooperative probability of misdetection using OR rule is

$P_{d,OR}$ = 1 - ($P_{d,OR}$)

= 1 - (1 - $\prod_{i=1}^{N}(1 - P_{d,i})$)

$=\prod_{i=1}^{N}(1-P_{d,i}).$ (3.28)

iii. Majority Rule : In this rule, if half or more of the local decisions sent to the decision maker are the final decision made by the decision maker is one. Cooperative detection performance with this fusion rule can be evaluated by setting $k = \lfloor N/2 \rfloor$ in eq. (3.21).

$$P_{d,MAJ} = \sum_{l=\lfloor N/2 \rfloor}^{N} \binom{N}{l} {P_{d,i}}^{l}(1-P_{d,i})^{N-l}, \quad (3.29)$$

where $\lfloor . \rfloor$ represents the floor operator.

3.2 Performance metrics and measurement

The metrics used for performance analysis of energy detection method for spectrum sensing are as follows:

i. The probability of detection, (PD).
ii. The probability of false alarm , (PFA),
iii. The probability of missed detection, (PM).

The receiver performance is quantized by depicting the receiver operating characteristics (ROC) curves. ROC graphs are employed to show trade-offs between detection probability and false alarm rates, (i.e. PD versus PFA), thus allowing the determination of an optimal threshold. Complementary ROC curves depict plots of probability of miss-detection (PM= 1-PD) versus the probability of false-alarm (PFA).These curves enable exploration of the relationship between sensitivity (probability of detection) and specificity (false alarm rate).

3.3 Algorithm and Flowchart

3.3.1 Algorithm of energy detection method for spectrum sensing

The algorithm used for the simulation of energy detection method for spectrum sensing is:

Step 1: The system parameters are set for the simulation. The parameters are: number of samples(N), signal to noise ratio(SNR), Noise variance(σ^2) which is considered as 1 in case of AWGN channel.

Step 2 : The output of the integrator of Energy Detection is considered to be Gaussian Random variable which is generated by Matlab code.

Step 3: The energy values of different samples from simulated signal is obtained by squaring the received sample signal.

Step 4: The threshold value is calculated on the basis of CFAR detection approach using equation (3.7).

Step 5: The energy values calculated in step 3 are compared with the threshold value calculated in step 4.

Step 6: If the calculated energy value is greater than the threshold value, then the decision is made as the detection of primary user (PU). If not then the decision of fail to detect the primary user(PU) is made.

Step 7: Then the probability of detection are calculated using equation (3.8) for the plot of ROC curve.

Step 8 : The above steps are repeated for different values of :

i.Signal to noise ratio (SNR)

ii. Number of samples(N)

iii.Coperative Rules(AND ,OR, Majority).

for the analysis of the performance of Energy detection method

3.3.2 Flowchart of energy detection method for spectrum sensing

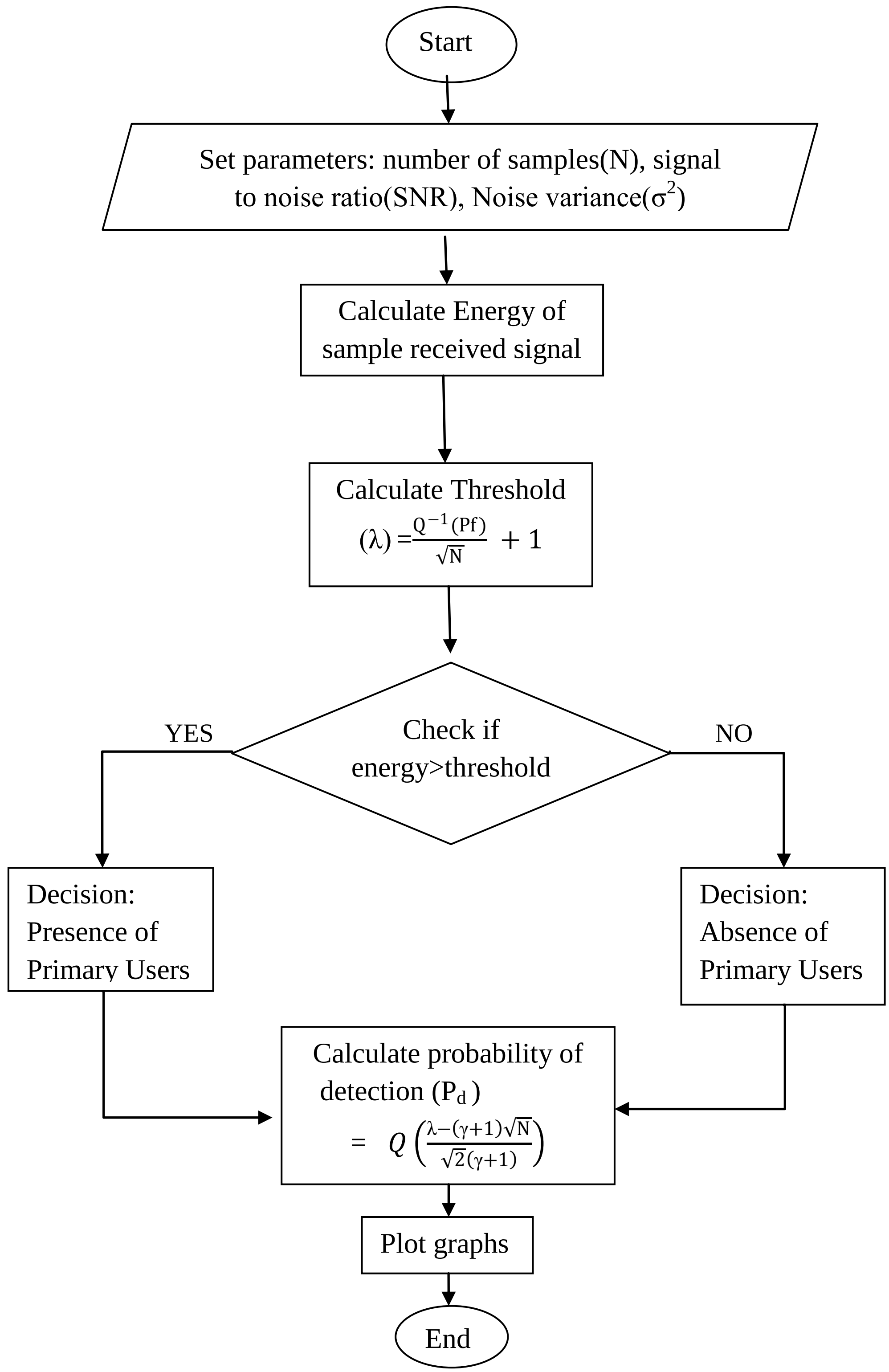

Figure 3.3 : Flowchart of energy detection method for spectrum sensing

3.3.3 Algorithm of eigen value based detection method for spectrum sensing

The algorithm used for the simulation of Eigen value based detection method for spectrum sensing is:

Step 1: The system parameters are set for the simulation. The parameters are: number of samples(N), signal to noise ratio(SNR), Noise variance(σ^2) which is considered as 1 in case of AWGN channel.

Step 2 : Compute the sample covariance matrix of the received signal

$$R_x(N) = \frac{1}{N}\sum_{n=1}^{N-1} \hat{x}(n)\hat{x}'(n)$$

where N is the number of collected samples.

Step 3: . Obtain the maximum and minimum eigenvalue of the matrix R_x (N) that is, λ_{max} and λ_{min}..

Step 4: The threshold value is calculated on the basis of Eigen value based detection approach using equation (3.16).

Step 5: The ratio λ_{max} / λ_{min}. value as calculated in step 3 is compared with the threshold value (γ_1) calculated in step 4.

Step 6: Decision: if λ_{max} / λ_{min}. > γ_1, signal exists i.e decision is made as the detection of primary user (PU). If not then the decision of fail to detect the primary user(PU) is made.

Step 7: Then the probability of detection are calculated using equation (3.20) for the plot of ROC curve.

3.3.4 Flowchart of eigen value based detection method for spectrum sensing

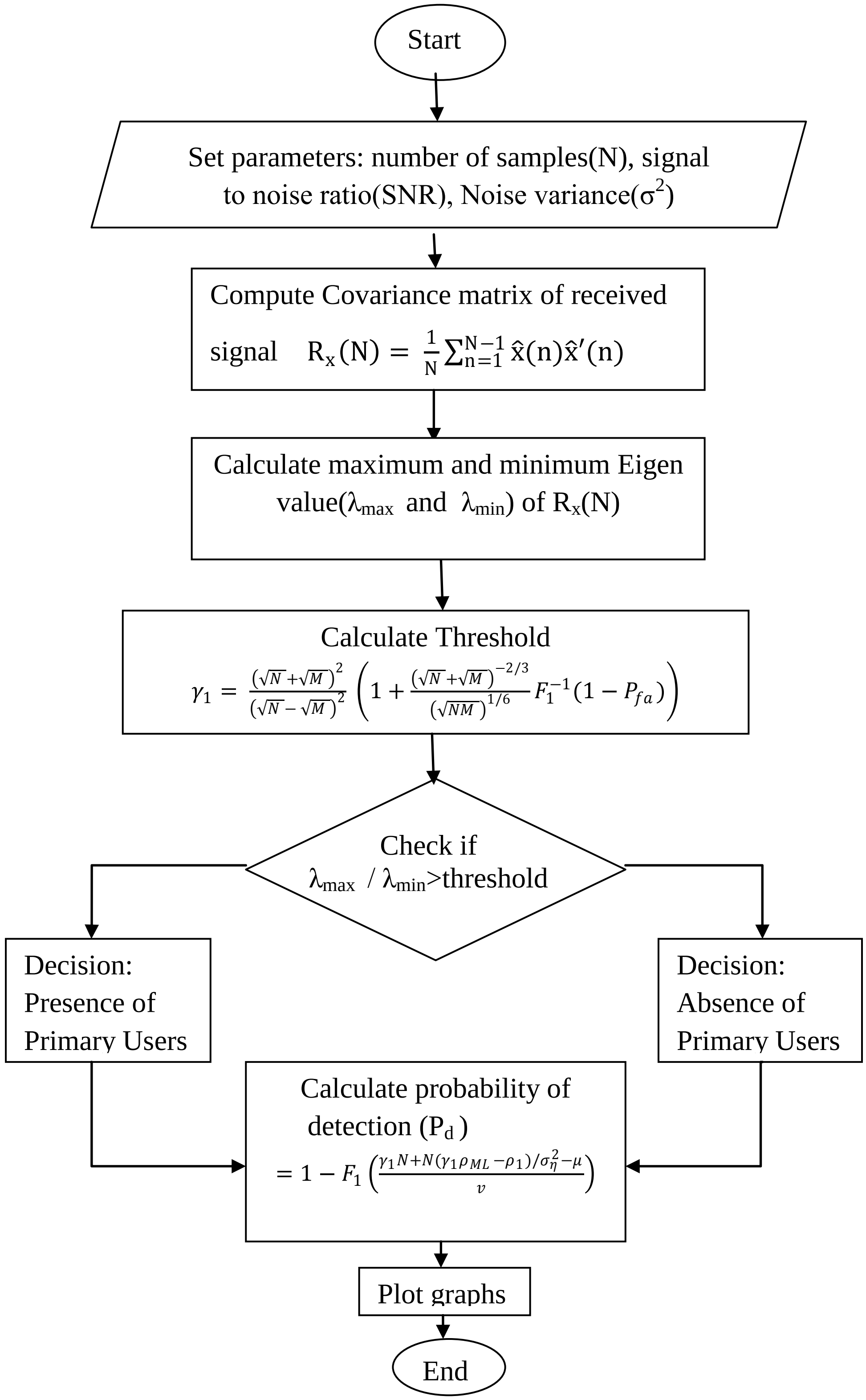

Figure 3.4 : Flowchart of eigen value based detection method for spectrum sensing

CHAPTER FOUR

SIMULATION RESULTS AND ANALYSIS

4.1 Simulation of energy detection of cognitive radio for AWGN channel

For the performance analysis of the performance of the Energy detection method of Spectrum Sensing, the output of the integrator is considered as the Gaussian random variable which is generated using following parameters:

Signal to noise ratio (SNR) = -12 dB

Number of samples(N) = 250

The output signal can be shown as in Figure 4.1.

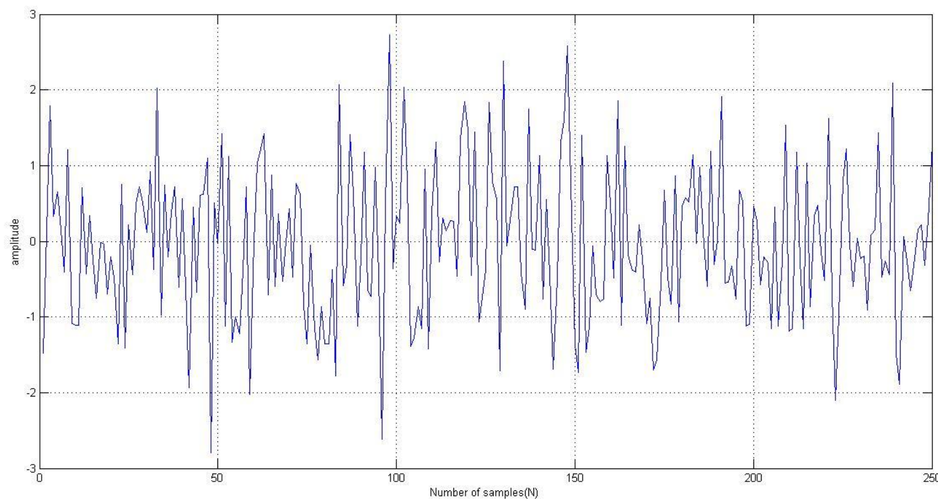

Figure 4.1 : Output Signal of AWGN sampled signal

4.1.1 For Varying number of samples (N)

Figure 4.2 and Figure 4.3 shows the performance of ED by varying the number of samples (N) i.e. the detection duration through ROC and Complementary ROC curves respectively .From graph it is observed that the performance of ED is improved with the increase of the number of samples(N).In this case the parameters assumed for the simulation are: range of false alarm, Pf ϵ [0,1], SNR = -12 dB, and varying number of samples (N=100, 200, 500).

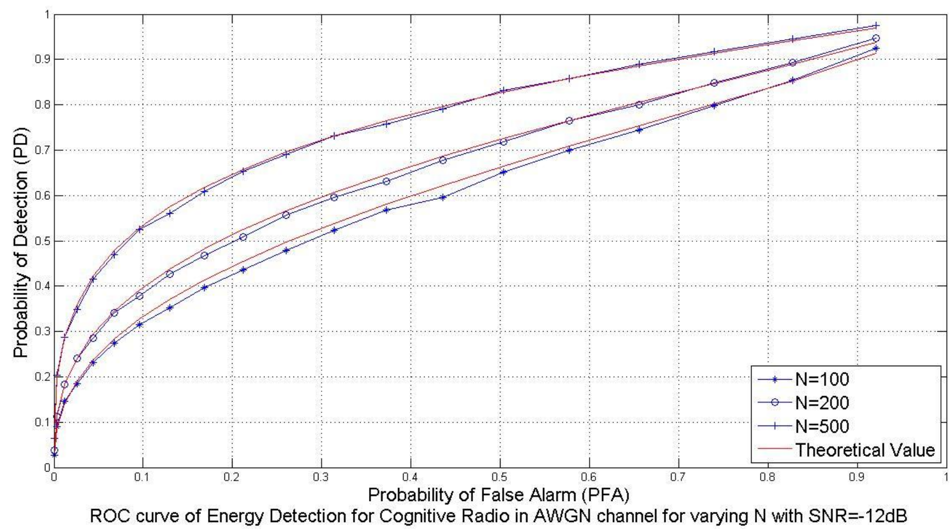

Figure 4.2 : ROC curve of ED by varying number of samples(N)

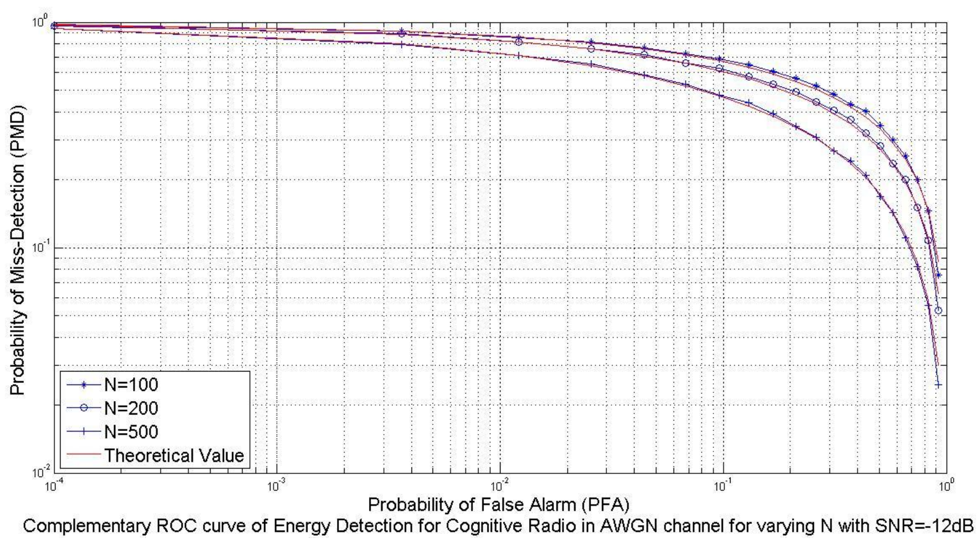

Figure 4.3 : Complementary-ROC curve of ED by varying number of samples(N)

4.1.2 For Varying Signal to Noise Ratio (SNR)

Figure 4.4 and Figure 4.5 shows the performance of ED by varying signal to noise ratio (SNR) through ROC and Complementary ROC curves respectively. From graph it is observed that the performance of ED is improved with the increase of signal to noise ratio (SNR). In this case the parameters assumed for the simulation are: range of Probability of false alarm, Pf ϵ [0,1], number of samples (N=250), varying signal to noise ratio (SNR) =-5db, -10dB, -15dB.

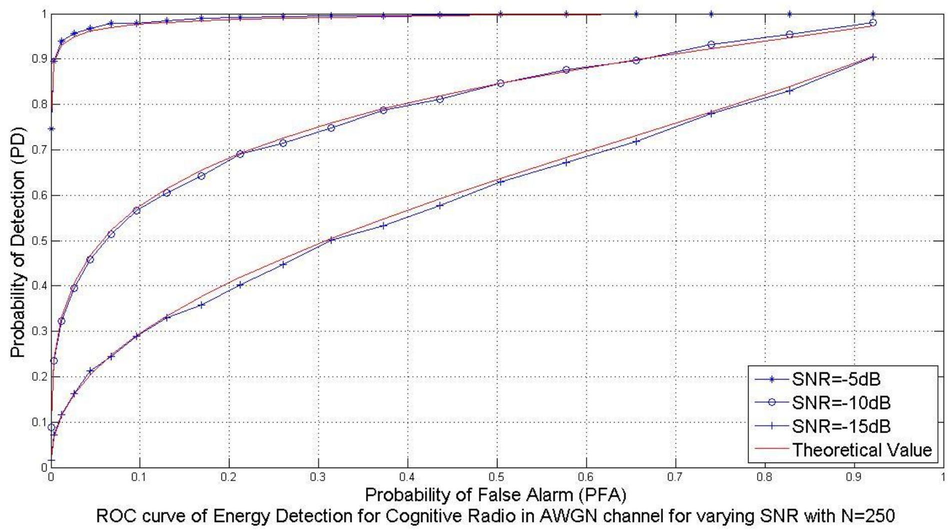

Figure 4.4 : ROC curve of ED for varying Signal to noise ratio (SNR)

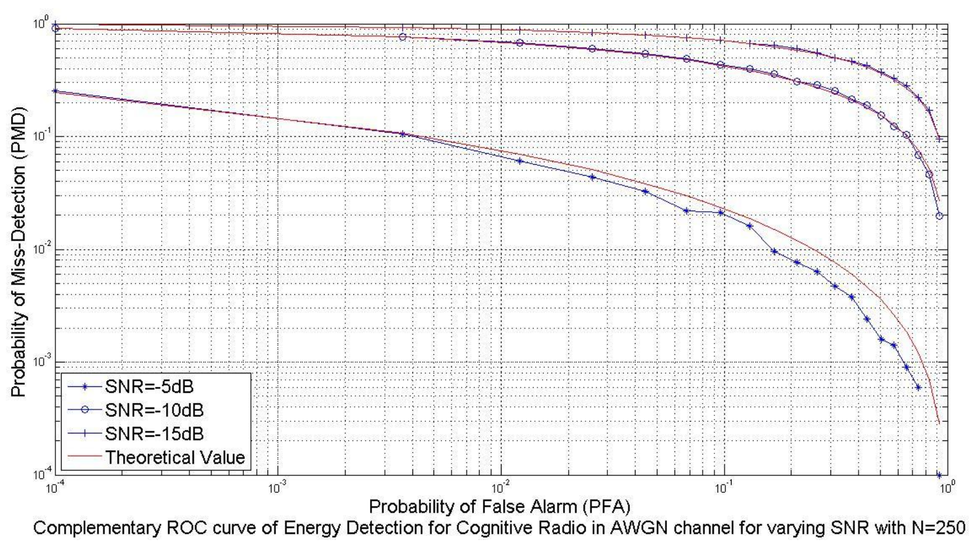

Figure 4.5 : ROC curve of ED for varying Signal to noise ratio (SNR)

4.2 Simulation of eigen value based detection of cognitive radio for AWGN channel

For the performance analysis of the performance of the Eigen value based detection method of Spectrum Sensing, the output of the transmitter is considered as the Gaussian random variable which is generated using following parameters:

Signal to noise ratio (SNR) = -12 dB

Number of samples(N) = 250

The output signal can be shown as in figure 4.6.

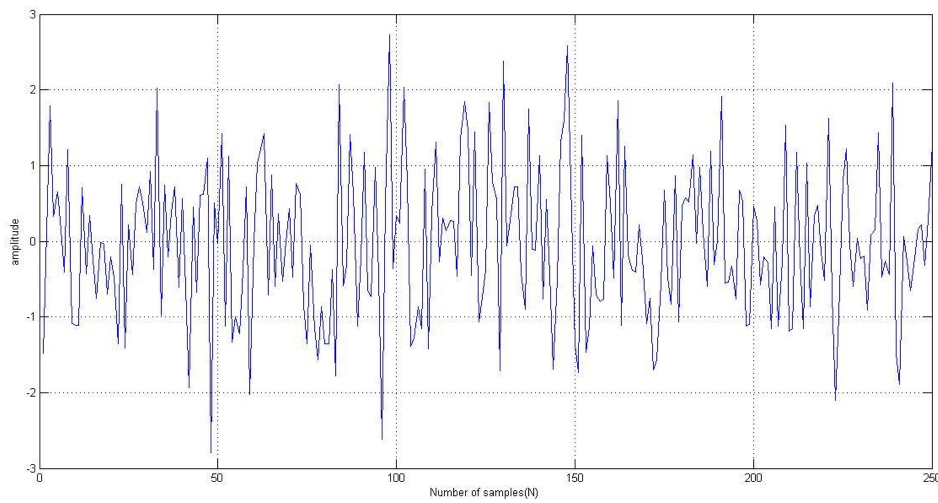

Figure 4.6 : Output Signal of AWGN sampled signal

4.2.1 For Varying number of features(antennas)

Figure 4.7 and Figure 4.8 shows the performance of Eigen value based spectrum sensing by varying the number of features (antennas) i.e. the detection through ROC and Complementary ROC curves respectively. From graph it is observed that the performance of Eigen value based spectrum sensing is improved with the increase of the number of features (antennas) . In this case the parameters assumed for the simulation are: range of false alarm, Pf ϵ [0,1], SNR = -12 dB, and varying number of features (number of antennas=2, 3).

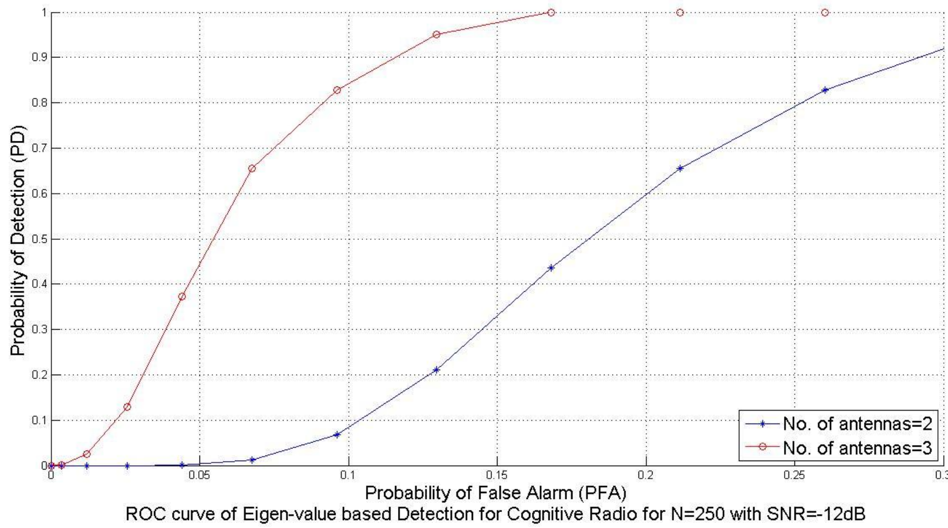

Figure 4.7 : ROC curve of Eigen value based detection for varying features (number of antennas)

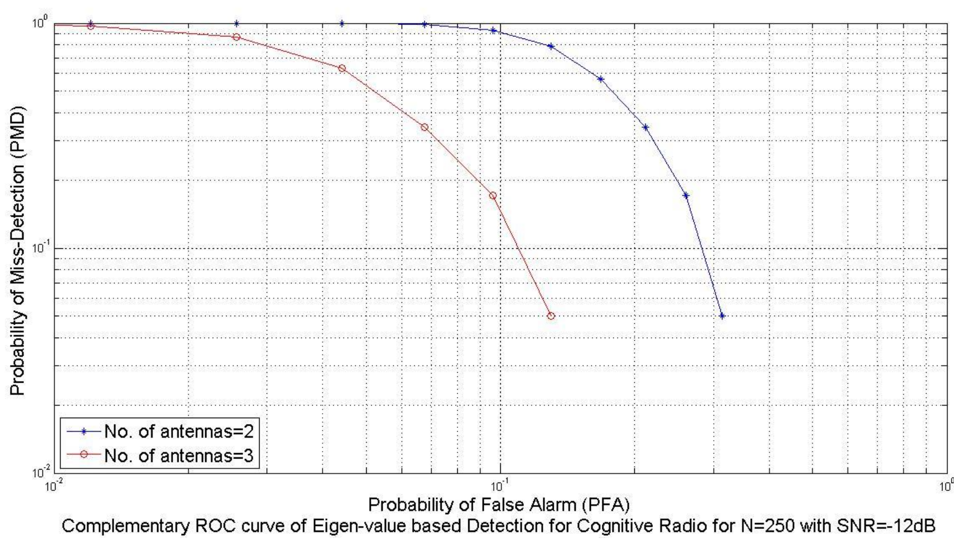

Figure 4.8 : Complementary ROC curve of Eigen value based detection for varying features (number of antennas)

4.3 Cooperative analysis of energy detection of cognitive radio

Figure 4.9 and Figure 4.10 show the ROC curves and Complementary ROC curves for k-out-of-n rule in decision fusion strategy for the analysis of performance of ED for cooperative cognitive radios, respectively. The fusion rules: OR, AND and Majority rules are considered. The average SNR in each link (from the primary user to each relay, and from each relay to the fusion center) is considered as -12 dB. For these cooperative cognitive radios, OR rule outperforms Majority rule and AND rule, and in comparison of cooperative analysis of homogeneous, heterogeneous cooperative nodes performance is better. For this the statistical data are presented for comparison in Table 2.

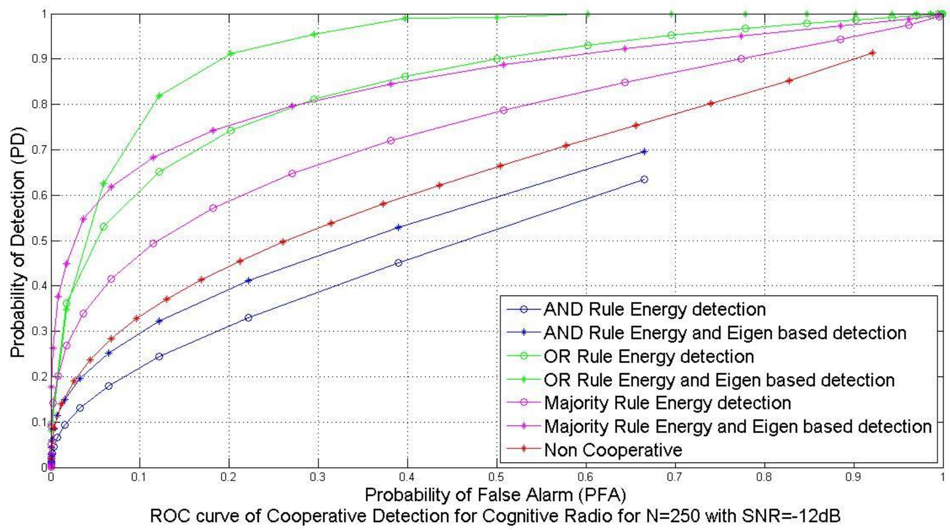

Figure 4.9 : ROC curve for the Cooperative Analysis of Cognitive Radio

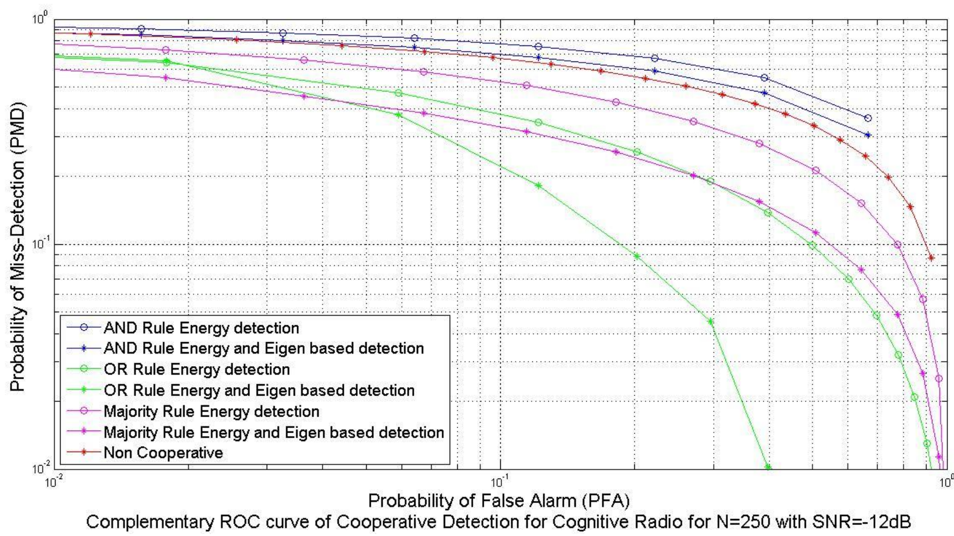

Figure 4.10 : Complementary-ROC curve for the Cooperative Analysis of Cognitive Radio

Table 2 : Comparison of data of PFA and PD for Non-Cooperative, Cooperative Analysis for Energy based detection and Cooperative Analysis for Energy and Eigen-value based detection (Based on ROC curve Figure 4.9)

PFA	PD (Non Cooperative)	PD for energy and eigen based detection (AND)	PD for Energy detection (AND)	PD for energy and eigen based detection (OR)	PD for Energy detection (OR)
0.0001	0.0351	0.0000	0.0000	0.1334	0.1638
0.0036	0.1305	0.0000	0.0000	0.4537	0.5030
0.0121	0.2017	0.0004	0.0003	0.6995	0.6758
0.0256	0.2633	0.0024	0.0013	0.8539	0.7829
0.0441	0.3190	0.0077	0.0033	0.9440	0.8535
0.0676	0.3707	0.0156	0.0070	0.9730	0.9013
0.0961	0.4192	0.0285	0.0130	0.9911	0.9339
0.1296	0.4654	0.0446	0.0218	0.9959	0.9563
0.1681	0.5095	0.0674	0.0343	1.0000	0.9716
0.2116	0.5521	0.0929	0.0513	1.0000	0.9820
0.2601	0.5932	0.1238	0.0735	1.0000	0.9889
0.3136	0.6333	0.1608	0.1018	1.0000	0.9934
0.3721	0.6724	0.2044	0.1374	1.0000	0.9962
0.4356	0.7108	0.2553	0.1814	1.0000	0.9980
0.5041	0.7487	0.3142	0.2353	1.0000	0.9990
0.5776	0.7863	0.3823	0.3006	1.0000	0.9996
0.6561	0.8240	0.4611	0.3799	1.0000	0.9998
0.7396	0.8623	0.5529	0.4767	1.0000	1.0000
0.8281	0.9020	0.6621	0.5972	1.0000	1.0000
0.9216	0.9458	0.8002	0.7568	1.0000	1.0000

CHAPTER FIVE

CONCLUSION

5.1 Discussion

In this thesis, the performance of an Energy detector and Eigen value based detection in detecting unused (vacant) spectrum was evaluated. Receiver Operating Characteristics (ROC) and Complementary Receiver Operating Characteristics (Comp-ROC) curves were employed for the performance measurement at different SNR levels, different number of samples and the receiver performance were studied for both single user detection and a network of cooperative detector nodes for Energy detection method . Similarly, Receiver Operating Characteristics (ROC) and Complementary Receiver Operating Characteristics (Comp-ROC) curves were employed for the performance measurement for different number of features(antennas) and thus the receiver performance were studied for both non cooperative nodes and a network of cooperative detector nodes with Eigen value based detection method.

Thus the cooperative analysis of spectrum sensing is done for both the homogenous and heterogeneous cooperating nodes. For homogeneous cooperating nodes it was done for the Energy Detection method of Spectrum Sensing and for the heterogeneous cooperating nodes the nodes with different detection method i.e. some nodes with the capabilities of Energy Detection method of Spectrum Sensing and others with the Eigen value based Spectrum Sensing method. Then the ROC and Complementary ROC curves were employed for the performance analysis of the homogeneous and heterogeneous cooperating nodes.

5.2 Conclusion

This study provides useful insight to the behavior of the energy detection technique and the eigen value based spectrum sensing technique, as it relates to detecting signals in a band for opportunistic access. These both techniques were advantageous as both do not require the prior knowledge of the received signal. In this work, the performance of an energy detector and eigen value based detector in detecting unused (vacant) spectrum was evaluated. Employing Receiver Operating Characteristics (ROC) curves and complementary Receiver Operating Characteristics (ROC) curves, receiver performance is quantified for both single user detection and a network of cooperative detector nodes.

Energy detection technique was simple to implement than the Eigen value based detection but the performance of the Eigen value based detection technique was better than the Energy detection Spectrum Sensing technique.

Simulation results indicate that depending on the threshold of a single user energy detector, performance varies for various average values of SNR. As SNR increases, detection probability increases for a single user detector node in a channel. Similarly, with increase number of samples the performance of the spectrum sensing technique increases.

A simulation comparison of AND, OR and MAJORITY cooperative decision fusion rules for both homogeneous and heterogeneous cooperating nodes was undertaken and results show that in both cases OR rule (corresponding to considering the decision of at least one detector out of k available detectors) out- performs the AND and MAJORITY combining rules. The simulation comparison also shows that the performance of the cooperating nodes can be increased with the addition of nodes with different sensing capabilities. Thus the performance is increased for the heterogeneous cooperating nodes over homogeneous cooperating nodes.

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