Two Stage Cooperative Spectrum Sensing for Interweave Cognitive Radio with SNR Enhancement by Using Signal Transformation Over AWGN Channel

Yonas Taye Bekele

A Thesis Submitted to

The Department of Electronics and Communication Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Electronics and Communication Engineering

Office of Graduate Studies

Adama Science and Technology University

Adama, Ethiopia

July, 2021

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Advisor: Dr. Satyasis Mishra (PhD)

Co-Advisor: Dr. Ram Sewak Singh (PhD)

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APPROVAL PAGE OF M.SC. THESIS

We, the advisors of the thesis entitled "**Two Stage Cooperative Spectrum Sensing for Interweave Cognitive Radio with SNR Enhancement by Using Signal Transformation Over AWGN Channel**" and developed by **Yonas Taye Bekele**, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

________________________	________________________	________________
Major Advisor	Signature	Date
________________________	________________________	________________
Co-advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by **Yonas Taye Bekele** have read and evaluated the thesis entitled "**Two Stage Cooperative Spectrum Sensing for Interweave Cognitive Radio with SNR Enhancement by Using Signal Transformation Over AWGN Channel**" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in **Electronics and Communication Engineering**.

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Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

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DECLARATION

I hereby declare that this Master Thesis entitled "**Two Stage Cooperative Spectrum Sensing for Interweave Cognitive Radio with SNR Enhancement by Using Signal Transformation Over AWGN Channel**" is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Yonas Taye Bekele	________________________	________________
Name of the student	Signature	Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled "**Two Stage Cooperative Spectrum Sensing for Interweave Cognitive Radio with SNR Enhancement by Using Signal Transformation Over AWGN Channel**" prepared under our guidance by Yonas Taye Bekele submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Electronics and Communication Engineering. Therefore, we recommend the submission of revised version of the thesis to the department following the applicable procedures.

Dr. Satyasis Mishra (PhD)	______________________	_______________
Major Advisor	Signature	Date
Dr. Ram Sewak Singh (PhD)	______________________	_______________
Co-advisor	Signature	Date

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LIST OF ABBREVIATIONS

AUC	Area Under the Curve
AWGN	Additive white Gaussian noise
BTS	Base-station Transceiver System
CDF	Cumulative Density Function
CFAR	Constant False Alarm Rate
CR	Cognitive Radio
CRN	Cognitive Radio Network
CROC	Complementary Receiver Operating Characteristics
CSS	Cooperative Spectrum Sensing
DSA	Dynamic Spectrum Access
DWT	Discrete Wavelet Transform
ED	Energy Detection
FC	Fusion Center
FCC	Federal Communications Commission
FSA	Fixed Spectrum Allocation
HST	Hybrid Slantlet Transform
IEEE	Institute of Electrical & Electronic Engineers
IID	Independent, Identically Distributed
ME	Maximum Eigen value
MFD	Matched Filter Detector
MInT	Ministry of Innovation and Technology
MSE	Mean Square Error
OSA	Opportunistic Spectrum Access
PDF	Probability Distribution Function
PU	Primary User
RF	Radio Frequency
ROC	Receiver Operating Characteristics
SDR	Software Defined Radio
SNR	Signal to Noise Ratio

SSC	Shared Spectrum Company
SU	Secondary User
WD	Wavelet Denoising
WRAN	Wireless Regional Area Network
WT	Wavelet Transform

ABSTRACT

Spectrum Underutilization, along with the growing issue of spectrum scarcity, has promoted a reassessment of how the radio frequency spectrum is used. Cognitive Radio technology comes as a solution which enhance the utilization of spectrum with systematic use of the scarce resource by Opportunistic Spectrum Access. One of the important functions of cognitive radio is Spectrum Sensing which enable cognitive radio to detect spectral opportunity also called White Space or Spectrum Whole. Among many spectrum sensing algorithms available, Energy Detector(ED) is preferred since it doesn't need the prior information about primary user's signals and having low computational complexity. However, the performance of ED is directly proportional to signal to noise ratio(SNR) which leads to poor performance at the low SNR regime. In order to alleviate the detection problem at low SNR, Discrete Wavelet Transform(DWT) based denoising of the primary user signal is applied in the front end of ED. The effect of denoising prior to ED is analysed by employing six different wavelets as Haar, Daubechies, Bi Orthogonal Splines, Reverse Bi Orthogonal, Coiflet, Fejer-Korovkin and the performance metrics of ED is analysed using single stage wavelet denoising based ED. Based on the best performing wavelet, Two Stage Spectrum Sensing is developed which composed of CED as a first stage and Denoising based ED as a second stage which consist of wavelet denoising prior to ED that will perform signal to noise ratio enhancement. The detection performance of proposed Two Stage Spectrum Sensing approach is compared against ED alone and Single Stage wavelet based ED in terms of different performance metrics given as probability of detection, probability of miss detection, Receiver operating Characteristic and Complementary Receiver Operating Characteristics in the case of single node and cooperative cognitive radio. Simulation results show that the proposed Two Stage Spectrum Sensing using Reverse Biorthogonal wavelet approach improves the performance of CED and Single Stage Reverses Bi Orthogonal by 97.6% and 42.18% respectively. Also the proposed approach improves the performance of Cooperative CED by 54.32% in the case of 3 users.

Key Words: *Cognitive radio, Denoising, Discrete Wavelet Transform, Energy Detector, Performance Matrices, Spectrum Sensing, White Space*

CHAPTER ONE

1 INTRODUCTION

1.1 Background

The enormous increase in the number of wireless devices due to emergence of new wireless services and applications, combined with the static assignment of the radio spectrum, has resulted in a radio spectrum shortage [1]. One of the most serious challenges at the forefront of future network research is the scarcity of radio frequency spectrum, which has yet to be overcome Traditionally, radio spectrum is allotted to licensees for long periods of time and it is meant to be utilized exclusively by licensees [2]. The type of scheme which uses such static assignment technique is called Fixed Spectrum Allocation (FSA) and within this technique the spectrum is divided into bands and assigned to different technology-based applications. This scheme ensures that the spectrum is fully licensed to a single authorized user with no interference. The allocation of spectrum bands to operators is the responsibility of a governmental agency. The Ministry of Innovation and Technology (MInT) in Ethiopia is in charge of this exercise, whereas Federal Communications Commission (FCC) in the United States. This static spectrum allocation policy adopted by governments in many countries has resulted in underutilization of spectrum because a large segment of licensed radio spectrum is not efficiently used [3]. The problem of underutilization of allocated spectrum or the underutilized area is technically defined as a *Spectrum Hole* or *White Space*. A spectrum hole is band of frequencies assigned to the licenced user but at a particular instant of time these frequency bands are not being utilized [4]. This is mostly due to the fact that license owners are not transmitting always in all geographic areas where their license covers. Supporting this, according to FCC statistics, spectrum allotted in bands below 3GHz has a 15 percent usage range [5]. The measurements obtained by the Shared Spectrum Company (SSC) to assess spectrum occupancy from several sites are shown in figure 1.1. This measurement indicates that the average spectrum occupancy across the seven sites is approximately 5.2 percent [6]. These findings revealed that a large proportion of the radio frequency spectrum is underutilized, leading to massive “spectrum holes”.

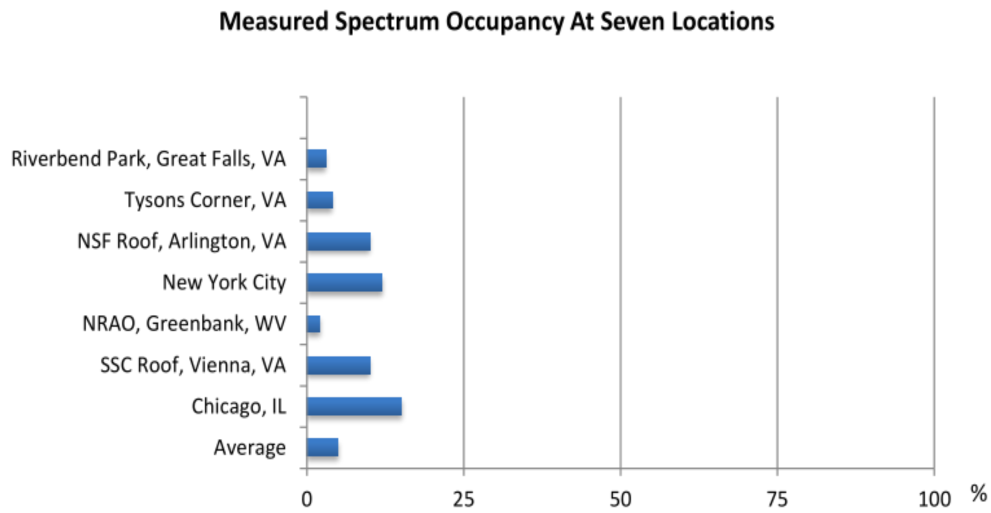

Figure 1.1: Spectrum occupancy measurement over seven locations [6]

This problem of spectrum underutilization, along with the growing issue of spectrum scarcity, has promoted a reassessment of how the radio frequency spectrum is used. As a result, FCC recommend that the utilization of the spectrum can be enhanced by sharing vacant channels with unlicensed users dynamically, allowing unlicensed users to use the specified spectrum range alongside licensed users called Primary Users [6]. This kind spectrum allocation scheme is called, Opportunistic Spectrum Access (OSA), also known as Dynamic Spectrum Access (DSA). DSA lets unlicensed user to access licensed user's spectrum band according to the activity of primary user. These users should have the ability to utilize the available resources while causing the least amount of interference to the Primary users [7]. This lead to the development Software Defined Radio (SDR) that can consistently sense the spectral opportunity over the bandwidth, recognize the presence or absence of licensed users, and use the spectrum only if communication does not interfere with any licensed user. Cognitive Radio is a smart system that senses and understands its operating environment and can be educated to dynamically and independently modify its radio operating settings accordingly [8]. The main target of Cognitive Radio (CR) is to improve spectrum utilization and efficiency by opportunistically accessing the licensed spectrum ensuring non-interfering coexistence with the licensed uses [9]. In order to avoid interference with Primary User, CR has to determine the existence of primary user (PU) by sensing the wireless spectrum. This scanning of spectrum opportunity called Spectrum Sensing. The concept of CR and Dynamic Spectrum Access is illustrated in figure 1.2. The spectrum hole or white space is dynamically and opportunistically accessed by the CR user while avoiding access to the spectrum that is currently in use by the PU's. Cognitive radio users should relocate to a different spectrum hole or stay in the same band by altering transmission power to avoid interference when licensed users use this band [3].

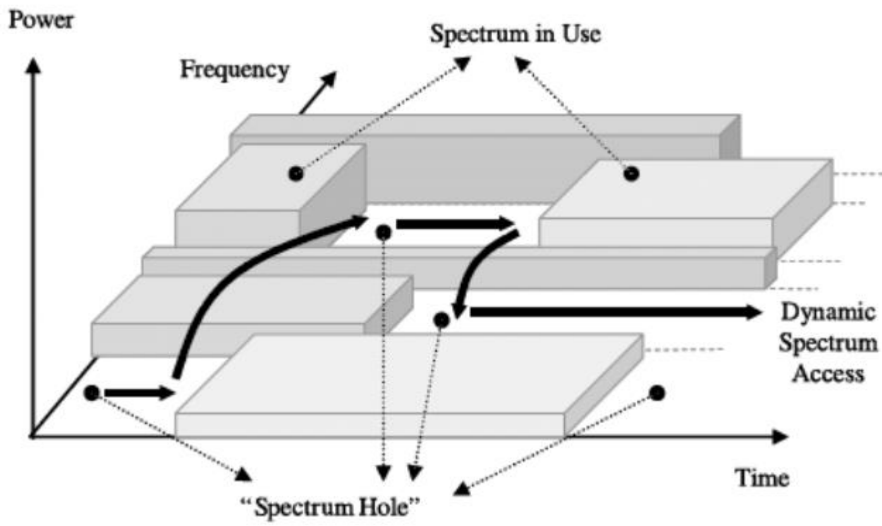

Figure 1.2: Spectrum holes [10]

Conventionally, Spectrum Opportunity defined as "a band of frequencies that are not being used by the PU at a particular time in a particular geographic area", and it exploits three dimensions of the spectrum space: Frequency, Time, and Space [11]. Table 1.1 shows these dimensions of spectral opportunity with some description. We may have spectral opportunity in Frequency, where some of licensed band might be currently unused. These bands can be accessed by SU's. Also, our opportunity could be in time, where a particular frequency band is free for a moment. There might be some geographical regions where some frequency bands are unused by PU.

Table 1.1: Three-dimensional spectral opportunities [12]

Dimension	Opportunity In	Remark
Frequency	Frequency	All bands are not used simultaneously at the same time.
Time	Time	There will be a time where the band will be available for opportunistic usage.
Geographical Space	Primary users location (latitude, longitude, and elevation) and distance of primary users	At any particular time, the spectrum may be accessible in certain areas of the geographical region while it is occupied in others.

1.2 Motivation

CR technology comes as a solution which enhance the utilization of spectrum with systematic use of the scarce resource by DSA. In order to obtain knowledge of possible transmission possibilities, a cognition capability or spectrum sensing unit must be implemented in the CR System. The first step of this cognitive capability is to assess the activity of a PU at a given time interval in a specified bandwidth. In order to enhance the utilization of spectrum and avoid interference with existing PU, effective detection of PU is a major issue of CR. The effectiveness of PU detection algorithm determines ultimate protection of PU and level of spectrum utilization. Reliable spectrum sensing algorithm will increase the detection of PU in the frequency band, decrease missing opportunity of white space, decrease harmful interference caused to PU and eventually enhance spectrum utilization. As a result, this thesis focus on enhancing one of spectrum sensing algorithm called Energy Detection (ED), having less computational complexity, to detect the presence of PU in a given frequency band.

1.3 Statement of the Problem

One of the spectrum sensing techniques which does not require prior knowledge of PU signal and having less amount of computational complexity is ED. Despite this, the performance indicator matrices reveal that the ED performs poorly when the received signal to noise ratio (SNR) is low. This is due to the fact that at low SNR, the signal is distorted and the received energy is below the

ED threshold value, making it impossible for the system to differentiate between noise and signal. The goal of this thesis is to denoise the signal by using Discrete Wavelet Transform(DWT) prior to ED in order to reduce to effect of noise, achieve SNR gain enhance the performance of ED.

1.4 Objectives

1.4.1 General Objectives

The general objective of this thesis is to enhance the performance of CED at low SNR by using Two Stage Spectrum Sensing.

1.4.2 Specific Objectives

- To study the fundamental characteristics and behaviors of ED algorithm.
- To study and analyze the effect of DWT denoising on the front end of ED for AWGN channel and compare the result with ED.
- To evaluate the performance of different detection techniques (ED, Single Stage DWT based ED, and proposed Two Stage ED) with different performance metrics.
- To evaluate Receiver Operating Characteristics (ROC) of the detection techniques.
- To evaluate Complementary Receiver Operating Characteristics (CROC) of the detection techniques.
- To compare the performance of ED, Single Stage DWT based ED and Two Stage ED method in single node and cooperative scenario.

1.5 Thesis Contributions

Spectrum sensing is a critical component of cognitive radio. However, there are a number of variables that make spectrum sensing difficult in practice. First, the primary user SNR may be quite low. This thesis is dedicated to solve low SNR problem that decrease the performance of ED. Therefore, the major contributions of this thesis are:

- We analyze the effect of denoising by different wavelets and compare the result in terms of Probability of Detection (P_d), Probability of False Alarm (P_f), Probability of Miss detection (P_m), Receiver Operating Characteristics (ROC) and Complementary Receiver Operating Characteristics (CROC) by using single node and Cooperative detection.
- Based on the result found from the comparison, we develop Two Stage ED approach and the performance comparison is done with different performance metrics.

1.6 Limitation of the Study

The thesis works is:

- Is limited to simulation-based investigation which relies on theoretical analysis.

1.7 Thesis Outline

The outline of this thesis is summarized as follows:

Chapter Two presents regarding different definitions and concepts of Cognitive Radio, Cognitive Radio Network, Cognitive Radio Cycle and technology which have been given by different researchers, benefits and limitation of Cognitive Radio.

Chapter Three describes the research methods used in this thesis including the derivation of performance metrics for ED, single stage Wavelet Denoising based ED and proposed Two Stage spectrum sensing for CR.

Chapter Four is devoted to discuss the proposed results and discussions.

Chapter Five presents the conclusions and recommendations.

CHAPTER TWO

2 REVIEW OF LITERATURE

2.1 Introduction to Cognitive Radio

A Cognitive Radio (CR) is a smart radio that can sense its surroundings to enhance spectral efficiency by using spectrum wholes with modify their transmission parameter according to the environment [13]. The CR technology is designed to enable identification, use and management of vacant spectrum, known as Spectrum Hole [5].

2.1.1 Definitions of Cognitive Radio

CR has been defined in a variety of ways by various groups. It is necessary to provide the definitions of the various groups for better understanding.

Simon Haykin, defines cognitive radio as [13].

> *"An intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming Radio frequency (RF) stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind:*
>
> - *highly reliable communications whenever and wherever needed;*
> - *efficient utilization of the radio spectrum."*

Dr. Joe Mitola coined the term "Cognitive Radio" for the first time in the late 1990's. He defines cognitive radio as follows [14].

> *"The term cognitive radio identifies the point at which wireless personal digital assistants and the related networks are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to: detect user communications needs as a function of use context, and to provide radio resources and wireless services most appropriate to those needs."*

The Institute of Electrical & Electronic Engineers (IEEE) group define cognitive radio which has the following working definition [15].

“A cognitive radio is a radio frequency transmitter/receiver that is designed to intelligently detect whether a particular segment of the radio spectrum is currently in use, and to jump into (and out of, as necessary) the temporarily-unused spectrum very rapidly, without interfering with the transmissions of other authorized users.”

2.1.2 Cognitive Radio Network Architectures

Cognitive Radio Network (CRN) architectures can be defined as a network that of smart cognitive radios integrating wireless users, and dynamic spectrum access capabilities. CRN was originally proposed to address the problem of spectrum scarcity and network congestion faced when employing the unlicensed spectrum band. Using the smart cognitive radio communication devices and the fact of spectrum scarcity in unlicensed spectrum band, a CRN was introduced, in order to give the cognitive radio users; named secondary users (SU’s); the permission to access and share the licensed spectrum band with its original users; named PU, but with the guarantee that the original users performance won't be affected [5]. CRN architecture can be categorized into two groups.

1. Primary Network
2. Cognitive Radio Network

Primary Network: is pre-existing network which has a sole right over a certain spectrum band. The most famous examples for this network are the TV broadcast networks and the cellular networks. This network is composed of two components [16].

i. **Primary User (PU)**: they are the genuine users of the licensed network; they can also be called the licensed users. They have authorization to operate and access the section of the frequency band allotted to the primary network, as long as the primary network base station, which controls all users' communications processes, gives them permission.

ii. **Primary Base-Station (licensed base-station)**: it is the licensed spectrum band base station which concerned on the activities of a primary user. A cellular system's base-station transceiver system (BTS) is an example.

Cognitive Radio Network, also called Secondary User Network, which does not have license to operate in a predefined licensed band and its spectrum access is granted opportunistically. Cognitive radio networks are made up of the following components [16].

i. **Secondary User (SU)**: Unlicensed user who is obliged to use the spectrum only opportunistically. The SU's are also known as cognitive users.

ii. **Cognitive Radio Base-Station (unlicensed base-station)**: A fixed infrastructure component with CR capabilities providing a single-hop connection to CR users. In cooperative spectrum sensing, the CR Base-Station is Fusion Center that gather the information from cooperative users and make the final spectrum sensing decision.

iii. **Spectrum Broker**: A central network entity that controls spectrum resource sharing among the CR users.

2.1.3 Cognitive Radio Cycle

A CR device can sense the spectrum, identify unoccupied channels and decide to use which of those free channels. The process of spectrum sensing and spectrum allocation methods are divided into four main categories described as Cognitive Cycle. The actions performed by a CR device are spectrum sensing, spectrum management, spectrum sharing and spectrum mobility [17].

i. **Spectrum Sensing** – Spectrum sensing is continually scanning the spectrum and detect the presence or the absence of primary user. CR monitors the surroundings in real time and determines the spectrum that isn't being used. Spectrum sensing can be done by single cognitive radio, by multiple cognitive radio terminals using cooperating techniques.

ii. **Spectrum Management** – The spectrum management function enables secondary users in the selection and decision of the best available channel that satisfies specific targeted objectives. Before using the spectrum hole, CR examines data rates, transmission modes, and user requirements to find the best accessible spectrum. It entails making a choice based on spectrum sensing data to allow cognitive radio to choose when to begin operation, the operating frequency, and the technical aspects that go with it.

iii. **Spectrum Sharing** – Because a lot of SU's might be there and using available spectrum gaps, offering a fair scheduling mechanism among coexisting users, defines fair spectrum scheduling approaches is needed.

iv. **Spectrum Mobility** – When the primary user start transmission, CR must cease its operation or leave currently used radio spectrum immediately in order to avoid the collision with primary licensed user. CR should provide a smooth handoff and maintain communication through the shift to a superior spectrum hole, ensuring that the application presently executing at the secondary user is unaffected by the handoff and suffers minimal performance deterioration. Radio must constantly seek for alternatives spectrum gaps in order to maintain faultless transmission.

The cognition cycle by which a cognitive radio interact with the environment is shown in figure 2.1 below.

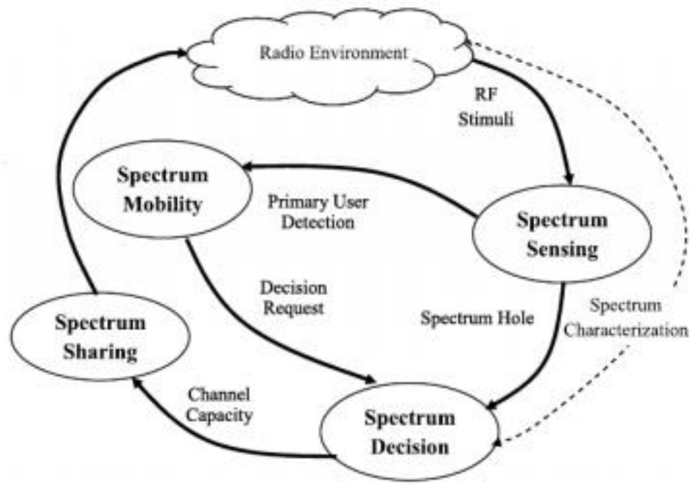

Figure 2.1: Cognitive Radio Cycle [17]

2.1.4 Spectrum Access Techniques

Spectrum exploitation process (i.e., DSA) can be achieved by either allowing a SU to coexist with the PU in its spectrum band or allowing the SU to opportunistically access PU's spectrum band. Accordingly, there are three distinct models used to implement DSA practically. Two of those models allows CR to concurrently transmit its data along with the PU over its spectrum band. They are called underlay and overlay models, while the third model allows CR to transmit only if the PU's band is vacant. This model is called interweave model. Each model has its own working principle and requirement [5].

2.1.4.1 Underlay Model

In underlay model, CR's are allowed to operate if the interference caused to PU's is below a particular transmission power threshold. Therefore, a CR should always monitor its transmission power and maintain it below a level that might degrade the PU communication. In other words, the communication between CR transmitter and receiver has always to consider the level of interference that might cause to the PU [5].

2.1.4.2 Overlay Model

Contrary to underlay model, an overlay model allows CR's to simultaneously share PU's spectrum bands without imposing any constraint on CR's transmission power. To achieve this, it is assumed that a CR transmitter has a full knowledge of PU's signal characteristics. Therefore, CR can employ this knowledge to significantly reduce or cancel any simultaneous interference that might occur between CR's transmitter and PU's receiver. In other words, CR should be able to decode the PU message and encode its message so that interference is avoided [5].

2.1.4.3 Interweave Model

By using the previous two models, avoidance of interference is not guaranteed. The attempt to avoid interference completely results in another model and interweave model was proposed. In this model it's not allowed for a CR to exploit PU's spectrum band unless PU is being absent. Opposing to the previous two methods, CR cannot transmit simultaneously and share PU's band. Therefore, CR should periodically detect the existence of the PU over the band and then utilize the band if it is idle. An accurate detection process of PU existence is a key functional component for an interweave model. Many research works have been focused on designing accurate and efficient detection techniques [5].

2.1.5 Cognitive Radio Networks Applications

Cognitive radio networks are used in a variety of applications. Some of its uses are described as follows.

i. **Military Networks**: This is the most essential application, because military networks carry sensitive information, it is difficult to protect them against jamming or hacking. Because of their flexibility in functioning on multiple frequency bands, the military employs cognitive radio networks. For instance, a system that uses cognitive radio technique like SPEAKeas radio has been developed by the department of defense in the United States [16].

ii. **Disaster Relief and Emergency Networks**: Natural disasters such as earthquakes, hurricanes, and wildfires, as well as significant calamities such as mining accidents, can partially or totally impair networks. Because assigning a network(s) to communicate vital and meaningful information is a big challenge in such emergency situations, cognitive radio networks can be used to create such emergency networks. As a result, emergency networks can opportunistically access licensed spectrum bands, allowing them to have a substantial amount of spectrum capacity to send important, accurate information [16].

iii. **TV White Spaces**: TV white space is the spectrum in the VHF/UHF bands, which is already granted to licensed users e.g. TV broadcasters, however TV white space are not heavily used as before, so cognitive radio networks can benefit from it [16].

2.1.6 Advantage of Cognitive Radio

- It can dynamically reconfigure itself according to the current transmission conditions.
- Minimize the unused spectral portion, and increases the spectral efficiency.
- Allow the licensed user to reinvest in the licensed portion of the spectrum it has paid for it by leasing apart of it to the unlicensed users.

2.1.7 Limitations of Cognitive Radio

- While ideal Cognitive Radio assumes no influence on other radio listeners, in practice, some influence is predicted on licensed users.
- The secondary user may not achieve the required quality of service even when sharing the licensed spectrum band.
- Hidden node problems.

2.2 Spectrum Sensing for Cognitive Radio

Spectrum sensing defines the task of reliably finding spectrum opportunities (also called spectrum holes), i.e., bands that are temporarily unused by the licensed primary user and put them to use. The Institution of Electrical and Electronics Engineers (IEEE) has created a working group (IEEE 802.22) to make an air interface standard for Wireless Regional Area Network (WRAN) opportunistic secondary access using cognitive radio technology in the TV bands between 54 and 862 MHz [18]. The underlying idea of cognitive radio is to allow for universal spectrum maximizing as long as unlicensed users do not cause service deterioration to the original license holders. In practice, unlicensed users, also known as cognitive users, must constantly monitor primary user activity to locate an appropriate spectrum band for opportunistic usage while avoiding potential interference with licensed users, also known as primary users. Since the primary users have the priority of service, the above spectrum sensing by cognitive users incorporate detection of possible collision relocation when a primary user becomes active again in the spectrum band.

2.2.1 System Model

One of the most essential functions of cognitive radio systems is spectrum sensing. Spectrum sensing relies on the well-known signal detection method. Signal detection can be simplified to a simple identification problem [13],[19] , which may be formulated as a hypothesis test. That can be may be described as.

$$s(n) = \begin{cases} w(n) & H_0: Primary\ User\ is\ Absent \\ x(n) + w(n) & H_1: Primary\ User\ is\ Present \end{cases} \quad (2.1)$$

Where $n = 1, \ldots N$, N is the number of samples, $s(n)$ is the SU received signal, $x(n)$ is the PU signal, $w(n)$ is the additive white Gaussian noise $(AWGN)$ with zero mean and variance δ^2 . Where H_0 denote the absence of primary user and H_1 express the presence of the primary user. The determination of available primary user in the given spectrum band reduced to an identification problem. This is formalized as hypothesis test as:

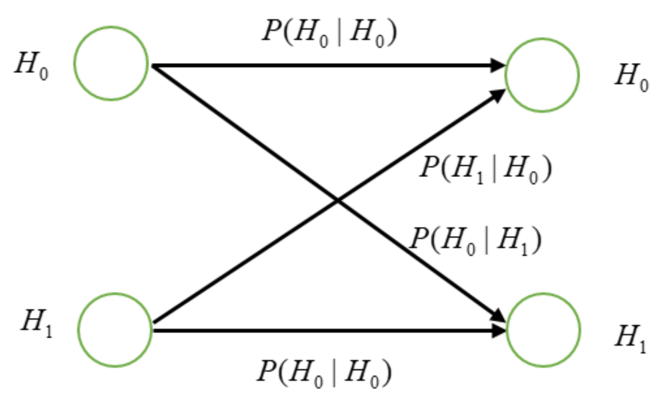

Figure 2.2: Hypothesis test with possible outcomes and their corresponding probabilities [20]

From figure 2.2, four possible cases can be stated for the detected signal;

- Case 1: Declaring H_0 when H_0 is true $P(H_0| H_0)$
- Case 2: Declaring H_1 when H_1 is true $P(H_1| H_1)$
- Case 3: Declaring H_0 when H_1 is true $P(H_0| H_1)$
- Case 4: Declaring H_1 when H_0 is true $P(H_1| H_0)$

The performance of spectrum sensing can be evaluated by probability of detection $\left(P_d = P(H_1 | H_1)\right)$,the Probability of False Alarm $\left(P_f = P(H_1 | H_0)\right)$ and probability of miss detection ($P_m = 1 - P_d$). The Probability of false alarm is defined as the probability that a secondary user falsely decides the presence of PU when the PU is actually not present. It represents the extent to which the SU has missed spectral opportunity. Probability of detection also called correct detection is defined as the probability that a SU decides truly that the PU is active when the PU is actually active. The probability of miss detection shows the level of interference on the PU due to the failure in exactly detecting the activity of PU. In order to protect PU, P_m should be restricted below an acceptable level.

Case 2 is referred to as a proper detection, whereas instances 3 and 4 are referred to as a missed detection and a false alarm, respectively. Clearly, the signal detector's goal is to achieve perfect detection every time; but, due mainly to the statistical nature of the problem, this will never be achievable practically. As a result, signal detectors are built to function within certain error limits. Missed detections are the most serious problem in spectrum sensing, as they might cause collision with the primary user.

In spectrum sensing, one of the primary user signal detection techniques detection is performed to decide between the two hypotheses H_0 and H_1. The output of the detector, also called the test statistic T, is then compared against some threshold λ in order to make a decision upon the existence or presence of PU. The sensing decision is performed as

$$\text{Decision } = \begin{Bmatrix} T \geq \lambda & , H_1 \\ T < \lambda & , H_0 \end{Bmatrix} \tag{2.2}$$

Generally, spectrum sensing process can be depicted with the figure 2.3 below. Test statistics for a given spectrum sensing algorithm is calculated and compared against the threshold in order to decide whether the spectrum is free or occupied.

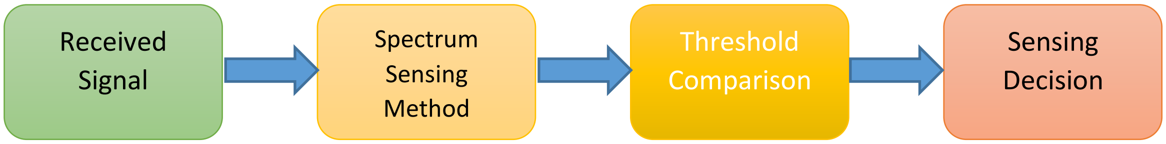

Figure 2.3: General model of spectrum sensing [21]

2.2.2 Spectrum Sensing Techniques

In cognitive radio, spectrum sensing techniques can be categorized in to: Transmitter Detection, Interference Based Detection and Cooperative Detection [22]. Figure 2.4 shows the classification of spectrum sensing.

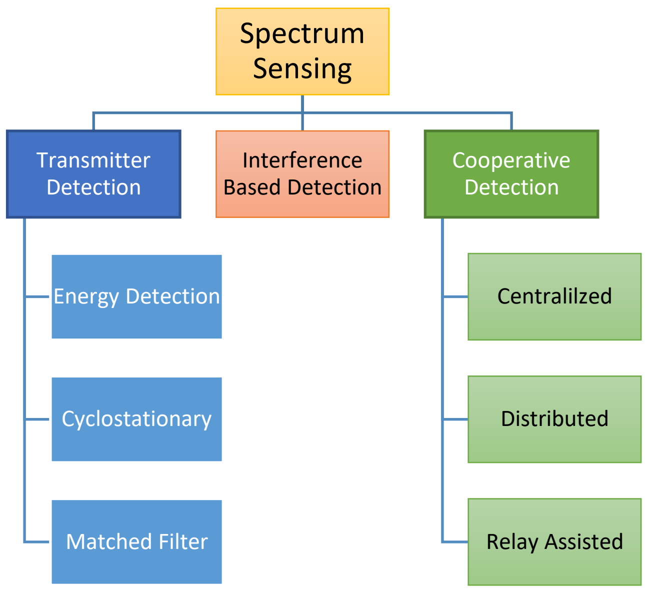

Figure 2.4: Classification of spectrum sensing techniques [22]

2.2.3 Transmitter Detection

This is the most widely used mechanism for detecting the presence of a licensed user over the frequency range in which it is operating. In transmitter detection, a PU transmitting at a given time must be identified. On the basis of the received signal at the secondary user end, a main user i.e., PU is recognized. The goal of transmitter detection in general is to decide the existence or absence of PU on the basis of local measurement and observation at a given time [22].

2.2.3.1 Energy Detection

Energy Detection (ED) is the most widely used method spectrum sensing algorithm due to the fact that it does not require prior information of PU signal and having low computational complexity. The need of prior information is defined as the requirement of primary user signal characteristics such us modulation type, cyclic prefixes, in order to calculate the test statistics. This algorithm needs only to take the sample of the received signal in order to calculate the test statistics. In ED algorithm, the occupancy of the spectrum is decided based on the threshold obtained depending on the noise floor. It works based on the idea that the energy of the PU signal to be detected is always greater than the noise energy.

Assuming that the received signal at the SU, i.e., $s(n)$ has the following form.

$$s(n) = x(n) + w(n) \qquad (2.3)$$

where $x(n)$ is the PU signal, $w(n)$ is the Additive White Gaussian Noise ($AWGN$), and n is the sample index. When there is no PU transmission i.e., $x(n) = 0$ and equation 2.3 becomes

$$s(n) = w(n) \qquad (2.4)$$

The Test statistics of ED is given as

$$T = \sum_{n=0}^{N-1} |s(n)|^2 \qquad (2.5)$$

Where N defines the size of observation. In order to determine the occupancy of a band, the test statistics T is compared against a threshold λ. If the received signal's energy at the SU is greater than λ, hypothesis H_1 is validated and the licensed user is declared to be present. If the energy is lower than the given threshold, the alternate null hypothesis H_0 is validated thus indicating the presence of a White Space. The threshold is determined based on noise energy and its accuracy significant to the performance of the ED. In order to detect decision threshold λ accurately, both the signal and noise strength should be known. Since the information about PU signal strength is difficult to obtain, a Constant False Alarm Rate ($CFAR$) is assumed to select λ.

System model of Energy Detection

Figure 2.5 shows ED system model which is intended to classify the presence or absence of PU. According to the given block diagram, the received signal pass through BPF initially to eliminate noise outside the band of interest having bandwidth W and center frequency f_0, the output of BPF is squared and integrated over the observation interval T. Eventually, the output of the integrator, Y, is compared against a threshold, λ, to determine whether a PU is present or not [16].

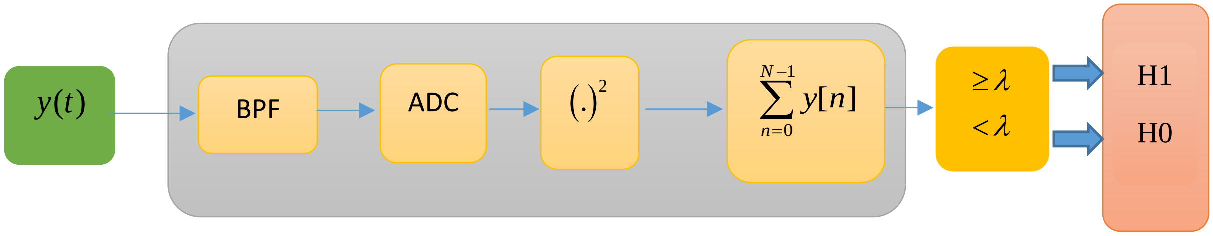

Figure 2.5: Block diagram of Energy Detection [23]

2.2.3.2 Cyclostationary Feature Detection

Cyclostationary Feature Detection (CFD) uses the periodicity characteristics of primary signal to identify its presence or absent. Despite the fact that the data represents a stationary random process, these modulated signals are classified as Cyclostationary because their mean and autocorrelation statistics are periodic [24]. A spectral correlation function is used to detect these characteristics. Periodicity is often seen in sinusoidal signal carriers, pulse trains, spread code hopping sequences, and primary user cyclic prefixes. If the mean and autocorrelation of a signal is a periodic function, it is said to be Cyclostationary. Feature detection refers to the process of extracting features from a received signal and performing detection based on those characteristics. Using the information inherent in the PU signal that is not present in the noise, CFD identify PU signal from noise at extremely low SNR detection. The primary disadvantage of this approach is the computational complexity which results in long sensing period. Since it requires large calculation dealing will all of the frequency. Spreading, hopping sequences, and cyclic prefixes are all examples of built-in periodicity. If we assume a signal a signal $y(k)$ to be a discrete zero mean signal with autocorrelation function $R_x(n,k)$ having cyclic period T as in [25] eqn. (2.6).

$$R_x(n,k) = R_x(n+T, k+T) \tag{2.6}$$

The Cyclic Autocorrelation Function (CAF) is important parameter used to in feature detection. The Spectral Correlation Function (SCF) which is frequency domain of eq. (2.6) is also given by eq. (2.7). It shows the degree of correlation between frequency shifts of the signal as given by [25] eq. (2.7) and (2.8).

$$S_x^\alpha = \sum_{k=-\infty}^{\infty} R_x^\alpha(k) e^{i2\pi k} \tag{2.7}$$

$$R_x^\alpha(k) = \lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x(n)x^*(n-k)e^{-j2\pi\alpha n} e^{j\pi\alpha k} \tag{2.8}$$

Where, $R_x^{\alpha}(k)$ is the CAF of the discrete signal and α cyclic frequency. $S_x{}^{\alpha}(f)$ is the power spectrum of the signal for $\alpha = 0$.

System Model of Cyclostationary Feature Detection

The block diagram representation of Cyclostationary detection system is shown in figure 2.6 below.

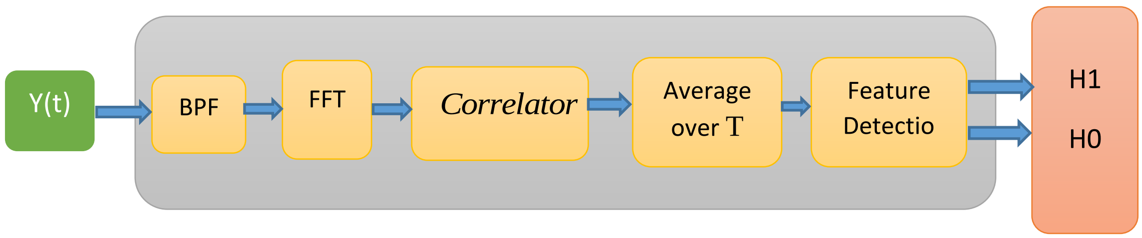

Figure 2.6: Cyclostationary feature detection [24]

2.2.3.3 Matched Filter Detector

This is a coherent sensing technique that requires prior knowledge of the PU's transmitted signal. Such knowledge includes the operating frequency, bandwidth and modulation. this information is used for demodulating the received signal [26]. The PU signal is first and handled as input to the Matched Filter Detector (MFD) and all the information needed to make the matching process is extracted by MFD. Figure 2.7 depicts the implementation of a matched filter using a Finite Impulse Response (FIR) of the known signal $S(k)$ to generate filter coefficients. The received signal $x(k)$

$$y[n] = \sum_{k=0}^{n} h[n-k]x[k] \tag{2.9}$$

Where, $y[n]$ is the output of the FIR filter for the received signal and the response $h[n] = S[N-1-n]$ for $n = 0,......., N-1$. The major advantage of the MFD is that it takes less time to acquire high processing gain due to typical coherent detection. However, If the information is not accurate, the MFD performs poorly. Also, a CR would need a dedicated receiver for every type of PU signal. The block diagram of matched filter is as shown in figure 2.7.

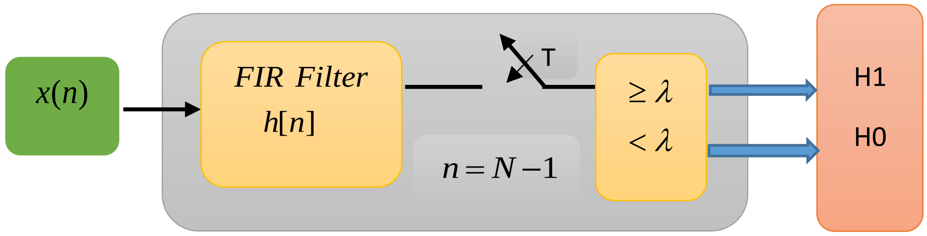

Figure 2.7: Matched Filter Spectrum Sensing [10]

2.2.4 Interference Based Detection

This model relies on the fact that received signal power at a main receiver decreases exponentially with distance, until till it reaches to noise level. Despite the fact that a primary transmitter is still operational at this moment, the receiver treats this as noise rather than communication. This allows a SU to access the channel because there is no interference introduced with the PU's [10].

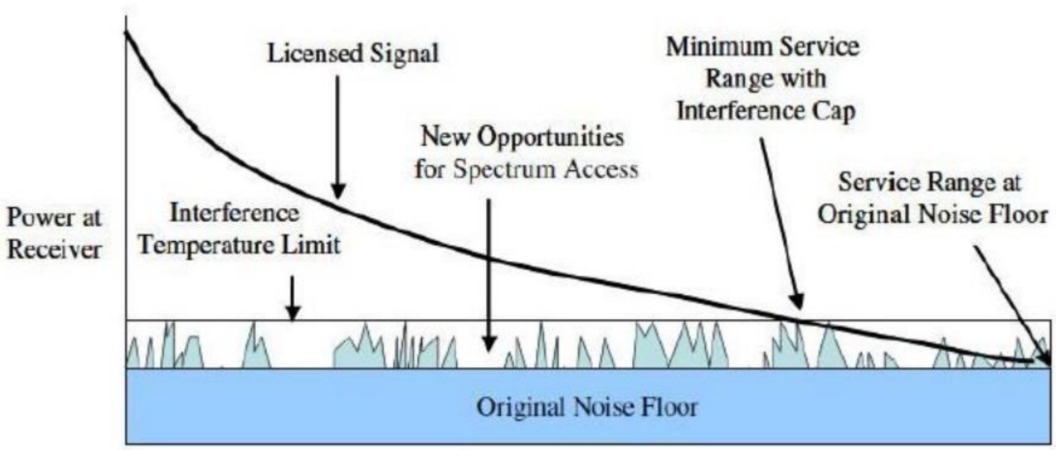

Figure 2.8: Interference Temperature Model [10]

2.2.5 Cooperative Detection

Multiple SU's work together in a centralized or decentralized sort of way to identify spectrum gaps for opportunistic access in cooperative detection. With this scenario, each participating node uses any of the previously specified spectrum sensing methods while exchanging the local decision information with other nodes depending on the cooperation strategy chosen. Because shadowing, multipath fading, and receiver uncertainty create serious problems to single user transmitter identification in spectrum sensing, this notion of cooperation is considered [27].

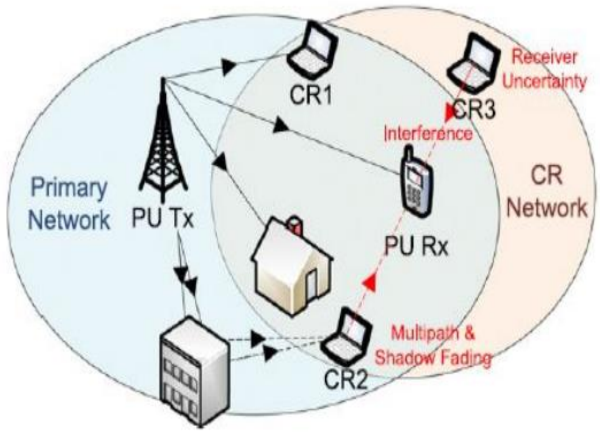

Figure 2.9: Multipath, Shadowing and Receiver Uncertainty [27]

From the figure 2.9 above, Cognitive Radio User 1 (CR1) and cognitive Radio user 2 (CR2) are in the communication range of PU transmitter on the other hand Cognitive Radio User 3 (CR3) is not. CR2 suffer shadowing and multipath as a result of obstruction from the house due to multiple copies of the PU signal has arrived and eventually this may lead CR2 incorrect decision. Also, CR3 is unaware of the PU transmission and existence of PU as well. Eventually the transmission from CR3 may interfere PU communication, this effect is called Receiver Uncertainty. However, by applying the advantage of spatial diversity, it's unlikely that all SU within the network experience fading or receiver uncertainty. Since SU that receive strong PU signal, like CR1, can sense and share the result with other SU's. By applying cooperation among CR users, the detection of PU is enhanced [28].Three types of cooperative sensing are illustrated in figure 2.10.

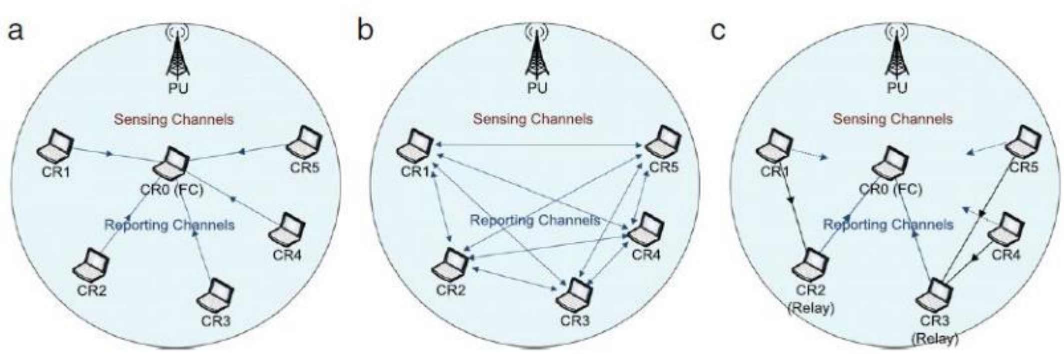

Figure 2.10: Cooperative Sensing Techniques: (a) Centralized, (b) Distributed (decentralized), and (c) Relay Assisted [10]

2.2.5.1 Centralized Cooperative Detection

In a centralized structure a central entity called the Fusion Center (FC) determines the presence of white space after combining local SS decision made cooperating CR's. This opportunity is either shared to all CR's or the FC manages traffic by efficiently handling discovered spectrum. Cooperating SU's could communicate gathered data to the FC, which would allow it to do data fusion to determine the presence of a PU, or they could transmit individual decisions to the FC. Soft Combining refers to the fusion process in which the SU delivers all of the local sensing data. While in the case of hard combining fusion, a one-bit decision made by SU is send the FC [28].

2.2.5.2 Distributed Cooperative Detection

SU's are not anticipated to rely on FC to make the ultimate choice in a distributed cooperative system; rather, SU's are expected to communicate among nodes to reach a global conclusion on the existence or lack of PU. This is done in three phases, each of which is specified by a distributed algorithm. To begin, each participating user communicates their local sensing data to other users in their immediate vicinity (defined by the transmission range of the users). Then, depending on the local criteria, cooperating users combine data with incoming sensing information from other users to determine the existence or absence of a PU. In this scheme each SU plays a role of FC in a distributed manner [19].

2.2.5.3 Relay Assisted Cooperative Detection

The above-mentioned systems' sensing and reporting channels may not function well in real-world circumstances. For example, one SU's reporting channel may be weak while its sensing channel is robust due to shadowing or multipath effects, whereas another SU's reporting channel may be powerful but its sensing channel is poor [19]. The relay-assisted detection paradigm suggests using an SU as a relay to transmit sensed data. The centralized and decentralized schema is referred to as one-hop cooperation in [28], whereas the relay-assisted method is referred to as multi-hop cooperation.

2.3 Summary of Spectrum Sensing Algorithm

Table 2.1: Summary of Spectrum Sensing Algorithms

Spectrum Sensing Algorithm	Advantage	Disadvantage
Transmitter Based Energy Detection		
Energy Detection	• Do not require prior information	• Poor performance in low SNR
Cyclostationary Features	• Valid in low SNR region	• Require the prior information of PU signal • High Sensing time
Matched filter	• Low computational cost	• Require the prior knowledge of the primary user signal
Cooperative Detection		
Centralized based detector	• Improve sensing performance in the fading, shadowing and noise uncertainty	• Require back bone infrastructure • Complexity in decision fusion
Distributed based detector	• Does not require any back bone Infrastructure • Less complexity with reduced overhead protocol	• User interference might happen
Relay Assisted	• higher accuracy in PU detection	• Traffic overhead
Interference Based Detection		
Interference temperature based detection	• The radiated power in the interference of the system is regulated at the transmitter	• Difficulty in determining specific receiver interference temperature levels for the various communication

2.4 Related Researches

Many contributions are advocated in order to solve CED performance in low SNR case.

Adaptive two-stage spectrum sensing model using energy detection and wavelet denoising for cognitive radio systems. is given in [29].in this two methods are cascaded in parallel structure with the help of SNR estimation. During high SNR conditioned is only implemented in order to identify the existence of primary user. In the case of low SNR problem, since ED has low performance a Wavelet Denoising is prior activated to reduce the effect of noise. In this paper wavelet denoising and ED are cascaded in parallel structure, either of the method is initiated by SNR estimator. This proposed method achieved a better probability of detection when compared to ED only.

Energy Detection with Adaptive Threshold for Cognitive Radio. is suggested in [30].this paper solve the classical problem of ED at low SNR by considering the noise uncertainty factor for calculating adaptive threshold. This method is based on the fact that increasing/decreasing the threshold will decrease/increase the performance of ED respectively. By considering this idea, a sliding window is proposed to re-sampling received signal to after estimate the noise uncertainty factor and the number of sample giving good result is considered for calculation adaptive threshold. Simulation results shows that ED having adaptive threshold has a significant improvement in case of low SNR, compared to ED.

Energy Detection Performance Enhancement Using RLS and Wavelet De-Noising Filters. Was suggested in [31],to solve the problem of Energy detector at low SNR. A single stage energy detection algorithm is designed by using denoising filters such us recursive least square, and wavelet denoising filters. The major aim of denoising is to achieve SNR gain so that the detection performance of ED is improved. The performance of proposed method shows that there is it exhibits noticeable increase in the throughput compared to Energy Detector.

A Two-Step Spectrum Sensing Scheme for Cognitive Radio Networks.is given [32].The problem of ED at low SNR is solved by using two stage approach. Low computational complex algorithm used for initial sensing followed by a complex algorithm which has good detection performance at low SNR is selected. In this paper Maximum Eigen value (ME) detection is used as Second stage detection. The goal of using two stage is, whenever the absences of primary user is decided in first stage, ME is executed for verification. The result of comparisons against ED and ME shows that the proposed method requires less sensing time while obtaining almost the same sensing performance with maximum eigenvalue detection.

Two-stage spectrum sensing for cognitive radios.in [33], is proposed to solve the problem of ED in low SNR case by combining two spectrum sensing mechanism in two stages. In this wok ED is used as first stage while, Cyclostationary detection in implemented in the second stage due to its computational complexity and long sensing time. The main target is to take the advantage of Cyclostationary detector in low SNR cases.

In [34], The improvement in ED during low SNR condition is based on the reduction of noise power by using Hybrid Slantlet Transform(HST). This approach is based on filter bank, which decompose the signal a set of coefficients. These coefficients composing high frequency components are considered as noise part of the signal and threshold is applied to eliminating these high frequency components. The rest of the coefficients are used to reconstruct the denoised signal. This paper is also limited to single stage prior denoising. The result is compared against ED and it shows the obvious superiority.

In [35], The problem of Energy detector in low SNR value is solved by using SNR enhancement. The effect of noise is reduced by inserting Adaptive Wiener Filter that enhance the response of the system by filtering the noise component. In this work, prior denoising is tested in single stage, not only that the effect has been analyzed in cooperative scheme also. It has been shown that the performance of conventional energy detector is enhanced with the insertion of adaptive wiener filter on the front end of conventional energy detector.

Two-stage Spectrum Sensing for Cognitive Radio under Noise Uncertainty.is proposed in [36].In this work two novel spectrum sensing techniques were proposed by using ED with maximum eigenvalue detection(MED) and ED along Covariance Absolute Value detection(CAV). In both cases ED is used as the first stage of the proposed algorithms because it performs spectrum sensing within short sensing time and gives reliable detection at high SNR environment. On the other hand, MED and CAV is employed only during low SNR condition. The performance of the proposed algorithm offers reliable detection Even though the proposed method requires long sensing time

In [37], Simulation Study of Double Threshold Energy Detection Method for Cognitive Radios is suggested to improve the performance of ED at low SNR by Double threshold based cooperative spectrum sensing(CSS). Considering uncertainty parameter, the single threshold value is ED's is translated to double threshold classified as upper threshold value and lower threshold value. In this method each secondary user Energy level is sent to Fusion Center in order to make the final decision. This will alleviate the problem of low SNR condition at some CR users. The analysis and simulation results show that of the proposed algorithm outperforms the conventional ED in low SNR region.

Efficient Multi Stage Spectrum Sensing Technique for Cognitive Radio Networks Under Noisy Condition. is given in[38]. In this work two spectrum sensing methods are combined named ED and combination of maximum- minimum eigenvalue detection (CMME). The first stage is employed with ED in order to detect primary user with less computation. CMME is employed whenever the first stage fails to detect the presence of primary user, i.e., at low SNR. Simulation result shows that the proposed method provides better detection in low SNR condition compared to those individual methods on the other the computational complexity led it to higher spectral sensing time.

CHAPTER THREE

3 METHODOLOGY

3.1 Introduction

In this thesis, previous researcher's studies about ED algorithm with its performance issue at low SNR region were revised. Also, in order to alleviate the problem of ED many researchers put forward their proposed method such as prior denoising the PU signal in order to improve SNR, not only that but also Two Stage method was also proposed to enhance the performance of ED. Having a basis on the previous works and keeping in mind the problem of ED at low SNR, the methodology of this thesis is depicted as follows.

3.2 Materials

For all computation and simulations works in this thesis, MATLAB/R2020a, was used. MATLAB is the computing platform which is used to analyze data, develop algorithm.

3.3 Methods

3.3.1 System Design

- Analyzing mathematical model of ED in terms of Probability of Detection, Probability of False Alarm, Probability of Miss detection.
- Analyzing the mathematical model of single stage wavelet based ED and two stage ED.

3.3.2 Simulation Methods

- Perform denoising performance comparisons for different wavelets.
- Perform Probability of Detection Versus SNR simulation.
- Perform Probability of False alarm versus Probability of Detection (ROC graph) simulation.
- Perform Probability of False alarm versus Probability of Miss Detection (CROC graph) simulation.
- Perform Cooperative Detection simulation with AND-Fusion and OR-Fusion with different number of users.
- Simulate and evaluate the performance of the proposed Two stage SS method against ED and single stage ED having denoising in single node and cooperative scenario.

3.3.3 Statistical Distributions and Random Variables

A Random Variable (RV) is a variable whose value depends on the randomness and it is statistically modeled by the distribution or the Probability Distribution Function (PDF) it follows. In this section, commonly used statistical distributions in wireless communication are presented with its PDF and Cumulative Density Function (CDF).

3.3.3.1 Gaussian Distribution

If a RV follows a Gaussian or Normal distribution, its PDF is defined by [39] , eq. (3.1)

$$f(y) = \frac{1}{\sqrt{2\pi\delta^2}} e^{\frac{-(y-\mu)}{2\delta^2}} \qquad -\infty < y < \infty \tag{3.1}$$

Where, μ and δ^2 are the mean and variance respectively [39]. The notation $y \sim N(\mu, \delta^2)$ means that a random variable y is Gaussian-distributed, with mean μ and variance δ^2. Its CDF is defined as [39], eq. (3.2)

$$\begin{aligned} F(y) &= P(Y \leq y) \\ &= \int_{-\infty}^{y} f(y)dy \\ &= \frac{1}{2}\left[1 + erf\left(\frac{x-\mu}{\sqrt{2\delta^2}}\right)\right] \end{aligned} \tag{3.2}$$

3.3.4 Chi-squared Distribution

A Chi-Squared or a central Chi-Squared distribution is defined as a summation of squares of independent standard normal RV's, Y with zero mean and unit variance. A RV Z is given by [39], eq. (3.3)

$$Z = \sum_{i=1}^{K} {Y_i}^2 \tag{3.3}$$

And It is distributed according to the Chi-Squared distribution with K degrees of freedom. It is also denoted as $Z \sim {X^2}_K$.The PDF for the Chi-Squared distribution is given by [39], eq. (3.4)

$$f(y) = \begin{cases} \dfrac{1}{2^{\frac{k}{2}}\Gamma\left(\frac{k}{2}\right)} y^{\frac{k}{2}-1} e^{\frac{-y}{2}} & ,0 \le y < \infty \\ 0 & ,\text{Otherwise} \end{cases} \tag{3.4}$$

Its CDF is defined as [39], eq. (3.5)

$$\begin{aligned} F(y) &= P(Y \le y) \\ &= \int_0^y f(y)dy \\ &= \frac{1}{\Gamma^{\frac{k}{2}}} \gamma\left(\frac{k}{2}, \frac{y}{2}\right) \qquad ,0 \le y < \infty \end{aligned} \tag{3.5}$$

and its CCDF is defined as [39], eq. (3.6)

$$\begin{aligned} CCDF(y) &= P(Y > y) \\ &= 1 - F(y) \\ &= \frac{1}{\Gamma^{\frac{k}{2}}} \Gamma\left(\frac{k}{2}, \frac{y}{2}\right), \qquad 0 \le y < \infty \end{aligned} \tag{3.6}$$

3.3.5 Non-central Chi-squared Distribution

A Non-Central Chi-Squared Distribution is defined as a summation of squares of independent Normal RV's, Y with mean μ and variance δ^2. A RV Z is given by [39], eq. (3.7)

$$Z = \sum_{i=1}^{k} \left(\frac{y_i}{\delta_i}\right)^2 \tag{3.7}$$

and it is distributed according to the Non-central Chi-Squared distribution with k degrees of freedom and the non-centrality parameter ψ, which is defined as [39], eq. (3.8)

$$\psi_{nc} = \sum_{i=1}^{k} \left(\frac{\mu_i}{\delta_i}\right)^2 \tag{3.8}$$

The PDF for Non-Central Chi-Squared distribution is [39], eq. (3.9)

$$f(x) = \begin{Bmatrix} \frac{1}{2} e^{\frac{-(y+\psi_{nc})}{2}} \left(\frac{y}{\psi_{nc}}\right)^{\frac{k}{4}-\frac{1}{2}} I_{\frac{k}{2}-1}\left(\sqrt{\psi_{nc} y}\right) & ,0 \leq y < \infty \\ 0 & ,otherwise \end{Bmatrix} \tag{3.9}$$

and it's *CDF* is defined as [39], eq. (3.10)

$$F(y) = 1 - \mathbb{Q}_{\frac{k}{2}}\left(\sqrt{\psi_{nc}}, \sqrt{y}\right), 0 \leq y < \infty \tag{3.10}$$

Where, $\mathbb{Q}_m(a, b)$ is Marcum-$\mathbb{Q}$ functioin

3.3.6 Summation of Two Random Variables

Let X and Y be independent RV's with the PDF of $f_X(x)$ and $f_Y(y)$. The summation of these two independent RV's is given by, $Z = X + Y$. The PDF of Z is given by [40], eq. (3.11)

$$\begin{aligned} f_Z(z) &= f_X(x) * f_Y(y) \\ &= \int_{-\infty}^{\infty} f_X(x).f_Y(z - x)dx \end{aligned} \tag{3.11}$$

In other words, $f_Z(z)$ is the convolution of $f_X(x)$ and $f_Y(y)$[40]. For instance, let Z be the summation of two independent Gaussian distributed X and Y with μ_x , δ_x^2 , μ_y and δ_y^2. The PDF of X can be written according to (3.1) as [40], eq. (3.12)

$$f_X(x) = \frac{1}{\sqrt{2\pi\delta_x^2}} e^{\frac{-(x-\mu_x)^2}{2\delta_x^2}} \tag{3.12}$$

and similarly the PDF of Y is [40], eq. (3.13)

$$f_Y(y) = \frac{1}{\sqrt{2\pi\delta_y^2}} e^{\frac{-(y-\mu_y)^2}{2\delta_y^2}} \tag{3.13}$$

The *PDF* of Z, which is $Z = X + Y$, becomes [40], eq. (3.14)

$$\begin{aligned} f_Z(z) &= f_X(x) * f_Y(y) \\ &= \int_{-\infty}^{\infty} f_X(x) * f_Y(z - x)dx \end{aligned}$$

$$f_z(z) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\delta_x^2}} e^{\frac{-(x-\mu_x)^2}{2\delta_x^2}} . \frac{1}{\sqrt{2\pi\delta_y^2}} e^{\frac{-(z-x-\mu_y)^2}{2\delta_y^2}} dx \tag{3.14}$$

$$f_z(z) = \frac{1}{\sqrt{2\pi(\delta_x + \delta_y)}} exp\left[\frac{-\left(z - (\mu_x + \mu_y)\right)^2}{2(\delta_x^2 + \delta_y^2)}\right] \tag{3.15}$$

This derivation shows that if X and Y are independent Gaussian distributed RV's such that [40], eq. (3.16) and (3.17).

$$X \sim N(\mu_x, \delta_x^{\,2}) \tag{3.16}$$

$$Y \sim N(\mu_y, \delta_y^{\,2}) \tag{3.17}$$

then Z which is a summation of X and Y , $Z = X + Y$ is distributed as[40], eq. (3.18)

$$Z \sim N(\mu_x + \mu_y, \delta_x^2 + \delta_y^{\,2}) \tag{3.18}$$

3.3.7 Central Limit Theorem

The Central Limit Theorem is defined that a sum of n independent, identically distributed $IID\ RV's$ can be approximated as a normal distribution when there is a large number of $RV's$ and the contribution for each of them is small compared to the total [40].

3.4 Performance Metrics Derivation for Energy Detection

The spectral availability information accuracy is determined by sensing quality factors. These factors are made up the performance metrics. The performance of the energy detector is described by the following general metrics:

- The probability of detection, (P_d)
- The probability of false alarm, (P_f)
- The probability of missed detection, (P_m)

In opportunistic spectrum sensing the P_d specifies that a detector makes a true decision that a given channel is occupied by the PU (H_1). Hence, a large P_d denotes exact sensing; which translate to small chance of collision with the licensed user. A false alarm event occurs when the detector assumes the presence of PU (H_1) however, the fact is the absence of the PU (H_0). Technically this event is event is specified as a P_f. This event prevents SU from utilizing the available free spectrum, i.e., Missing opportunity.in order to prevent underutilization P_f should be kept minimum as much as possible. The decision of ED can be modeled as:

$$R(t) = \begin{cases} w(t) & : \text{PU Absent}(\mathrm{H}_0) \\ s(t) + w(t) & : \text{PU present}(\mathrm{H}_1) \end{cases} \tag{3.19}$$

where R(t) is the signal received by the CR user, $s(t)$ is the signal transmitted by the PU, $w(t)$ is the noise introduced by AWGN. H_0 describe the null hypothesis when no PU is there and H_1 indicates the presence of PU. When the received signal at CR is zero mean Gaussian distributed noise only, the decision statistics Y follows central chi square distribution with $2TW$ (twice of time-bandwidth product) degrees of freedom. On the other hand, when the received signal is composed of PU's signal and noise, Y follows a non-central chi-squared distribution with $2TW$ degrees of freedom and non-centrality parameters 2γ.Where γ is the signal to noise ratio (SNR) in the linear scale. And the Test statistics Y is given by [41]

$$Y \sim \begin{cases} x_{2TW}^2 & , H_0 \\ x_{2TW}^2(2\gamma) & , H_1 \end{cases} \tag{3.20}$$

The PDF of test statistic Y of equation 3.20 can then be written as shown in equation 3.21 [41]:

$$f_y(y) = \begin{cases} \dfrac{1}{2^{TW}\Gamma(TW)} y^{TW-1} e^{\frac{-y}{2}} & , H_0 \\ \dfrac{1}{2}\left(\dfrac{y}{2\gamma}\right)^{\frac{TW-1}{2}} e^{\frac{-(2\gamma+\gamma)}{2}} I_{TW-1}\left(\sqrt{2\gamma y}\right) & , H_1 \end{cases} \tag{3.21}$$

Where $\Gamma(.)$ is gamma function and $I_v(.)$ is the $x^{th} - order$ modified Bessel functions of the first kind. The probability of detection P_d and false alarm P_f are then given as follows [41].

$$P_d = P(Y > \lambda | H_1) = \mathbb{Q}_{N=TW}\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) \tag{3.22}$$

$$P_f = P(Y > \lambda | H_0) = \frac{\Gamma\left(TW, \frac{\lambda}{2}\right)}{\Gamma(TW)} \tag{3.23}$$

By Central limit theorem, the distribution of Test Statistics T can be approximated to normal distribution when we consider sufficiently large sample size N. Hence the statistic is given by [41].

$$Y \sim \begin{Bmatrix} N(\mu_0, \delta_0^2) & , H_0 \\ N(\mu_1, \delta_1^2) & , H_1 \end{Bmatrix} \quad (3.24)$$

where, $N(\mu, \delta^2)$ is Gaussian distribution with mean μ and variance δ^2 and for the system model given above the mean and variance for both hypotheses H_0 and H_1 are given by:

$$\mu_0 = N\delta_n^{\ 2} \quad , \quad \delta_0 = 2N\delta_n^{\ 4} \quad (3.25)$$

$$\mu_1 = N(\delta_s^{\ 2} + \delta_n^{\ 2}) \quad , \quad \delta_1^2 = 2N(\delta_s^{\ 2} + \delta_n^{\ 2})^2 \quad (3.26)$$

Then the probability of detection and false alarm for large value of N could be calculated by substituting equation 3.25 and 3.26 into equation 3.24 and given as:

$$P_d = \mathbb{Q}\left(\frac{\lambda - N(\delta_s^{\ 2} + \delta_n^{\ 2})}{\sqrt{2N(\delta_s^{\ 2} + \delta_n^{\ 2})}}\right) = \mathbb{Q}\left(\frac{\lambda - N(1+\gamma)\delta_n^{\ 2}}{\sqrt{2N(1+2\gamma)\delta_n^{\ 4}}}\right) \quad (3.27)$$

$$P_f = \mathbb{Q}\left(\frac{\lambda - N\delta_n^{\ 2}}{\sqrt{2N\delta_n^{\ 4}}}\right) \quad (3.28)$$

$$\lambda = \mathbb{Q}^{-1}\left(P_f\right)\sqrt{2N}\delta_n^2 + N\delta_n^2 \quad (3.29)$$

Where $\mathbb{Q}(t) = \frac{1}{\sqrt{2\pi}}\int_t^\infty e^{\frac{-u^2}{2}}du.$

By considering large number of samples, we can achieve the desired probability of detection and probability of false alarm at the same time. The minimum number of samples required, which is a function of the signal to noise ratio $\gamma = \frac{\delta_s^2}{\delta_n^2}$ is evaluated by [41].

$$N = 2\left[\left(\mathbb{Q}^{-1}\left(P_f\right) - \mathbb{Q}^{-1}(P_d)\right)\gamma^{-1} - \mathbb{Q}^{-1}(P_d)\right]^2 \quad (3.30)$$

3.4.1 Cooperative Spectrum Sensing for AND-Fusion and OR-Fusion

3.4.1.1 AND-Fusion

In this rule, having N SU's, the FC only decided the availability of the PU when all of the local decisions made by SU's sent to the decision maker are one, the final decision made by the decision maker is one. The fusion center's decision is calculated by logic AND of the received hard decision statistics [42].

$$P_{d,AND} = P_{d,i}^{\ N} \quad (3.31)$$

3.4.1.2 OR-Fusion

In this rule, having N SU's, the FC only decides the availability of the PU, if any one of the CR make a decision of logical one, then final decision made by the FC maker is one [42].

$$P_{d,OR} = 1 - \left(1 - P_{d,i}^{N}\right) \tag{3.32}$$

3.4.2 Two Stage Spectrum Sensing

The major goal of implementing Two Stage Spectrum Sensing is to improve the probability of detecting PU by combining Two Algorithms. This is implemented by composing of first stage and second stage. The improvement on the detection is found when the first stage fails to detect, another stage is executed to verify the result of first stage. Two stage spectrum sensing is implemented as shown below.

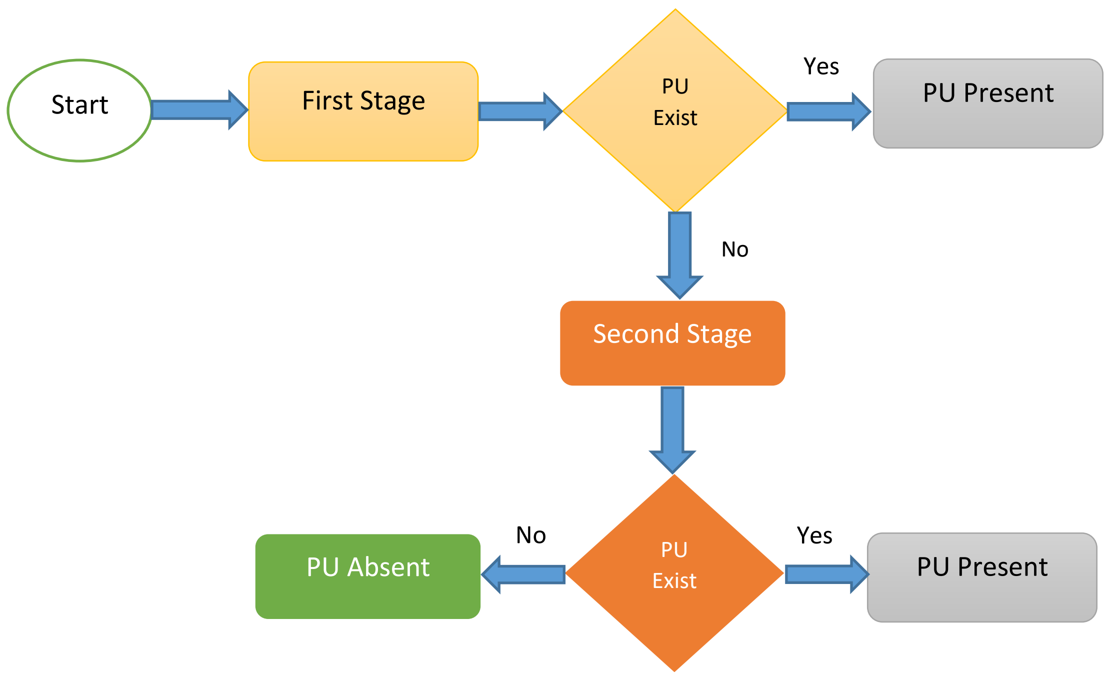

Figure 3.1: Two Stage Spectrum Sensing [43]

Probability of detection for Two Stage Spectrum Sensing is given by eqn. (3.33).

$$P_d^{Two\ Stage} = P_d^{Coarse\ Stage} + \left(1 - P_d^{Coarse\ stage}\right) P_d^{Fine\ Stage} \tag{3.33}$$

3.4.3 DWT Based Denoising

Mathematically, Wavelets are nothing but functions that decompose the original signal into components of high and low frequency. There are different small waves (also known as mother wavelets) that can be used for the implementation of Wavelet Transform (WT) such as Haar, Symlet. A family of wavelet basist $\psi_{u,s}(n)$ is generated by translating and scaling the mother wavelets [44]:

$$\psi_{u,s}(n) = \frac{1}{\sqrt{s}}\psi\left(\frac{n-u}{s}\right) \tag{3.34}$$

The wavelet coefficients are calculated to measure the frequency content resemblance between a signal and a selected wavelet function. These coefficients are calculated as a signal convolution in the scaled wavelet function. DWT of input signal $x(n)$ is expressed by

$$DWT(u,s) = \frac{1}{\sqrt{s}}\sum_{n} x(n)\psi\left(\frac{n-u}{s}\right) \tag{3.35}$$

Where n represent the discrete number, s and u are scaling and translation parameter respectively while ψ denote the mother wavelet. Thus, detecting the corruption within the signal and eliminating it becomes a relatively easy process. Discrete wavelet transform (DWT) denoising contains three procedures: forward transformation of the signal to the wavelet domain, reduction of the wavelet coefficients, and inverse transformation to the native domain.

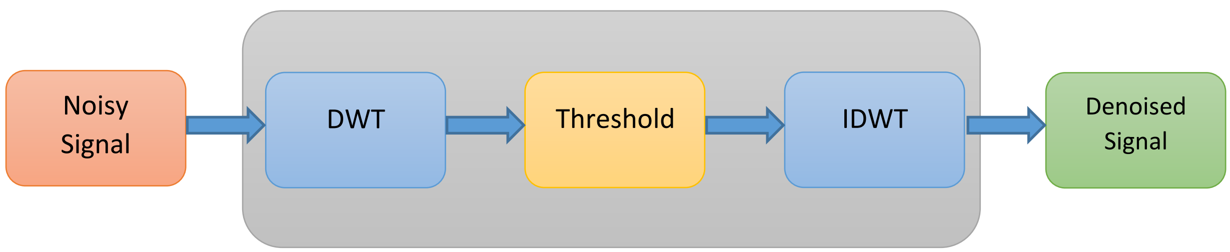

Figure 3.2: DWT Based Denoising Steps [29]

3.4.4 Wavelet threshold

After a Wavelet Decomposition with a specified mother wavelet, the given signal is decomposed into low frequency (approximation coefficients) and high frequency component (detail coefficients). A denoising process is implemented by applying a wavelet threshold to separate approximation coefficient from detail coefficient. A wavelet coefficient having a value greater than the wavelet threshold considered as signal part, a wavelet coefficient which is lower than the threshold is assumed as noise part. The universal threshold is given by [44].

$$t = \delta\sqrt{2lnN} \tag{3.36}$$

Where N is the sample data length, δ is the standard deviation of the noise. Practically δ is unknown, for this case it can be estimated by using the first detail part of the wavelet coefficient as, s

$$s \approx \frac{median(|\chi_i|)}{0.6745} \tag{3.37}$$

Where χ_i is the first detail part of wavelet coefficient.

3.4.5 Threshold function selection

In wavelet transform we have two kinds of threshold selection that will affect the value of wavelet coefficient when it is below or above the threshold value [44].

3.4.5.1 Hard threshold

In the case of hard threshold, wavelet coefficient having value less than the threshold are zeroed out and remain unchanged if its greater than the threshold [44].

$$x_i^* = \begin{cases} 0 & , if|x_i| \leq t \\ x_i & , if|x_i| > t \end{cases} \tag{3.38}$$

3.4.5.2 Soft threshold

The soft threshold function is defined as in [44].

$$x_i^* = \begin{cases} 0 & , if|x_i| \leq t \\ sign(x_i)(|x_i| - t) & , if|x_i| > t \end{cases} \tag{3.39}$$

3.4.6 Denoising Performance Metrics

The selection of the best wavelet in DWT cannot be identified visually. For such purposes the comparison is conducted based on SNR value after denoising and Mean Square Error (MSE).

3.4.6.1 Mean Squared Error (MSE)

MSE is used as a performance metrics to show the accuracy of the denoising. The lower the value, the denoised signal is closer or very similar to the original signal. Let $x(n)$ be the original signal and $x(n)'$ represent the denoised signal, MSE is given as:

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(x(n) - x(n)')^2 \tag{3.40}$$

3.4.6.2 Signal to Noise Ratio (SNR)

Higher SNR values shows as the best performance of denoising result. eqn.(3.41) was used to compute SNR after denoising process [44].

$$SNR_{dB} = 10log_{10}\frac{\sum_{n=1}^{N} x(n)^2}{\sum_{n=1}^{N}(x(n) - x(n)')^2} \tag{3.41}$$

Where n represent the sample number, n =1,2,3…., N.

3.4.7 System Design

3.4.7.1 Single Stage Wavelet Denoising Based ED

The performance of conventional ED is analyzed by adding prior denoising before ED. The performance of different wavelet is compared in terms of P_d, P_f and P_m.where γ^* is the new SNR of PU signal after denoising calculated by using eq. (3.41).

$$P_d = \mathbb{Q}\left(\frac{\lambda - N(1+\gamma^*)\delta_n^2}{\sqrt{2N(1+2\gamma^*)\delta_n^4}}\right) \tag{3.42}$$

$$\lambda = \mathbb{Q}^{-1}(P_f)\sqrt{2N}\delta_n^2 + N\delta_n^2 \tag{3.43}$$

$$P_m = 1 - P_d \tag{3.44}$$

3.4.7.2 Flow chart for Single Stage Wavelet Denoising (WD) Based ED

The flow chart for single stage ED having different wavelet for denoising algorithm is depicted below. For single stage wavelet denoising based ED, a prior denoising method using wavelet is implemented by using different mother wavelet prior to ED.

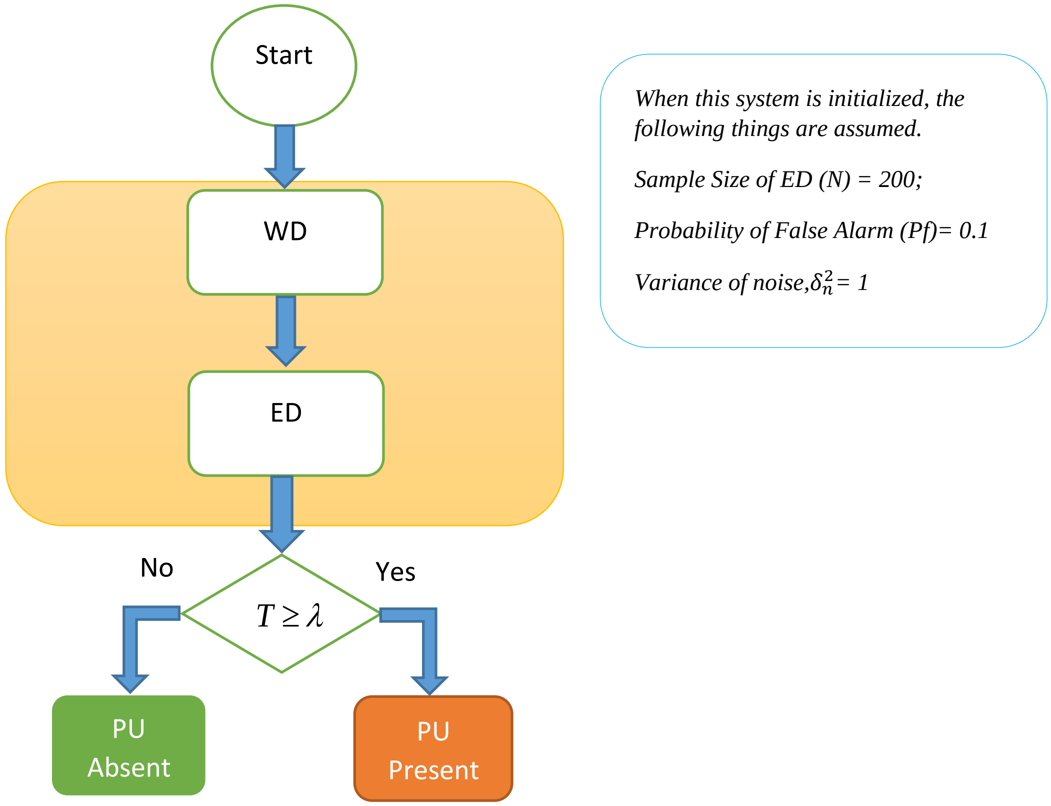

Figure 3.3: Single Stage Wavelet Denoising based ED

3.4.7.3 Proposed Two Stage Spectrum Sensing Approach

$$P_d^{Two\ Stage} = P_d^{first\ stage} + \left(1 - P_d^{first\ stage}\right) P_d^{second\ stage} \tag{3.45}$$

$$P_d^{Two\ Stage} = P_d^{CED} + (1 - P_d^{CED}) P_d^{Denoised\_ED} \tag{3.46}$$

$$P_d^{Two\ Stage} = \mathbb{Q}\left(\frac{\lambda - N(1+\gamma)\delta_n^2}{\sqrt{2N(1+2\gamma)\delta_n^4}}\right) + \mathbb{Q}\left(\frac{\lambda - N(1+\gamma^*)\delta_n^2}{\sqrt{2N(1+2\gamma^*)\delta_n^4}}\right) \tag{3.47}$$

$$\lambda = \mathbb{Q}^{-1}(P_d)\sqrt{2N}\delta_n^2 + N\delta_n^2 \tag{3.48}$$

3.4.7.4 Flow chart for Two Stage Wavelet Denoising Based ED

In order to improve the performance of single stage ED, a Two stage wavelet denoising based ED is developed by using the best wavelet which gives good result in single stage wavelet denoising based ED. The flow chart for Two stage energy detection having best denoising wavelet depicted below.

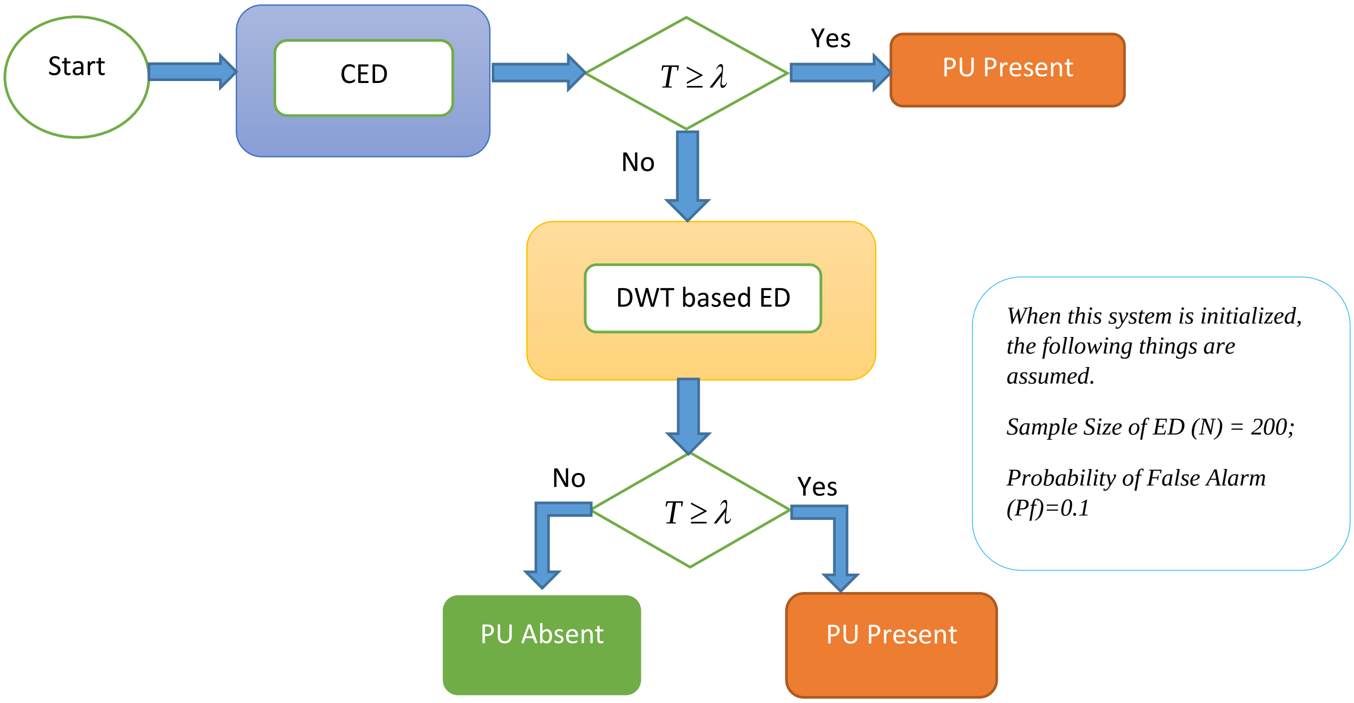

Figure 3.4: Two Stage Wavelet Denoising Based ED

CHAPTER FOUR

4 RESULTS AND DISCUSSION

In this chapter the simulation results of this thesis work are presented. Simulation results and discussions on the performances of CED, DWT based ED including, the performance comparison between wavelet families and cooperative detectors under AWGN channel are provided. Finally, simulation results and discussions for Two Stage Energy Detector are presented. All the simulation works are carried out with the consideration of required detection probability of 90%, probability of false alarm of 10% and probability of miss detection of 10%. Some of the simulation parameters for spectrum detector performance evaluation is listed in the table below.

Table 4.1: Simulation Parameters

No	Simulation Parameter	Type and Value	Remark
1	Primary User Signal	QPSK	
2	Noise	AWGN	
3	Channel	AWGN	
4	Probability of Detection	0.9	$P_d \geq 0.9$ (based on IEEE 802.22)
5	Probability of false alarm	0.1 and below	$P_f \leq 0.1$(based on IEEE 802.22)
6	SNR range	-20dB to 5dB	
7	Cooperative Network	Center fusion - AND Rule, OR Rule	
8	Number of users for CSS	1,2,3,4	
9	Noise Variance(δ_n^2)	1	Assumption
10	Wavelet Types	Haar, BiorSplines, Coiflets ReverseBior, Fejer-Korovkin, Daubechies	haar, bior2.4, coif2 , rbio1.2, fk4, db2
11	Threshold and level of decomposition	Hard Threshold,3	

4.1 Simulation Results and Discussion for Conventional Energy Detector

In order to evaluate the performance of Conventional Energy Detector (CED) algorithm, different performance metrics such as Probability of Detection, Probability of False Alarm, Probability of Miss detection, Receiver Operating Characteristics (ROC) and Complementary Receiver Operating Characteristics (CROC) are taken into account.

4.1.1 Detection Performance Comparison over Varying SNR

The simulation result shown in Figure 4.1 present the Probability of Detection for varying Signal to Noise Ratio of a single user for the threshold values that is defined based on probability of false alarm using Constant False Alarm Rate (CFAR) and noise variance. The results are taken for SNR vary form -20dB to 5 dB with 1dB increment to imitate low SNR condition and by setting probability of false alarm to 0.1 which is the maximum allowed according to the IEEE 802.22 standard and 200 sampled signals are taken into account.

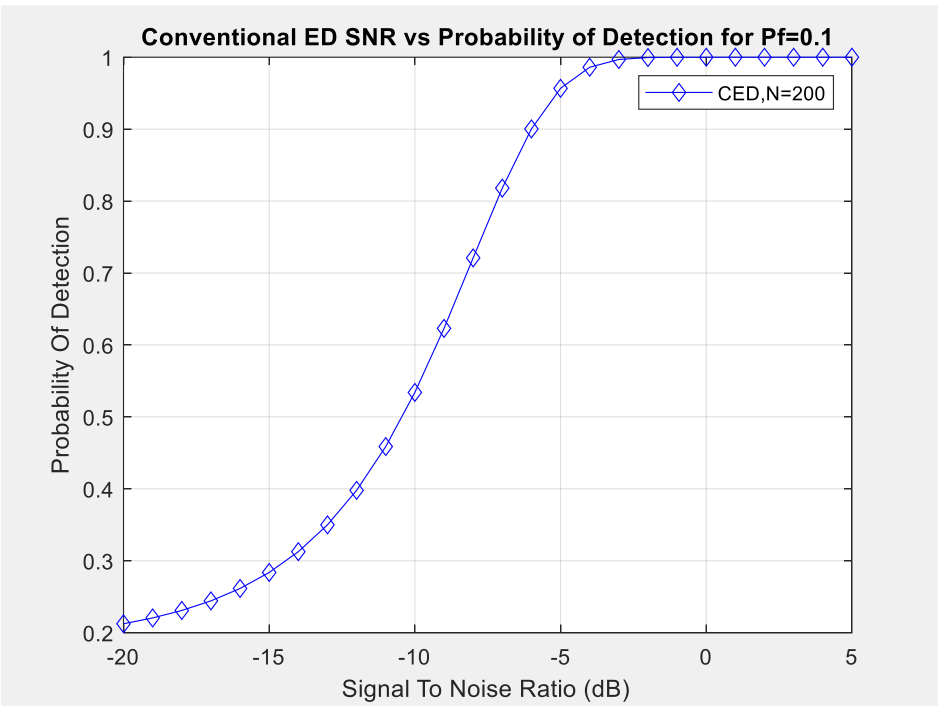

Figure 4.1: Probability of Detection of ED over varying SNR for P_f =0.1 and N=200

As shown in the above figure, CED has very poor detection performance at a very low SNR. For instance, for SNR values below -12dB, the probability of detection goes below 0.4. Despite the fact that detection values at lower SNR are very low, particularly for SNR values below -12dB, it is observed that when the SNR increases and exceed -6dB, the detection probability is getting improved and CED achieves the required Probability of Detection which is 0.9. As one can see from the simulations, Probability of Detection is directly proportional to the Signal to Noise Ratio. Since the result shows the transition from -10dB to -5dB leads to the performance improvement of the detector from 0.534 to 0.9567.

4.1.2 ROC of CED for different SNR

Another approach to see how the SNR affect the performance of CED is by plotting Probability of False Alarm versus Probability of Detection, which is called ROC graph which provide a precise, quantitative means of evaluating system's accuracy. Figure 4.2 shows the accuracy of CED at -17dB, -14dB and -6dB for the range of probability of false alarm between 0.01 to 1 with increment of 0.01 and 200 sample size. The Area Under the Curve (AUC) decreases as SNR reduce from -6 dB to -17 dB, as expected from literature. The result shows that at a given probability of false alarm, increasing SNR will increase the detection probability. For instance, the probability of detection for -17dB at probability of false alarm 0.1 is 0.4587, while it is 0.9003 for -6dB. This shows that only SNR of -6dB achieves the required values for probability of detection and probability of false alarm values according to the IEEE 802.22 WRAN standard.

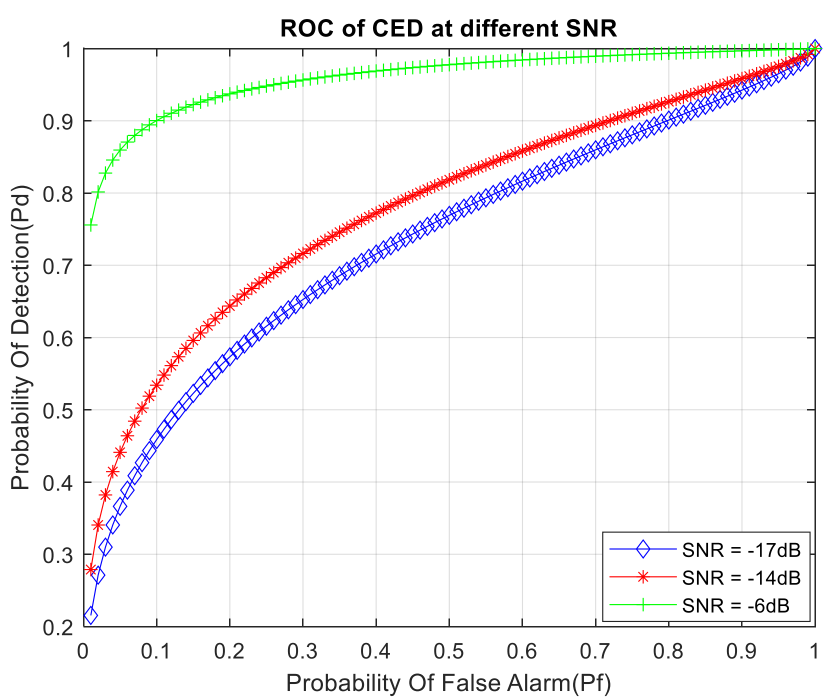

Figure 4.2: ROC of CED for SNR = -6dB, -14dB, -17dB and N=200

4.1.3 CROC of CED for different SNR

Figure 4.3 shows the relationship between Probability of false alarm and probably of miss detection described by CROC, for different SNR values. The probably of miss detection should be minimized and ultimate protection for primary user should be granted in order to avoid collision. The result shows that increasing SNR will reduce the failure of detecting the PU. For instance, for a given probability of false alarm 0.1, the probability of miss detection for -17dB is 0.6021 while it is 0.0996 for -6dB.

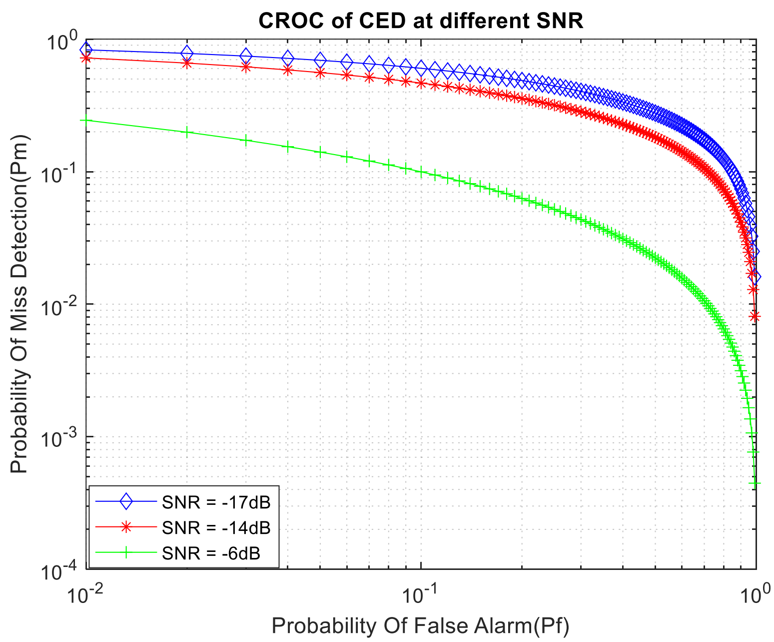

Figure 4.3: CROC of CED for SNR = -6dB, -14dB, -17dB and N=200

4.1.4 Detection Performance Comparison over Varying Number of Samples

The Performance of CED also greatly depend on Number of samples. Figure 4.4 shows the plot of signal strength (SNR = -25 dB to 5 dB) versus the probability of detection with varying sample size (N = 200, 400 and 600) having probability of false alarm set to 0.1. The plot shows that the performance of CED can be further enhanced with increasing number of samples in addition to the increasing SNR. For instance, the probability of detection at -20dB is 0.2124,0.2245,0.234 for 200,400 and 600 sample sizes respectively. This also shows that, even at low SNR increasing the number of samples will enhance the probability of detection. However, increasing number of samples will not always increase probability of detection due to SNR wall effect.

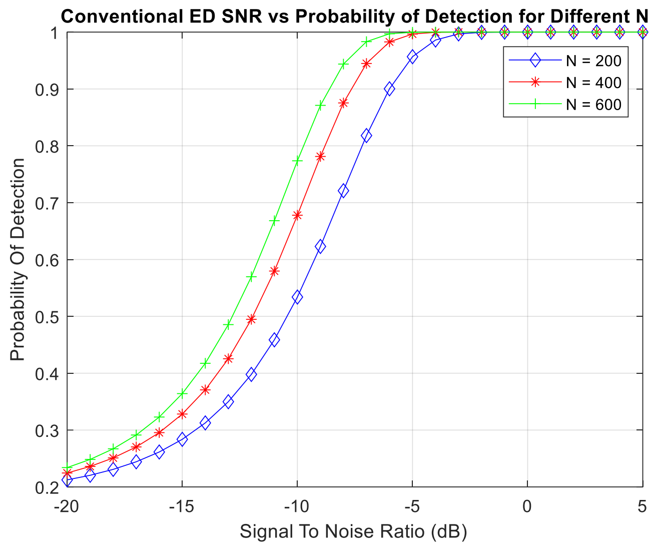

Figure 4.4: Probability of Detection versus SNR of CED for P_f = 0.1 and N=200,400 and 600

4.1.5 ROC of CED for different Sample Sizes

Figure 4.5 show, the results for the performance metrics of ROC of CED for different number of samples at -9dB. At a given probability of false alarm, the accuracy of CED can be enhanced by increasing the number of sample size. For instance, the probability of detection is enhanced from 0.623 to 0.7813 and 0.901 with increasing number of samples from 200 to 400 and 600 respectively at a given probability of false alarm, i.e., 0.1. One can note that, only a sample size of 600 achieve the standard of IEEE 802.22 at a given SNR and probability of false alarm.

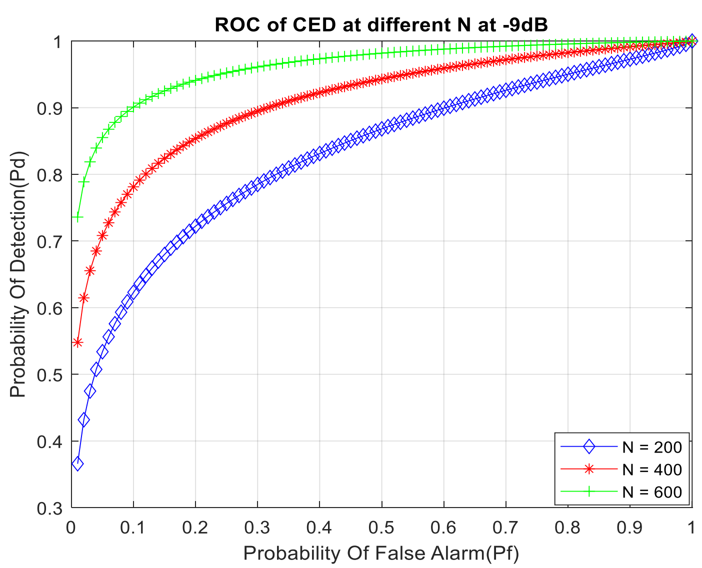

Figure 4.5: ROC graph of CED for SNR = -9dB, N=200,400 and 600

4.1.6 CROC of CED for different Sample Sizes

Figure 4.6 shows CROC of CED for different number of sample size. At a given probability of false alarm and SNR, the probability of miss detection is decreased with increasing number of sensing samples. For example, the probability of miss detection is decreased from 0.377 to 0.2187 and 0.0990, when the number of samples increased from 200,400 and 600 respectively. This can also be explained as, increasing the number of samples from 200 to 600, decreased the probability of miss detection by 97.37%.

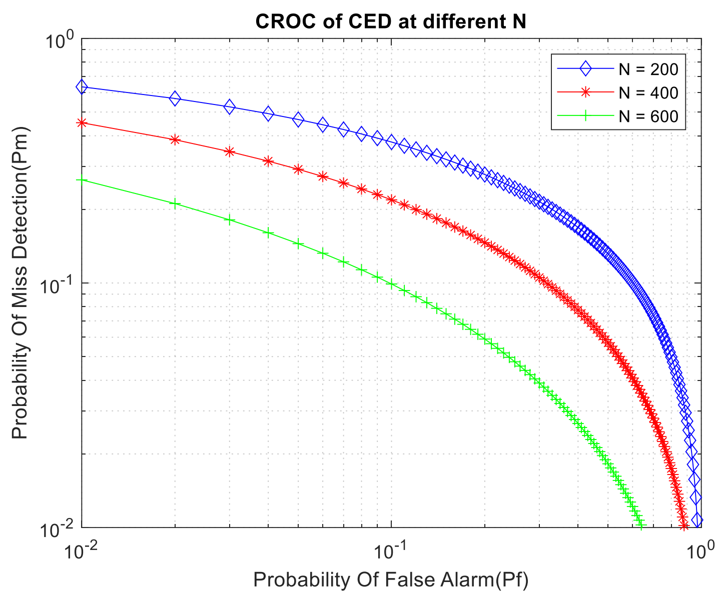

Figure 4.6: CROC graph of CED for SNR= -9dB, N=200,400 and 600

4.1.7 Effect of Probability of False Alarm on Probability of Detection

Figure 4.7 shows a plot of probability of detection versus SNR with various probability of false alarms given at 0.01,0.1and 0.2. Increasing the probability of false alarm will increase the probability of detection but it degrades the efficiency of the CR, since it generates so many false report when actually the PU is not present. The result form the plot shows that increasing the probability of false alarm increases the probability of detection. For instance, a given SNR of -20dB and probability of false alarm,0.1 has a probability of detection of 0.212, while it is 0.265 for the probability of false alarm of 0.15. Doubling the probability of false alarm to 0.2, further increases the probability of detection to 0.312.

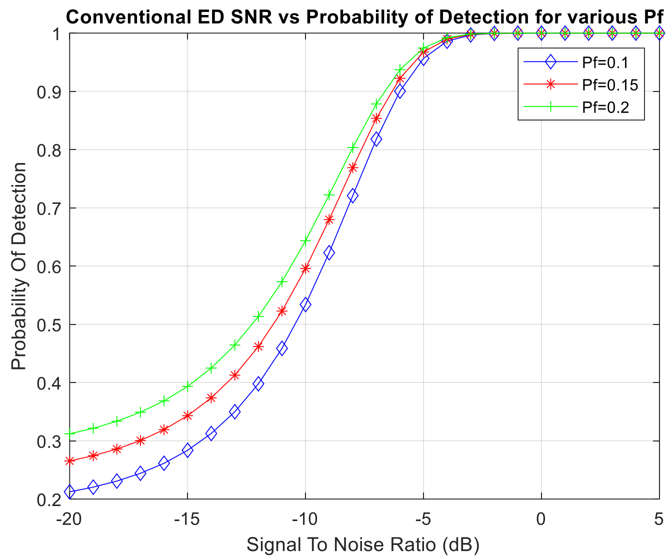

Figure 4.7: Probability of Detection versus SNR of CED for P_f = 0.1 ,0.15 and 0.2, and N=200

4.2 Cooperative Detection with CED

In this section, simulation results for cooperative based CED is presented. Figure 4.8 shows the plot of SNR versus probability of detection of single node CED and cooperative detection for "OR" and "AND" fusion scheme. The plot is generated with 6 number of cooperative users under both schemes. From this figure, the OR-Fusion rule shows a better performance compared to the CED and AND-Fusion rule. This is due to the fact that the OR-Fusion rule requires at least one user out of K CR nodes to announce the existence or absence of a PU. However, the AND-Fusion rule require that all users must agree on the existence of PU's in order to make a decision. Table 4.2 shows the comparison of cooperative detection and single node detection at -10dB.

Table 4.2: Performance Comparisons of Cooperative CED under AND/OR Fusion for SNR = -10dB, P_f = 0.1, N=200 and NU=6

Performance Metrics	CED	OR-FUSION	AND-FUSION
P_d	0.534	0.9898	0.0231
Gain over Conventional ED	-	**+85.3%**	**-95.6%**

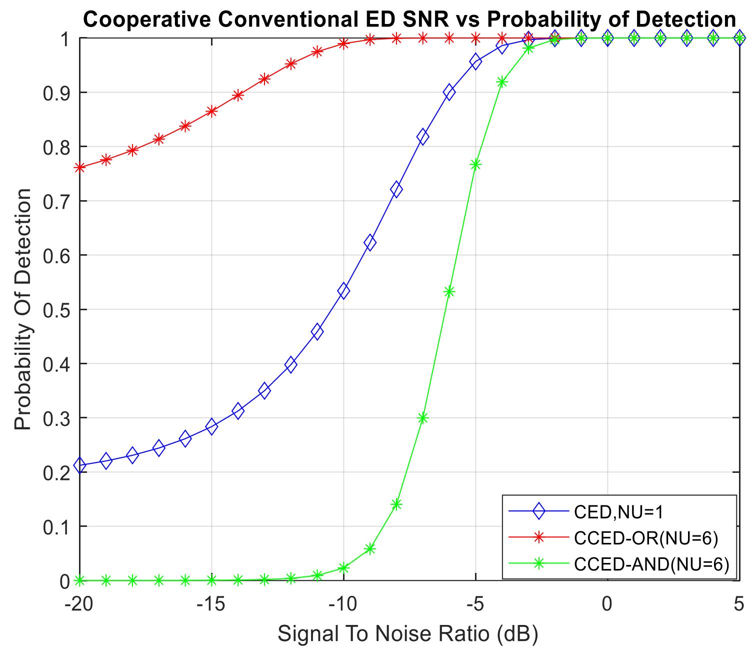

Figure 4.8: Probability of Detection versus SNR of cooperative CED under AND/OR fusion for P_f = 0.1, N=200 and NU=6

4.2.1 Effect of Number of User (NU) on Cooperative Conventional Energy Detection

Figure 4.9 demonstrate the effect number of user on the probability of detection for cooperative spectrum sensing in the case of OR-Fusion and AND-Fusion. The probability of detection greatly depends on the number of cooperating user besides the rule employed at the FC. When the cooperative number of user is 1, both cooperative scheme converges to single node detection which is CED. The plot shows when different number of user are cooperating at a given probability of false alarm, 0.1, and sample size of 200 with AND-Fusion and OR-Fusion. Different detection performance is observed when the number of user is varied from 1,2,3 and 4.

Table 4.3: Detection performance comparison of cooperative CED for SNR = -15dB, P_f = 0.1, N=200, NU=1,2,3 and 4

Number of User (NU)	1	2	3	4
P_d OR-Fusion	0.2837	0.4869	0.6325	0.7367
P_d AND –Fusion	0.2837	0.0804	0.0228	0.0064
Gain by OR-Fusion (%)	-	**+71.62%**	**+122.9%**	**+159.6%**
Loss by AND –Fusion (%)	-	**-71.66%**	**-91.63%**	**-97.74%**

Table 4.3 shows comparison of cooperative detection at -15dB. The result shows that increasing number of cooperative user greatly enhance the detection performance of OR-Fusion, on the other hand the performance of AND-Fusion greatly deteriorates. For instance, for a given probability of false alarm and SNR ,0.1, and -15dB respectively when 3 user cooperative with OR-Fusion, the probability of detection is 0.632 and when they are combine with AND fusion the probability of detection decrease to 0.022. This shows that the detection performance of AND-Fusion is decreased by 91.63% when compared with CED. On the other hand, the detection performance of OR-Fusion is better than CED by 122.9%.

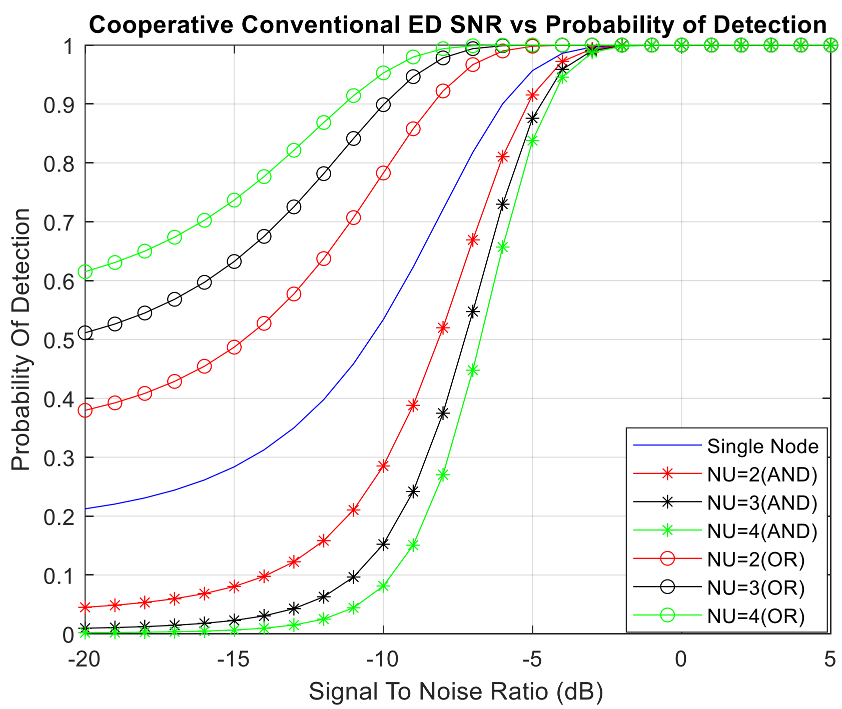

Figure 4.9: Probability of Detection versus SNR of Cooperative CED under AND/OR Fusion for P_f = 0.1, N=100 and NU=1,2,3 and 4

From the above figure one can note that increasing number participating user in the case of OR-Fusion increases the probability of detection even at low SNR. However, in the case of AND-Fusion, increasing number of cooperative user will decrease the performance of detection because all of the cooperative user must agree up on the presence of the PU, this might be difficult to achieve since some of cooperative users fail to detect due to low SNR.

4.2.2 ROC of Cooperative CED

Figure 4.10 shows the ROC curve for cooperative sensing when the number of users are 4 and assuming that all users receive -10dB signal on average. One can note that increasing number of cooperating users for OR fusion greatly enhance the detection probability. However, the performance of AND-Fusion decrease with increasing number of coopering users.

Table 4.4: ROC comparisons of cooperative CED for SNR = -10dB, P_f=0.1, N=200 and NU=1,2,3 and 4

Number of users (NU)	1	2	3	4
P_d OR-Fusion	0.326	0.5457	0.6938	0.7936
P_d AND-Fusion	0.326	0.1063	0.0346	0.0112
Gain by OR-Fusion (%)	-	**+67.39%**	**+112.8%**	**+143.43%**
Loss by AND-Fusion (%)	-	**-67.39%**	**-89.38%**	**-96.56%**

Table 4.4 shows that the performance comparison OR-Fusion with AND-Fusion at a given probability of false alarm and SNR of 0.1 and -10dB respectively.

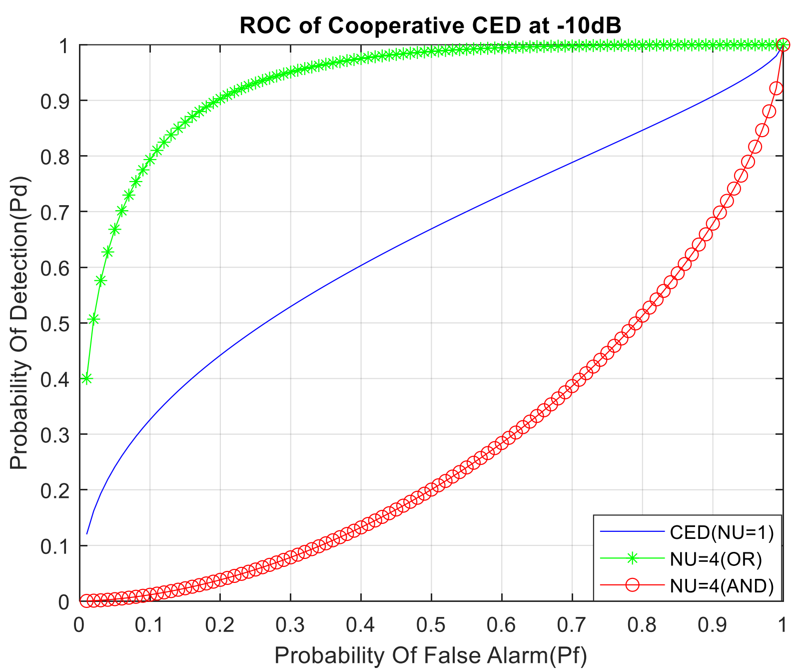

Figure 4.10: ROC graph of cooperative CED for SNR= -10dB , N=200 and NU=4

4.2.3 CROC of Cooperative CED

Figure 4.11 shows the CROC of cooperative CED under OR-Fusion and AND-Fusion rule. The result shows that probability of missing the primary user is decrease by using OR-Fusion instead of AND-Fusion. In addition, the number of users in cooperative network has also a great impact for the performance. In the case of OR-Fusion, increasing the number of user will greatly decrease the probability of miss detection, On the other hand the increasing cooperative users will deteriorate the performance of sensing in AND-Fusion.

Table 4.5 shows the effect of increasing number of user in the probability of miss detection. As the result shows, the performance of missing licensed user is increased from 0.446 to 0.9187 for cooperative AND-Fusion. However, the probability of missing is decreased from 0.466 to 0.0471 for OR-Fusion scheme. More Specifically, for 3 cooperating users, AND-Fusion increase the probability of missing the licensed user by 81.90% while OR-Fusion reduce the probability of missing by 78.28% when compared with CED.

Table 4.5: CROC comparison of cooperative CED for SNR = -10dB, P_f = 0.1, N=200, NU=1,2,3 and 4

Number of User (NU)	1	2	3	4
P_m OR-Fusion	0.466	0.2172	0.1012	0.0471
P_m AND-Fusion	0.466	0.7194	0.8477	0.9187
Gain by OR-Fusion (%)	-	**-53.39%**	**-78.28%**	**-89.89%**
Loss by AND-Fusion (%)	-	**+54.37%**	**+81.90%**	**+97.14%**

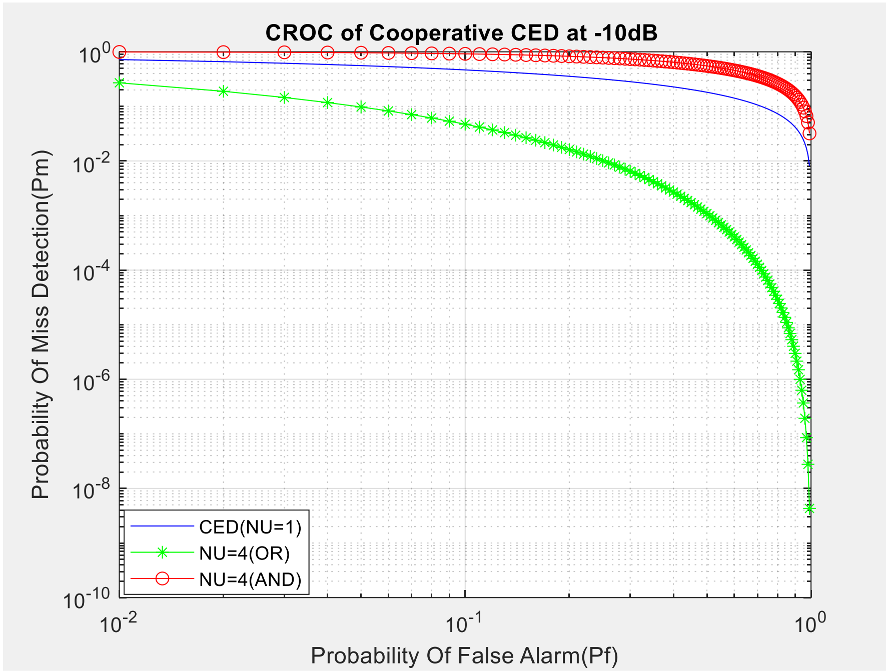

Figure 4.11: CROC graph of cooperative CED under AND/OR Fusion for SNR = -10dB, N=200, NU=4

4.3 Denoising of Performance Comparison of Wavelet Families

Figure 4.12 shows the relationship between input SNR and output SNR of the received signal. The received signal SNR prior to denoising is called input SNR, on the other hand the output signal after denoising having enhancement in SNR called output SNR.A good denoising capability can be expressed, for a given input SNR, that gives high output SNR, minimum MSE. The plot shows input output SNR relationship for different wavelet families for in the range of -20dB to -10dB. One can note that at -17dB of input signal, Reverse Bi Orthogonal (ReverseBior) outperform other wavelet families with having comparable result with Daubechies. For instance, we have output SNR of -14.0193dB with ReverseBior and -14.03291dB with Daubechies wavelet for the input SNR of -17dB. One can see that by using ReverseBior wavelet, SNR gain of 2.9807dB is achieved when compared to the input SNR. On the other hand, by using Daubechies wavelet SNR gain of 2.9671dB is found which is slightly small compared to ReverseBior wavelet. Comparing the two wavelets, it is found that ReverseBior wavelet outperform Daubechies wavelet by 0.0136 dB enhancement.

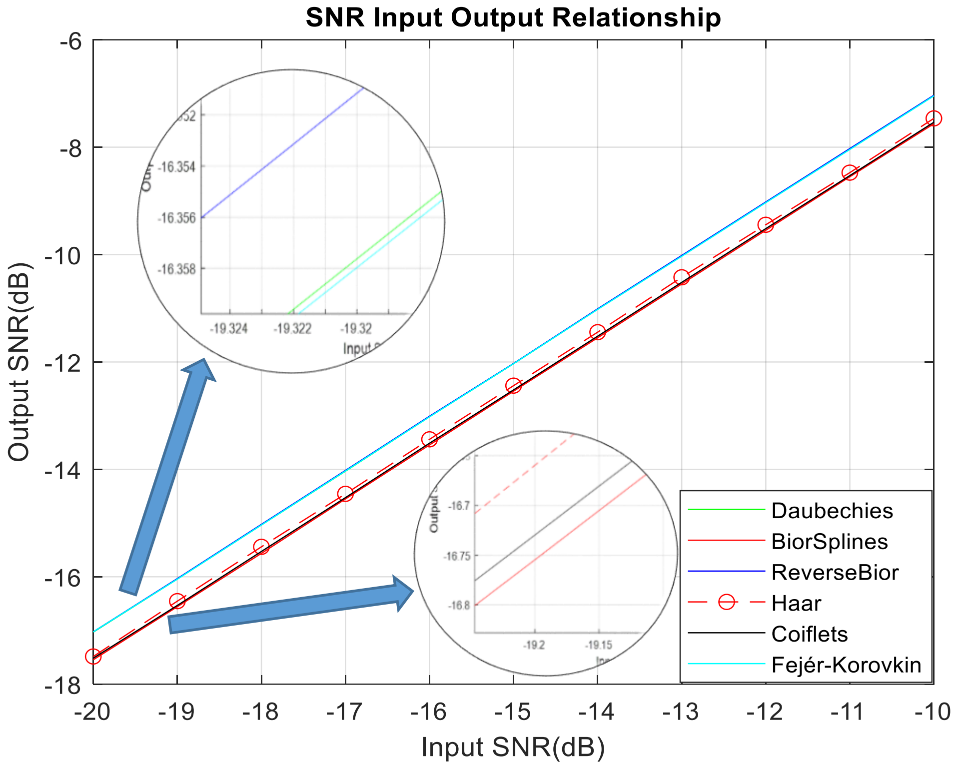

Figure 4.12: Input SNR and Output SNR Relationship

Table 4.6 shows comparison of different wavelet families denoising capabilities in terms of MSE, output SNR and SNR gain of each denoising starting for -20dB. A detail comparison of Input Output SNR form -20dB to -15dB with increment of 1dB is given in the Appendix Table-1. The difference between input SNR and output SNR is depicted as SNR gain. The result shows ReverseBior wavelet denoising performance is great compared to others. For instance, at a given input SNR of -20dB, denoising the signal by ReverseBior improve the input signal SNR by 14.8737% and the new SNR become -17.0254dB, where as if we use Daubechies wavelet, enhancement of 14.8705% is found giving a new SNR value of -17.0259dB. Also one can note that the performance of Reverse Bi Orthogonal (ReverseBior), Daubechies and Fejer-Korovkin are comparable. On the other hand, despite the fact that they have low SNR gain compared to others Haar, Coiflets and Bi Orthogonal Splines (BiorSplines) wavelet have comparable SNR gain. In order to enhance the probability of detection of CED in low SNR region, wavelet having high SNR gain is a candidate. since the probability of detection of CED is directly related to SNR.

Table 4.6: SNR Input Output relationship of different wavelets applied for denoising for SNR = -20dB

Input SNR(dB)	Wavelet family	MSE	Output SNR(dB)	SNR gain(dB)	%Enhancement
-20	Haar	0.01974	-17.4845	2.5155	12.5775
	Daubechies	0.01783	-17.0259	2.9741	14.8705
	BiorSplines	0.02184	-17.5451	2.4549	12.2745
	ReverseBior	**0.01591**	**-17.0254**	**2.9746**	**14.8737**
	Coiflets	0.02115	-17.5154	2.4846	12.4239
	Fejer-Korovkin	0.01880	-17.0263	2.9737	14.8685

4.4 Performance Evaluation Single Stage Wavelet Based Energy Detector

The simulation result shown in Figure 4.13 demonstrate the probability of detection versus SNR for wavelet based ED by using various wavelets. The results are taken for SNR vary form -20dB to 5 dB with 1dB increment to imitate low SNR condition and by setting probability of false alarm to 0.1, which is the maximum allowed according to the IEEE 802.22 standards and 200 sampled signals are taken into account. We can see that prior denoising in the front end of ED improved the performance of the system. Also, it is noted that all each wavelet has resulted better detection performance over the CED. Since the probability of detection is directly related to SNR, a denoising method which has high SNR gain outperform others. For that case, ReverseBior wavelet has achieved the best detection performance compared to others. For example, at given probability of false alarm 0.1, and SNR of -15dB, the probability of detection achieved by ReverseBior is 0.3957 while the probability of detection achieved by Daubechies is 0.3911 which is nearly comparable. Comparing this result with CED, the probability of detection by CED is 0.2837. This shows that the performance of CED is improved by 39.47% and 37.8% by using ReverseBior and Daubechies wavelet respectively.

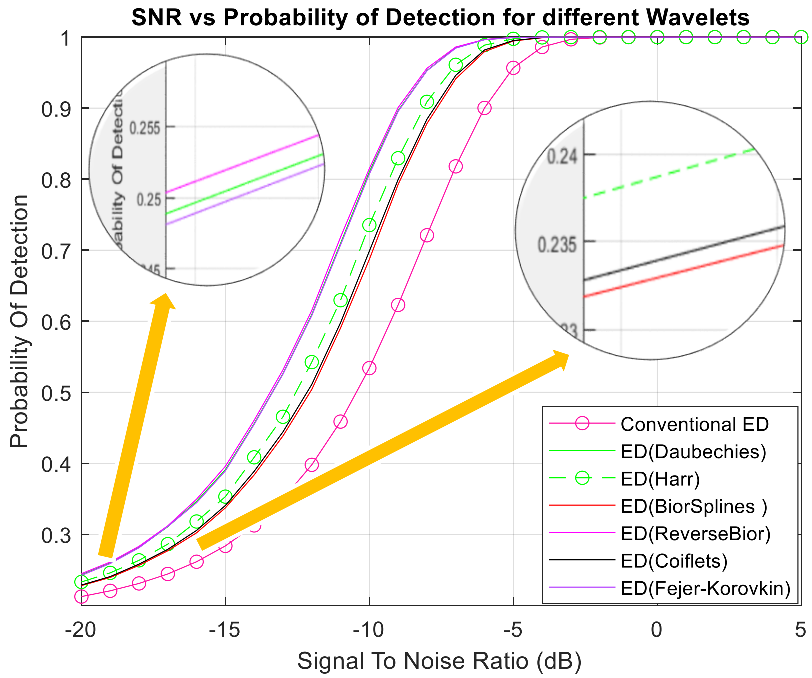

Figure 4.13: Probability of Detection versus SNR for Single Stage Wavelet based ED by using different wavelets for P_f = 0.1,N=200

Table 4.7 shows the performance comparison of wavelet families in terms of probability of detection. The result shows that ReverseBior wavelet improve the probability of detection compared to all other wavelet compared in this thesis. A detail comparison for each mother wavelet in terms of probability of detection at different SNR value is given in Appendix Table-2.

Table 4.7: Probability of detection comparison of Single Stage Wavelet based ED by different wavelets for SNR = -20dB , P_f = 0.1, N=200

SNR(dB)	Detection	P_d	Gain(%)
-20	Conventional ED	0.2124	-
	Haar	0.2330	9.6986
	Daubechies	0.2430	14.4067
	BiorSplines	0.2278	7.25047
	ReverseBior	0.2446	**15.1600**
	Coiflets	0.2286	7.62711
	Fejer-Korovkin	0.2422	14.0301

4.4.1 ROC of Single Stage Wavelet Based ED

Figure 4.14 shows the ROC curve for wavelet based ED. The result shows the performance of CED is greatly improved after denoising and different wavelet families have different ROC curve based on their SNR gain. One can note that all wavelet based detectors outperform CED at a given probability of false alarm and SNR and the area under the curve (AUC) is increased for wavelet based ED. Also, the detection performance of ReverseBior wavelet is the best one among other wavelets used for denoising of a given probability of false alarm. For instance, at a given probability of false alarm 0.01 and SNR of -10dB the probability of detection by ReverseBior is 0.2731 when compared to the CED which have the probability of detection 0.1335, we can see that the performance of detection is almost doubled. In other words, for a given probability of false alarm at 0.11 and SNR of -10dB, the detection performance of CED is improved by 104.56%. On the other hand, the detection performance of ReverseBior outperform the performance of Daubechies by 1.14%.

Table 4.8 shows the ROC comparison of different wavelet at different probability of false alarm. The result from the table shows that the best wavelet that gives high probability of detection for a given probability of false alarm is ReverseBior having highest gain at every stage. It is also noted that for a given high probability of false alarm, almost all detection methods can achieve a detection probability of 0.9 as required. For instance, when the probability of false alarm is 0.91, including CED, all detection methods achieve a probability of detection greater than 0.9. A detail comparison of single stage ROC wavelet based ED is given in the Appendix Table-3.

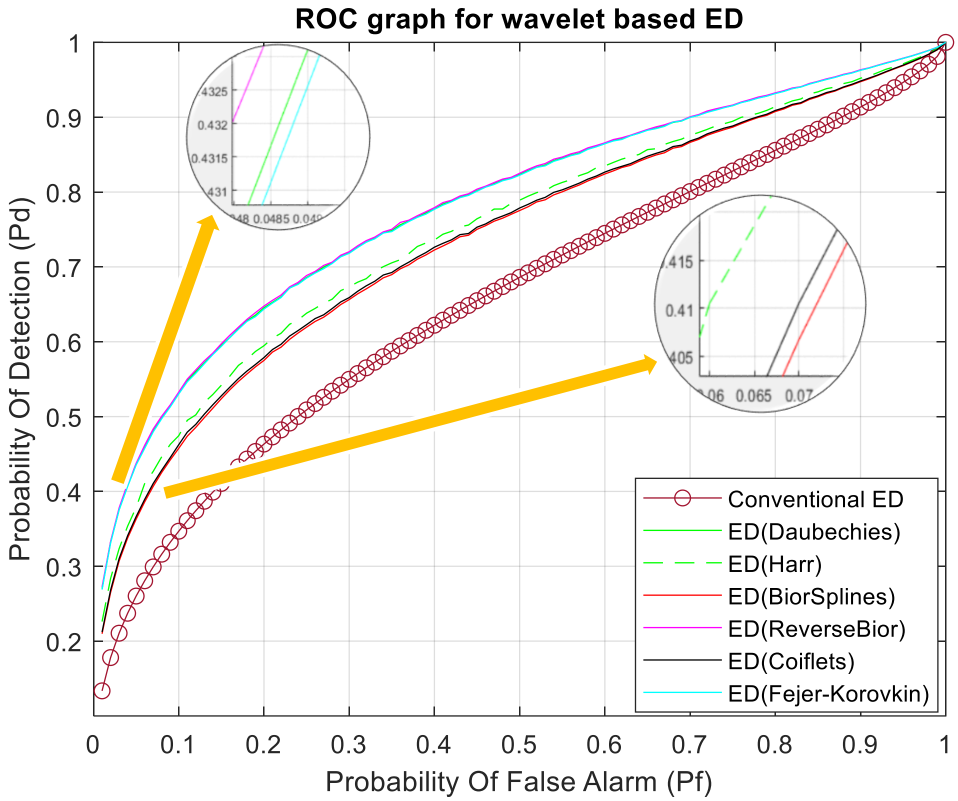

Figure 4.14: ROC of Single Stage Wavelet based ED for SNR = -10dB, N=200

Table 4.8: ROC graph of Single Stage wavelet based ED for SNR = -10dB, P_f = 0.1,N=200

P_f	Detection	P_d	Gain(%)
0.01	Conventional ED	0.1335	-
	Haar	0.2275	70.4119
	Daubechies	0.2700	102.2471
	BiorSplines	0.2108	57.9026
	ReverseBior	0.2731	**104.5692**
	Coiflets	0.2134	59.8501
	Fejer-Korovkin	0.2697	102.0224

4.4.2 CROC of Single Stage Wavelet Based ED

Figure 4.15 shows the CROC curve for Single Stage wavelet based ED. A comparison is made between different wavelets at -10dB. A better performing detector should have least probability of missing the primary user at a given probability of false alarm and SNR. Which means that the AUC should be minimum for a given detector. From the simulation result, Reverse Bi Orthogonal wavelet based detector gives the minimum probability of missing detection. For instance, at a given probability of false alarm, 0.11 and SNR of -10dB, ReverseBior detector has the probability of miss detection 0.3595 while the probability of miss detection for CED is 0.5905 which shows 39.11% reduction in probability of false alarm. A detail CROC comparison different wavelet is given in Appendix Table-4.

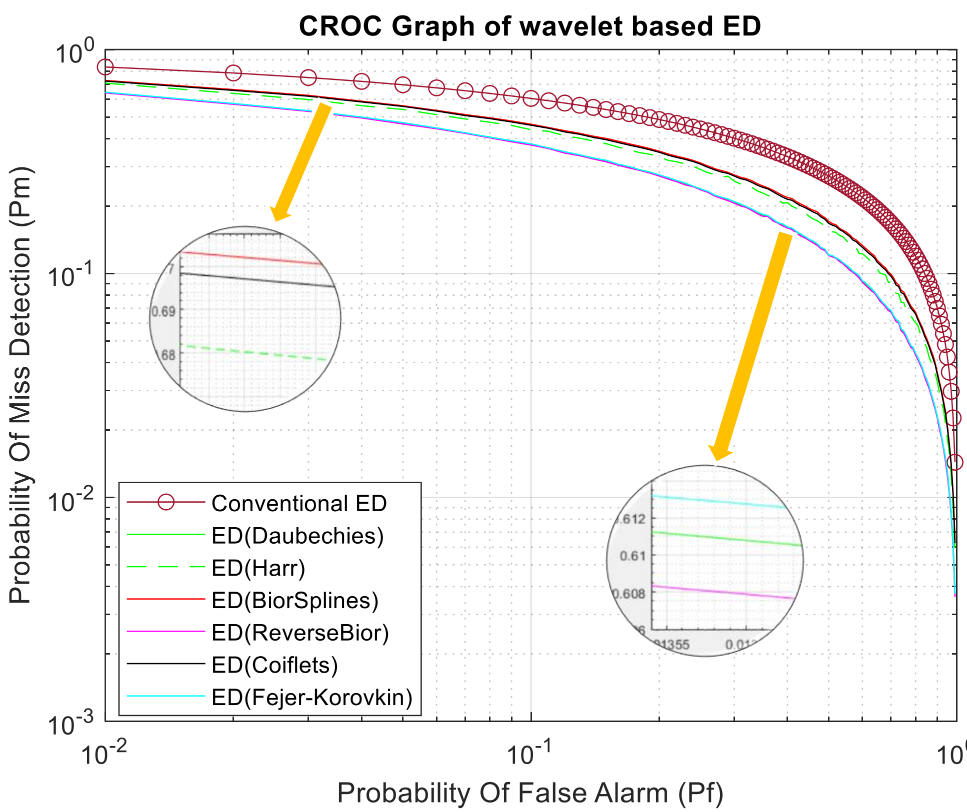

Figure 4.15: CROC of Single Stage Wavelet based ED for SNR = -10dB,N=200

Table 4.9 shows CROC of single stage wavelet based ED. The relation between probability of miss detection and probability of false alarm is depicted with the increment of 0.1. The comparison is done with referencing the CED and the improvement resulted by each wavelet denoising is presented in the table. ReverseBior based ED shows least probability of missing the PU, which is strictly required in order to avoid collision between the PU.

Table 4.9: CROC of Single Stage Wavelet based ED for SNR= -10dB, P_f = 0.01

P_f	Detection	P_m	Gain (%)
0.01	Conventional ED	0.8356	-
	Haar	0.7047	15.6653
	Daubechies	0.6469	22.5825
	BiorSplines	0.728	12.8769
	ReverseBior	0.6442	22.9056
	Coiflets	0.7239	13.3676
	Fejer-Korovkin	0.6474	22.5227

Generally, from the previous analysis and results, among different wavelet families compared for spectrum sensing ReverseBior wavelet is a best candidate for wavelet based ED in terms of performance metrics such as SNR versus Probability of Detection, ROC and CROC.

4.5 Cooperative Sensing with Single Stage Wavelet based ED

In this section, simulation results for cooperative Single Stage ReverseBior based ED is given. From the previous sections, we saw that one way of improving probability of detection is by cooperating participating users in OR-Fusion. Figure 4.16 is generated for 4 cooperative users in the case of cooperative single stage ReverseBior and cooperative CED. The probability of detection for the two algorithms is compared for the SNR range between -20dB to 5dB having probability of false alarm 0.1 and sample size of 200. The result form the plot demonstrates that, at a given SNR, probability of false alarm and number of cooperative users, cooperative single stage ReverseBior based ED outperform cooperative CED. For example, at a given probability of false alarm 0.1, SNR of -15dB and having 2 cooperative users, cooperative CED has a probability of detection 0.4869 whereas ReverseBior based has detection probability of 0.643 which is enhanced by 32.05%.

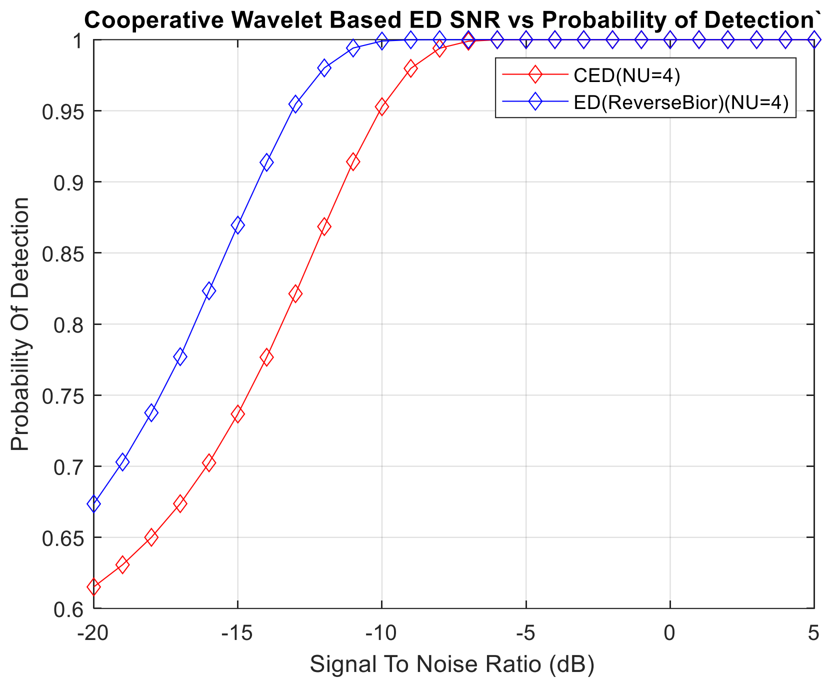

Figure 4.16: Comparison of cooperative Single Stage ReverseBior based ED and cooperative CED for P_f = 0.1,N=200, NU=4

Table 4.10 shows the comparison of cooperative CED with cooperative single stage ReverseBior based ED with different number of cooperative user at a given probability of false alarm 0.1, SNR of -12dB and 200 sample size. The result shows that for cooperative single stage ReverseBior based ED has better detection performance when compared with cooperative CED. For instance, at a given probability of false alarm 0.1, SNR of -10dB, sample size of 200 and 3 cooperative users, the probability of detecting the licensed user by cooperative CED is enhanced by 11.22% by employing cooperative single stage ReverseBior based ED.

Table 4.10: Probability of detection comparison for cooperative Single Stage ReverseBior and cooperative CED for SNR = -10dB, P_f = 0.1, N=200,NU=1,2,3 and 4

Number of User (NU)	1	2	3	4
P_d cooperative CED	0.2124	0.3796	0.5114	0.6152
P_d cooperative single stage ReverseBior ED	**0.2449**	**0.4289**	**0.5688**	**0.6736**

Gain by cooperative single stage ReverseBior ED	**+15.30%**	**+12.98%**	**+11.22%**	**+9.49%**

4.5.1 CROC of Cooperative Single Stage ReverseBior Based ED

Figure 4.17 shows the CROC graph comparison between cooperative single stage ReverseBior based ED and CED. The plot is generated for 4 cooperative user's scenario. One can note that the probability of missing primary user is largely decreased by implementing single stage ReverseBior based cooperative detection when compared with cooperative CED. Generally, we can say that, increasing the number of cooperating user will enhance the probability of detecting the PU and at the same time it will decrease the probability of missing the licensed user. For instance, at a given probability of false alarm 0.1, SNR of -10dB and considering 4 cooperative users, results in least probability of miss detection which is 0.0192 when employing cooperative single stage ReverseBior based ED. On the other hand, the performance of cooperative CED at this point is 0.1339. This result shows that; the probability of missing the licensed user is reduced by 37.76% when implementing cooperative single stage ReverseBior based ED instead of cooperative CED.

Table 4.11 shows that the probability of miss detection of single stage ReverseBior based ED can be further reduced by cooperating a number of users with OR-Fusion. For a given probability of false alarm 0.1 and SNR of -10dB, the probably of missing the PU is further reduced by 85.66% by cooperating 4 SU with cooperative single stage ReverseBior based ED.

Table 4.11: Comparison of probability of miss detection with different number of users at -20dB and P_f =0.1

Number of User	1	2	3	4
P_m (CED)	0.6049	0.3659	0.2214	0.1339
P_m (Single Stage ReverseBior based ED)	**0.3689**	**0.1388**	**0.0514**	**0.0192**
Loss by Single Stage ReverseBior based ED	**-39.01%**	**-62.06%**	**-76.78%**	**-85.66%**

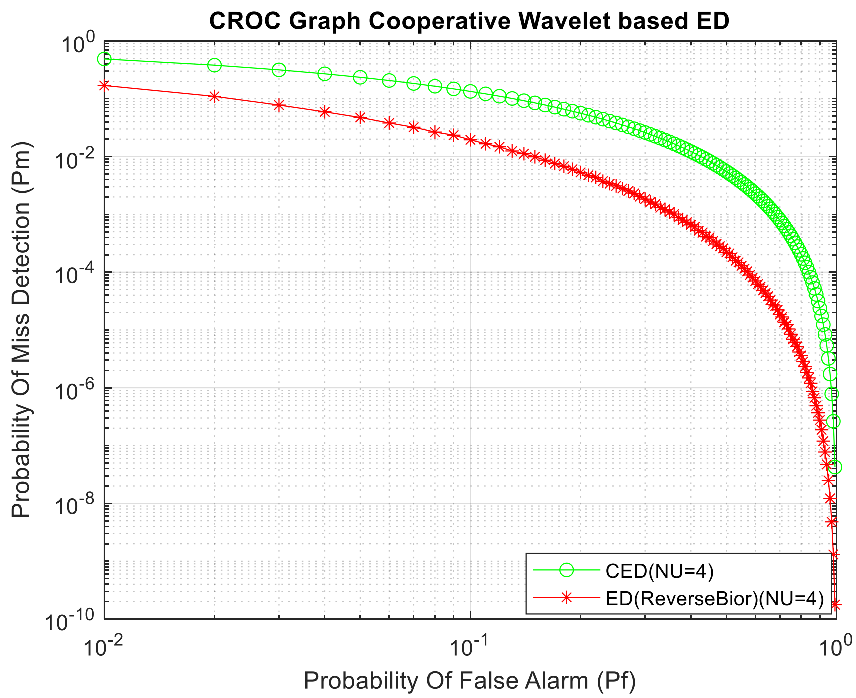

Figure 4.17: CROC comparison of cooperative Single Stage ReverseBior based ED and cooperative CED for SNR = -10dB, N=200, NU=4

4.6 Proposed Two Stage ED Based Spectrum Sensing Algorithm

Figure 4.18 shows the comparison between conventional ED, ReverseBior based ED and the combination of the two algorithm in two stage. Poor detection performance of conventional ED at low SNR is resolved by Single Stage ReverseBior wavelet based ED. Two stage spectrum sensing is composed of First Stage with low computational complexity which is CED, and Second Stage having high computational complex method. The simulation result shows that the proposed Two Stage sensing method has better performance at low SNR region. For instance, the probability of detecting the PU by using Proposed two stage method is 0.91 at -11.5dB SNR, while this value is achieved by single stage ReverseBior at -9dB on the other hand by using CED this value is archived at -6dB.

Table 4.12 shows the comparison between the proposed Two Stage spectrum sensing approach, Single Stage ReverseBior based ED and CED. The comparison result shows that the detection probability of CED is improved by 40.21% by using single stage ReverseBior based ED, and 97% by employing the proposed Two Stage sensing approach. On the other hand, the Performance of Single Stage ReverseBior based ED is further improved by 42% with employing the proposed sensing method.

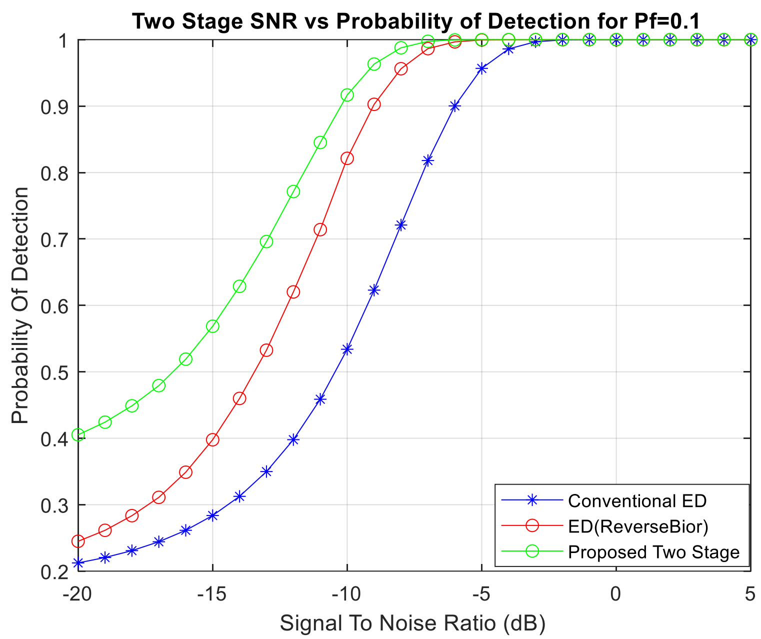

Figure 4.18: Comparison of proposed Two Stage, Single Stage ReverseBior and CED for P_f = 0.1, N=200

Table 4.12: Comparison of Two Stage, Single Stage ReverseBior based ED and CED at SNR = -15dB, P_f = 0.1, N=200

Performance metric	CED	Single Stage ReverseBior based ED	Two Stage ED
P_d	0.2837	0.3978	0.5686
Gain by Single Stage ReverseBior over CED (%)	40.21%		
Gain by Two Stage over CED (%)	**+97.6%**		
Gain by Single Two Stage over Single Stage ReverseBior (%)	**+42.18%**		

4.6.1 ROC of Two Stage ED

Figure 4.19 shows the comparison between ROC curve between Two Stage spectrum sensing approach, Single Stage ReverseBior based ED and CED. The plot shows the behavior of 3 algorithms at a given SNR of -15dB with various probability of false alarm. The result shows that the AUC is increased by employing Two stage spectrum sensing approach. For instance, at a given probability of false alarm 0.1, the probability of detecting the PU is 0.6925 by using Two Stage approach while it is 0.5291 and 0.3469 by using Single Stage ReverseBior based ED and CED respectively.

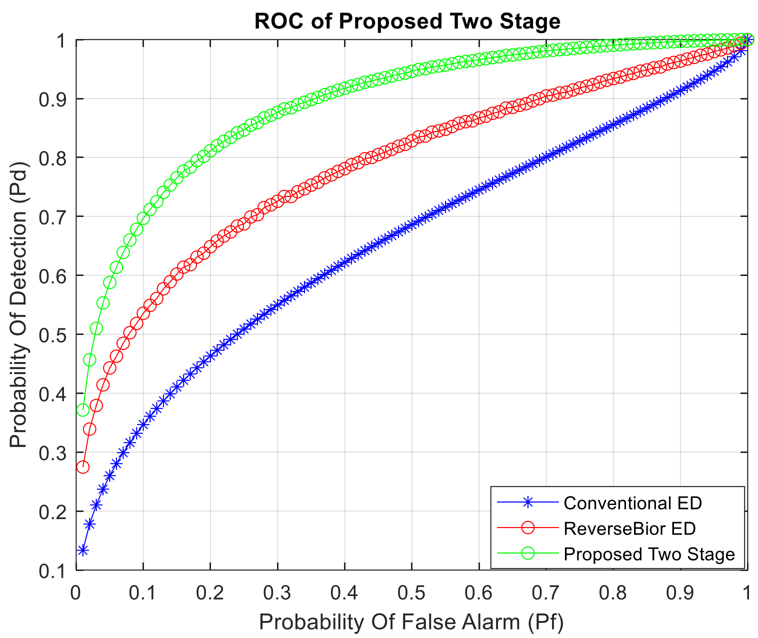

Figure 4.19: ROC comparison of Two Stage approach, Single Stage ReverseBior ED,CED for SNR = -15dB,N=200

Table 4.13 shows the comparison for ROC for the given three spectrum sensing methods at a given probability of false alarm 0.1. The comparison result shows that the proposed approach outperforms CED by 97.8% and this approach also improve the detection probability of Single Stage ReverseBior based ED by 30.8%.

Table 4.13: Comparison of ROC for Two Stage ED, Single Stage ReverseBior ED and CED for SNR= -15dB, P_f = 0.1,N=200

Performance Metric	CED	Single Stage ReverseBior based ED	Two Stage ED
P_d	0.3469	0.5291	0.6925
Gain by Single Stage ReverseBior over CED(%)	52.52%		
Gain by Two Stage over CED (%)	**+99.6%**		
Gain by Two Stage over Single Stage ReverseBior(%)	**+30.8%**		

4.6.2 CROC of Two Stage ED

Figure 4.20 shows the CROC graph of the proposed Two stage approach, Single stage ReverseBior based and CED at a given SNR of -15dB.The comparison result shows that, the probability of missing the PU is reduced by employing Two Stage spectrum sensing approach. For instance, at a given probability of false alarm 0.1, the probability of missing the PU after employing Two stage approach is reduced to 0.2261 while the probability of missing the licensed user is 0.3737 and 0.6049 for Single stage ReverseBior and CED respectively.

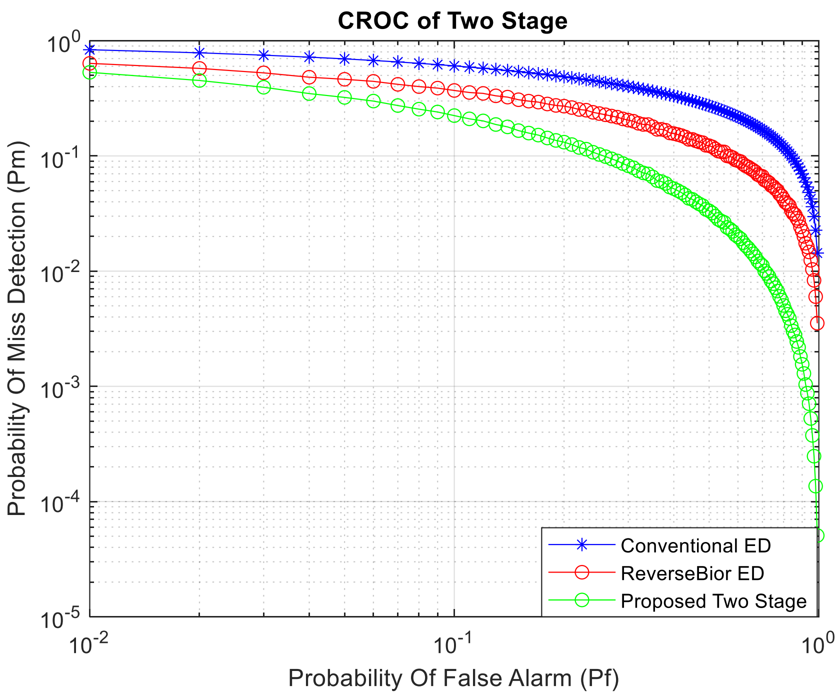

Figure 4.20: CROC comparison of Two stage ED, Single Stage ReverseBior ED,CED for SNR= -15dB,N=200

Table 4.14: CROC Comparison of Two Stage ED, Single Stage ReverseBior ED,CED for SNR= -15dB, P_f= 0.1,N=200

Performance Metric	CED	Single Stage ReverseBior based ED	Two Stage ED
P_m	0.6049	0.3737	0.2261
Loss by Single Stage ReverseBior over CED (%)	-38.22%		
Loss by Two Stage ED over CED (%)	**-62.61%**		
Loss by Two Stage ED over Single Stage ReverseBior (%)	**-39.49%**		

Table 4.14 shows the comparison of missing the PU with the aforementioned three algorithms. Based on the comparison, the probability of missing licensed used is reduced by 62.61% over the CED by employing Two stage approach. On the other hand, the probability of missing the PU is less by 39.49% when compared to Single Stage ReverseBior based ED.

4.6.3 Comparison of Cooperative Two Stage Approach, ReverseBior based detection and CED over varying SNR

Figure 4.21 show the simulation result for cooperative Two stage approach comparing with cooperative Single Stage ReverseBior based ED and cooperative CED method. These three algorithms are compared for the SNR range between -20dB and 5dB having probability of false alarm 0.1 and sample size of 200 with 4 cooperating users. The result form the plot demonstrates that at a given SNR, probability of false alarm and number of cooperative users, Cooperative proposed two stage sensing method outperform cooperative CED and ReverseBior based ED. For example, a given probability of false alarm 0.1, SNR of -20dB and 2 cooperative users CED has the probability of detection 0.3796, by using Cooperative Single Stage ReverseBior, 0.429 is achieved and by employing the proposed two stage the performance in enhanced to 0.6457.

Table 4.15: Comparison of Cooperative Two Stage Approach, Cooperative Single Stage ReverseBior ED and cooperative CED for SNR = -20dB, P_f = 0.1, N=100, NU=1,2,3 and 4

Number of User (NU)	1	2	3	4
P_d (Cooperative CED)	0.2124	0.3796	0.5114	0.6152
P_d (Cooperative Single Stage ReverseBior ED)	0.2441	0.429	0.5686	0.6744
P_d (Cooperative Two Stage ED)	**0.4046**	**0.6457**	**0.7892**	**0.8747**
Gain of cooperative Two Stage ED over cooperative CED (%)	**+90.48%**	**+70.1%**	**+54.32%**	**+42.18%**
Gain of cooperative Two Stage ED over Single Stage Cooperative ReverseBior ED (%)	**+65.75%**	**+50.51%**	**+38.79%**	**+29.7%**

Table 4.15 shows the comparison of three algorithms detection probability using OR-Cooperative scheme at a given probability of false alarm 0.1 and SNR of -20dB. The result shows that for a given number of cooperating user the proposed method outperforms the previous two algorithms. For instance, after employing the proposed two stage using three cooperative users the probability

of detection is improved by 54.32% when compared with cooperative CED. Similarly, the detection probability is enhanced by 38.79% when compared with cooperative ReverseBior based ED.

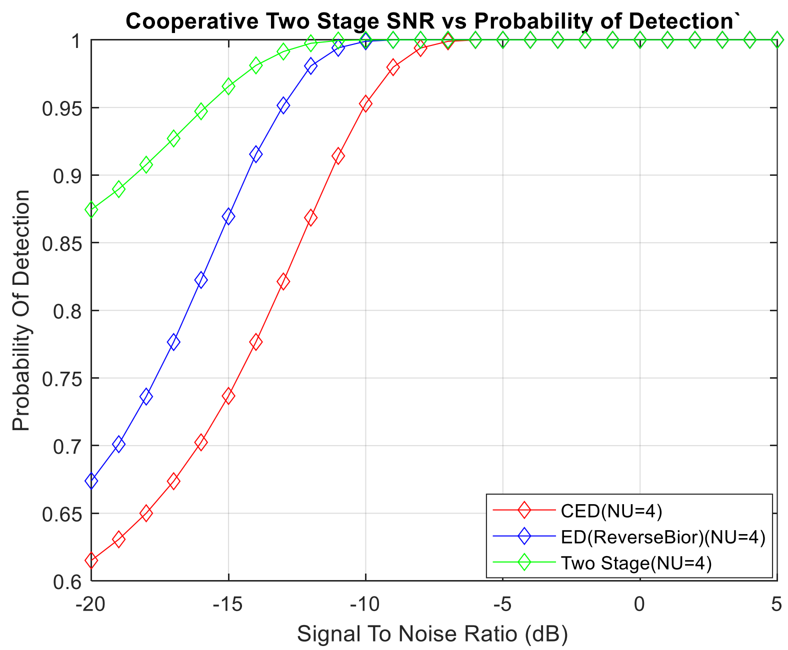

Figure 4.21: Comparison of cooperative Two Stage Approach, ReverseBior Based ED and CED for P_f = 0.1, N=200, NU=4

4.6.4 ROC of Cooperative Two Stage ED

Figure 4.22 shows the comparison between ROC curve between Two Stage Spectrum approach, Single Stage ReverseBior based ED and CED in cooperative scenario. The plot shows the behavior of those algorithms in cooperative manner at a given SNR of -15dB with different probability of false alarm. The result shows that AUC is largely increased by employing cooperative Two Stage spectrum sensing approach. For instance, at a given probability of false alarm 0.1 and three cooperating users, the probability of detecting the PU is 0.9885 by using cooperative Two Stage approach while it is 0.9479 and 0.7784 by using cooperative Single Stage ReverseBior based ED and cooperative CED respectively.

Table 4.16 shows the ROC comparison of three algorithms detection probability using OR-Cooperative scheme at different probability of false alarm value and given SNR of -15dB. The result shows that for a given number of cooperating user the proposed two stage method outperforms the previous two algorithms in cooperative scenario by giving the highest probability of detection for a given probability of false alarm. For instance, at given probability of false alarm,0.1, SNR of -15dB and 3 cooperative users. The performance of CED is improved by 26.9% by employing cooperative two stage sensing method, on the other hand the performance of cooperative ReverseBior based ED is also enhanced by 4.28%.

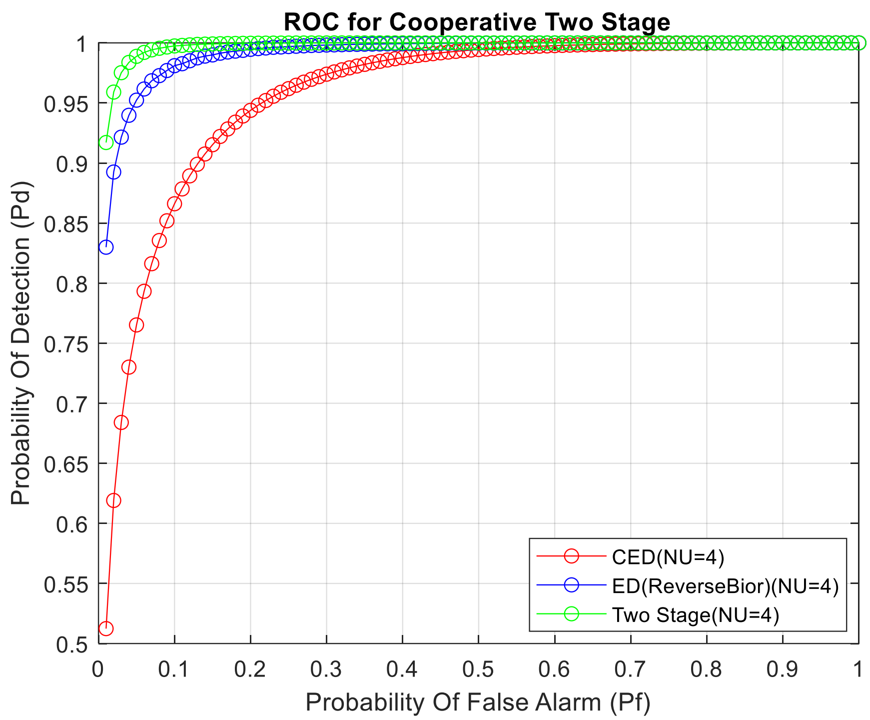

Figure 4.22: ROC comparison for cooperative Two Stage Approach, Single Stage ReverseBior based ED , CED for SNR = -15dB, N=200, NU=4

Table 4.16: ROC comparison for cooperative Two Stage Approach, Single Stage ReverseBior based ED and CED for SNR = -15dB, P_f = 0.1,N=200

Number of User (NU)	1	2	3	4
P_d (Cooperative CED)	0.3951	0.6341	0.7786	0.8661
P_d (Cooperative Single Stage ReverseBior based ED)	0.6279	0.861	0.9479	0.9804
P_d (Cooperative Two Stage)	**0.7758**	**0.9491**	**0.9885**	**0.9974**
Gain of cooperative Two Stage ED over cooperative CED (%)	**+96.35%**	**+49.67%**	**+26.9%**	**+15.15%**
Gain of cooperative Two Stage ED over Single Stage Cooperative ReverseBior based ED (%)	**+23.55%**	**+10.23%**	**+4.28%**	**+1.73%**

4.6.5 CROC of Cooperative Two Stage ED

Figure 4.23 shows the CROC graph of Two stage approach, Single Stage ReverseBior based ED and CED in cooperative scenario at a given SNR of -15dB with varying probability of false alarm. The comparison result shows that the probability of missing the PU is further reduced by employing cooperative Two Stage spectrum sensing approach. For example, at a given probability of false alarm 0.1, SNR of -15dB and 3 cooperative users the probability of missing the PU was 0.2214 by using cooperative CED while this result is reduced by applying cooperative ReverseBior based ED to 0.0505, also this result is further reduced by employing cooperative Two stage approach to 0.0112.

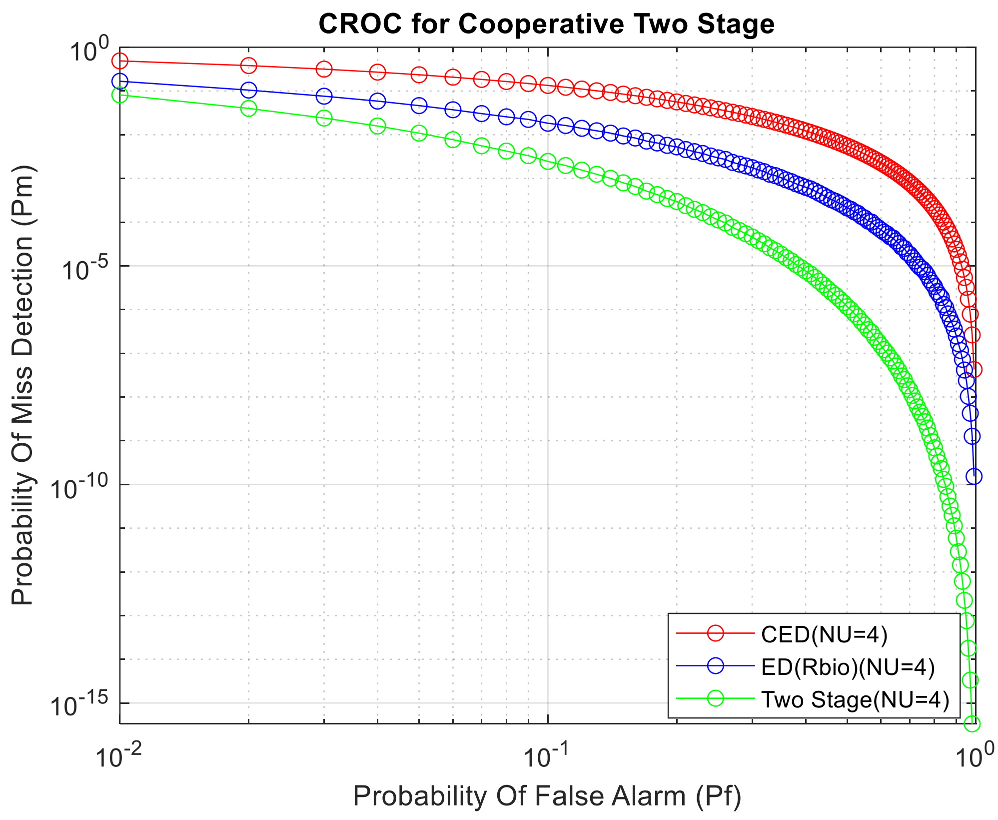

Figure 4.23: CROC comparison of Cooperative Two Stage Approach, Single Stage ReverseBior based ED, CED for SNR= -15dB, N=200, NU=4

Table 4.17 shows the CROC comparison of three algorithms using OR-Cooperative scheme at a given probability of false alarm and SNR for 4 cooperating users. The result shows that for a given number of cooperating user the proposed two stage method gives the lest probability of miss detection and outperforms the previous two algorithms in cooperative scenario by providing small probability of missing the licensed user. For instance, at given probability of false alarm ,0.1, SNR of -15dB and 3 cooperative users. The probability of missing the PU by CED is reduced by 94.91% by employing the proposed two stage approach. On the other hand, the probability missing licensed user by cooperative ReverseBior based ED is also minimized by 77.82%.

Table 4.17: CROC comparison of cooperative Two Stage Approach, Single Stage ReverseBior based ED, CED for SNR=-15dB, P_f = 0.1, N=200, NU=1,2,3 and 4

Number of User (NU)	1	2	3	4
P_m(Cooperative CED)	0.4049	0.3659	0.2214	0.1339
P_m(Cooperative Single Stage ReverseBior based ED)	0.3689	0.135	0.0505	0.0187
P_m(Cooperative Two Stage ED)	0.2242	0.0494	0.0112	0.0025
Loss of cooperative Two Stage ED over cooperative CED (%)	-77.58%	-86.49%	-94.91%	-98.10%
Loss of cooperative Two Stage ED over Single Stage Cooperative ReverseBior based ED (%)	-44.62%	-63.40%	-77.82%	-86.63%

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In this thesis we investigate one of the spectrum sensing algorithm called Energy detection. Effective detection of Primary User is crucial task for cognitive radio for two reasons. The first one is, CR should utilize the available white space by detecting the absence of licensed user. The second point is that, CR should have accurate detection in order to avoid the interference to Primary User. The major problem of Energy Detection algorithm is its low detection performance during low SNR region. In order to solve this problem, we have applied prior denoising achieve SNR gain for single stage. Based on the simulation results, the following conclusion can be drawn.

- The Performance of Energy detector drops at low SNR region. In order to reduce the probability of interfering primary users, increasing number of sample, increasing probability of false alarm, increasing SNR and cooperative detection are solutions.
- A primary user signal is prior denoised by using different mother wavelets and the comparison result shows that ReverseBior wavelet gives the highest SNR gain. This wavelet also gives the highest probability of detection and the lowest miss detection, since the probability of detection is directly relationship with SNR, in single node and cooperative detection.
- The performance of CED is improved by 97.8% by employing Two Stage approach in single node. On the other hand, cooperative Two Stage approach improve the performance of cooperative CED by 54.32% for the case of 3 users.
- The proposed Two Stage Spectrum Sensing Algorithm improve the performance of Conventional Energy Detector and Single Stage Wavelet Denoising Based Algorithm in single node detection and cooperative scheme in terms of the performance matrices considered in this thesis.
- The OR-Fusion Cooperating scheme delivers high performance.

5.2 Recommendations

In this thesis The performance of Conventional Energy Detector is enhanced by applying a wavelet denoising prior to ED. The following issues are the future scope of this thesis.

- The proposed technique was evaluated under AWGN channel only. The proposed technique can also be evaluated under the different channel mode like Rayleigh, Nakagami and Rician fading channel.
- Filters Such as FIR having different window size can also be employed for denoising.
- The proposed technique was evaluated in simulation level only. Its practical performance could also be investigated by combining spectrum sensing, management and hand-off (mobility) by using real-time platform using open source toolkit GNU radio.

References

[1] A. M. Joykutty and B. Baranidharan. (2020), “Cognitive Radio Networks: Recent Advances in Spectrum Sensing Techniques and Security,” *Proc. - Int. Conf. Smart Electron. Commun. ICOSEC 2020*, pp. 878–884

[2] A. Rai, A. Sehgal, T. L. Singal, and R. Agrawal. (2020) ,“Spectrum Sensing and Allocation Schemes for Cognitive Radio,” *Mach. Learn. Cogn. Comput. Mob. Commun. Wirel. Networks*, pp. 91–129

[3] J. Mitola and G. Q. Maguire. (1999) ,“Cognitive radio: making software radios more personal,” *IEEE Pers. Commun.*, vol. 6, no. 4, pp. 13–18

[4] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan. (2011) “Cooperative spectrum sensing in cognitive radio networks: A survey,” *Phys. Commun.*, vol. 4, no. 1, pp. 40–62

[5] A. Nasser, H. A. H. Hassan, J. A. Chaaya, A. Mansour, and K. C. Yao.(2021), “Spectrum sensing for cognitive radio: Recent advances and future challenge,” *Sensors*, vol. 21, no. 7, pp. 1–29

[6] A. U. Khan, G. Abbas, Z. H. Abbas, T. Baker, and M. Waqas. (2020), “Spectrum efficiency in CRNs using hybrid dynamic channel reservation and enhanced dynamic spectrum access,” *Ad Hoc Networks*, vol. 107, p. 102246

[7] I. F. Akyildiz, W. Y. Lee, M. C. Vuran, and S. Mohanty.(2006), “NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey,” *Comput. Networks*, vol. 50, no. 13, pp. 2127–2159

[8] Y. Arjoune and N. Kaabouch. (2019), “A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions,” *Sensors (Switzerland)*, vol. 19, no. 1

[9] S. Pandit and G. Singh. (2017), “An overview of spectrum sharing techniques in cognitive radio communication system,” *Wirel. Networks*, vol. 23, no. 2, pp. 497–518

[10] O. Bhatia. (2014), “Dynamic Spectrum Access Techniques in Cognitive Radio Networks : A Survey Dynamic Spectrum Access Techniques in Cognitive Radio Networks : A Survey,” no. June, pp. 0–7

[11] Z. Honggang and G. Y. Li.(2013),*Cognitive radio networks*, vol. 10, no. 8

[12] I. E., O. O., V. M., and S. Mneney.(2015), “Spectrum Sensing Methodologies for Cognitive Radio Systems: A Review,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 6, no. 12

[13] J. Walko.(2005), “Cognitive radio,” *IEE Rev.*, vol. 51, no. 5, pp. 34–37

[14] J. M. Iii.(2000), “Cognitive Radio An Integrated Agent Architecture for Software Defined Radio Dissertation,”.

[15] “IEEE Std 1900.1-2019 (Revision of IEEE Std 1900.1-2008) 2019,: IEEE Standard for Definitions and Concepts for Dynamic Spectrum Access: Terminology Relating to Emerging Wireless Networks, System Functionality, and Spectrum Management.,”.

[16] D. Tarek and M. Ibrahim. (2021). "Development of Spectrum Sharing Protocol for Cognitive Radio Internet of Things"

[17] R. N. Yadav and R. Misra. (2014). "An analysis of different TCP variants in cognitive radio networks," *Proc. - 2014 Int. Conf. Cyber-Enabled Distrib. Comput. Knowl. Discov. CyberC 2014*, pp. 414–419

[18] Y. C. Liang, A. T. Hoang, and H. H. Chen.(2008), "Cognitive radio on TV bands: A new approach to provide wireless connectivity for rural areas," *IEEE Wirel. Commun.*, vol. 15, no. 3, pp. 16–22

[19] R. Umar and A. U. H. Sheikh.(2013), "A comparative study of spectrum awareness techniques for cognitive radio oriented wireless networks," *Phys. Commun.*, vol. 9, pp. 148–170

[20] J. D. Gadze, A. Michael, and N. Damilola. (2014), "A Performance Study of Energy Detection Based Spectrum Sensing for Cognitive Radio Networks," vol. 4, no. 4, pp. 21–29

[21] F. Salahdine, H. El Ghazi, N. Kaabouch, and W. F. Fihri.(2016), "Matched filter detection with dynamic threshold for cognitive radio networks," *Int. Conf. Wirel. Networks Mob. Commun. WINCOM 2015*

[22] T. Mor and T. Mehta. (2015), "Simulation of Probability of False Alarm and Probability of Detection Using Cyclo Stationary Detection Technique in Coginitive Radio," vol. 7109, pp. 62–66

[23] J. H. Baek, H. J. Oh, and S. H. Hwang.(2008), "Improved reliability of spectrum sensing using energy detector in cognitive radio system," *Int. Conf. Adv. Commun. Technol. ICACT*, vol. 1, no. December, pp. 575–578

[24] M. S. V.(2019), "Cyclostationary Feature Detection for Spectrum Sensing in Cognitive Radio Network," *2019 Int. Conf. Intell. Comput. Control Syst.*, pp. 1250–1254

[25] A. Al-dulaimi, N. Radhi, and I. S. Member.(2009),"Cyclostationary Detection of Undefined Secondary Users," pp. 230–233

[26] F. M. Salem, M. H. Ibrahim, I. A. Ali, and I. I. Ibrahim.(2014),"Matched-Filter-based Spectrum Sensing for Secure Cognitive Radio Network Communications," vol. 87, no. 18, pp. 41–46

[27] R. Umar and A. U. H. Sheikh.(2012), "Cognitive Radio Oriented Wireless Networks : Challenges and Solutions,"

[28] S. M. Mishra, A. Sahai, and R. W. Brodersen.(2015), "Cooperative Sensing among Cognitive Radios,"

[29] A. Fawzi, W. El-Shafai, M. Abd-Elnaby, A. Zekry, and F. E. Abd El-Samie.(2020), "Adaptive two-stage spectrum sensing model using energy detection and wavelet denoising for cognitive radio systems," *Int. J. Commun. Syst.*, vol. 33, no. 16, pp. 1–25

[30] A. Nasrallah, A. Hamza, T. Boukaba, G. Baudoin, and A. Messani.(2019), "Energy

Detection with Adaptive Threshold for Cognitive Radio," *Proc. - Int. Conf. Commun. Electr. Eng. ICCEE 2018*, no. 1, pp. 1–5

[31] M. A. Ezzat, A. H. Hussein, and M. A. Attia.(2017), "Energy Detection Performance Enhancement Using RLS and Wavelet De-noising Filters," *Wirel. Pers. Commun.*, vol. 96, no. 2, pp. 1781–1801

[32] G. Eappen and T. Shankar.(2020),*A Survey on Soft Computing Techniques for Spectrum Sensing in a Cognitive Radio Network*, vol. 1, no. 6. Springer Singapore

[33] Eindhoven.(2010),"TWO-STAGE SPECTRUM SENSING FOR COGNITIVE RADIOS , The Netherlands Faculty of Electrical Engineering , Delft University of Technology , The Netherlands," *Simulation*, pp. 2946–2949

[34] H. Al-Hmood and H. S. Al-Raweshidy.(2013), "Energy detection performance enhancement for cognitive radio using noise processing approach," *Glob. Inf. Infrastruct. Symp. GIIS 2013*

[35] A. A. Univeristy.(2016),"SNR Enhancement of Energy Detector Algorithm using Adaptive Wiener Filter in Cognitive Radio,"

[36] K. Srisomboon, A. Prayote, and W. Lee.(2015), "Two-stage spectrum sensing for cognitive radio under noise uncertainty," *2015 8th Int. Conf. Mob. Comput. Ubiquitous Networking, ICMU 2015*, pp. 19–24

[37] P. Verma and B. Singh .(2015), "Simulation study of double threshold energy detection method for cognitive radios," *2nd Int. Conf. Signal Process. Integr. Networks, SPIN 2015*, pp. 232–236

[38] G. S. Rathore and S. Bharatula.(2017), "Efficient multi stage spectrum sensing technique for cognitive radio networks under noisy condition," *Int. J. Appl. Eng. Res.*, vol. 12, no. 9, pp. 1831–1835

[39] A. C. Rencher and W. F. Christensen.(2012),Methods of multivariate analysis,Third Edition,Willy Series, ISBN 978-0-470-17896-6 (hardback), vol. 709

[40] G. Schay.(2007),Introduction to probability with statistical applications, Birkh¨auser Boston, c/o Springer Science, ISBN-13: 978-0-8176-4497-0

[41] F. F. Digham, M. S. Alouini, and M. K. Simon .(2007),"On the energy detection of unknown signals over fading channels," *IEEE Trans. Commun.*, vol. 55, no. 1, pp. 21–24

[42] S. Kyperountas, N. Correal, Q. Shi, and Z. Ye.(2007), "Performance analysis of cooperative spectrum sensing in Suzuki fading channels," *Proc. 2nd Int. Conf. Cogn. Radio Oriented Wirel. Networks Commun. CrownCom*, no. 3, pp. 428–432

[43] A. H. Hussien, H. M. Kasem, and M. A. Ezzat.(2017), "Efficient spectrum sensing technique based on energy detector, compressive sensing, and de-noising techniques," *Int. J. Eng. Technol.*, vol. 6, no. 1, pp. 1–8

[44] B. Ergen.(2013), "Comparison of Wavelet Types and Thresholding Methods on Wavelet Based Denoising of Heart Sounds," *J. Signal Inf. Process.*, vol. 04, no. 03, pp. 164–167

Appendix

Table 1: Input Output SNR relationship of denoising with different wavelets

Input SNR(dB)	Wavelet family	MSE	Output SNR(dB)	SNR gain(dB)	%Enhancement
-20	Haar	0.01974	-17.4845	2.5155	12.5775
	Daubechies	0.01783	-17.0259	2.9741	14.8705
	BiorSplines	0.02184	-17.5451	2.4549	12.2745
	ReverseBior	**0.01591**	**-17.0254**	**2.9746**	**14.8737**
	Coiflets	0.02115	-17.5154	2.4846	12.4239
	Fejer-Korovkin	0.01880	-17.0263	2.9737	14.8685
-19	Haar	0.01901	-16.4536	2.5464	13.4021
	Daubechies	0.01681	-16.0412	2.9588	15.5726
	BiorSplines	0.02129	-16.5569	2.4431	12.8584
	ReverseBior	**0.01567**	**-16.0339**	**2.9661**	**15.6110**
	Coiflets	0.02019	-16.5333	2.4667	12.9826
	Fejer-Korovkin	0.01763	-16.0439	2.9561	15.5584
-18	Haar	0.01879	-15.4421	2.5579	14.2105
	Daubechies	0.01652	-15.0341	2.9659	16.4772
	BiorSplines	0.02104	-15.5636	2.4364	13.5355
	ReverseBior	**0.01501**	**-15.0243**	**2.9757**	**16.5316**
	Coiflets	0.02003	-15.5288	2.4712	13.7288
	Fejer-Korovkin	0.01719	-15.0357	2.9643	16.4683
-17	Haar	0.01803	-14.4556	2.5444	14.9670
	Daubechies	0.01640	-14.0295	2.9671	17.4535

	BiorSplines	0.02091	-14.5503	2.4497	14.41
	ReverseBior	**0.01492**	**-14.0193**	**2.9807**	**17.5335**
	Coiflets	0.01986	-14.5262	2.4738	14.5517
	Fejer-Korovkin	0.01656	-14.0303	2.9697	17.4688
-16	Haar	0.01782	-13.4403	2.5597	15.9981
	Daubechies	0.01589	-13.0187	2.9813	18.6331
	BiorSplines	0.02018	-13.5439	2.4561	15.3506
	ReverseBior	**0.01368**	**-13.0101**	**2.9899**	**18.6868**
	Coiflets	0.01902	-13.5129	2.4871	15.544375
	Fejer-Korovkin	0.01601	-13.0217	2.9783	18.614375
-15	Haar	0.01669	-12.4406	2.5594	17.06266667
	Daubechies	0.01502	-12.0307	2.9693	19.79533333
	BiorSplines	0.02001	-12.5436	2.4564	16.376
	ReverseBior	**0.01349**	**-12.0274**	**2.9726**	**19.81733333**
	Coiflets	0.01871	-12.5197	2.4803	16.53533333
	Fejer-Korovkin	0.01551	-12.0320	2.968	19.78666667

Table 2: SNR versus probability of detection for wavelet based ED with different wavelets

SNR (dB)	Detection	P_D	Gain(%)	SNR (dB)	Detection	P_D	Gain(%)
-20	Conventional ED	0.2124	-	-14	Conventional ED	0.3126	-
	Haar	0.2330	9.69868		Haar	0.4084	30.6461
	Daubechies	0.2430	14.4067		Daubechies	0.4559	45.8413
	BiorSplines	0.2278	7.25047		BiorSplines	0.3837	22.7447
	ReverseBior	0.2446	**15.1600**		**ReverseBior**	0.4606	**47.3448**
	Coiflets	0.2286	7.62711		Coiflets	0.3887	24.3442
	Fejer-Korovkin	0.2422	14.0301		Fejer-Korovkin	0.4549	45.5214
-19	Conventional ED	0.2205	-	-13	Conventional ED	0.3499	-
	Haar	0.2458	11.4739		Haar	0.4655	33.0380
	Daubechies	0.2595	17.6870		Daubechies	0.5262	50.3858
	BiorSplines	0.2393	8.52607		BiorSplines	0.4386	25.3501
	ReverseBior	0.2609	**18.3219**		**ReverseBior**	0.5315	**51.9005**
	Coiflets	0.2405	9.07029		Coiflets	0.4442	26.9505
	Fejer-Korovkin	0.2589	17.4149		Fejer-Korovkin	0.5256	50.2143
-18	Conventional ED	0.2309	-	-12	Conventional ED	0.3979	-
	Haar	0.2634	14.0753		Haar	0.5425	36.3407
	Daubechies	0.2816	21.9575		Daubechies	0.6093	53.1289
	BiorSplines	0.2563	11.0004		BiorSplines	0.5039	26.6398
	ReverseBior	0.2831	**22.6071**		**ReverseBior**	0.6151	**54.5865**
	Coiflets	0.2580	11.7366		Coiflets	0.5110	28.4242
	Fejer-Korovkin	0.2811	21.7410		Fejer-Korovkin	0.6080	52.8022
-17	Conventional ED	0.2442	-	-11	Conventional ED	0.4587	-
	Haar	0.2862	17.1990		Haar	0.6296	37.2574
	Daubechies	0.3107	27.2317		Daubechies	0.7096	54.6980
	BiorSplines	0.2769	13.3906		BiorSplines	0.5905	28.7333
	ReverseBior	0.3120	**27.7641**		ReverseBior	0.7184	**56.6165**

	Coiflets	0.2789	14.2096		Coiflets	0.5980	30.3684
	Fejer-Korovkin	0.3112	27.4365		Fejer-Korovkin	0.7075	54.2402
-16	Conventional ED	0.2614	-	-10	Conventional ED	0.5340	-
	Haar	0.3180	21.6526		Haar	0.7353	37.6966
	Daubechies	0.3464	32.5172		Daubechies	0.8103	51.7415
	BiorSplines	0.3021	15.5700		BiorSplines	0.6871	28.6704
	ReverseBior	0.3495	**33.7031**		**ReverseBior**	0.8149	**52.6029**
	Coiflets	0.3055	16.8706		Coiflets	0.6987	30.8426
	Fejer-Korovkin	0.3446	31.8286		Fejer-Korovkin	0.8072	51.1610
-15	Conventional ED	0.2837	-	-9	Conventional ED	0.6230	-
	Haar	0.3531	24.4624		Haar	0.8295	33.1460
	Daubechies	0.3911	37.8568		Daubechies	0.8965	43.9004
	BiorSplines	0.3373	18.8931		BiorSplines	0.7927	27.2391
	ReverseBior	**0.3957**	**39.4783**		**ReverseBior**	0.9009	**44.6067**
	Coiflets	0.3406	20.0563		Coiflets	0.7996	28.3467
	Fejer-Korovkin	0.3894	37.2576		Fejer-Korovkin	0.8955	43.7399

Table 3: ROC comparison of wavelet based ED by using different wavelet

P_f	Detection	P_d	Gain(%)	P_f	Detection	P_d	Gain(%)
0.01	Conventional ED	0.1335	-	0.51	Conventional ED	0.6921	-
	Haar	0.2275	70.4119		Haar	0.7936	14.6655
	Daubechies	0.2700	102.247		Daubechies	0.8289	19.7659
	BiorSplines	0.2108	57.9026		BiorSplines	0.7806	12.7871
	ReverseBior	0.2731	**104.5692**		**ReverseBior**	0.8302	**19.9537**
	Coiflets	0.2134	59.8501		Coiflets	0.7835	13.2061
	Fejer-Korovkin	0.2697	102.0224		Fejer-Korovkin	0.8278	19.6069
0.11	Conventional ED	0.3609	-	0.61	Conventional ED	0.7505	-
	Haar	0.4945	37.0185		Haar	0.8402	11.9520
	Daubechies	0.5490	52.1197		Daubechies	0.8701	15.9360
	BiorSplines	0.4757	31.8093		BiorSplines	0.8294	10.5129
	ReverseBior	0.5515	52.8124		**ReverseBior**	0.8714	**16.1092**
	Coiflets	0.4801	33.0285		Coiflets	0.8317	10.8194
	Fejer-Korovkin	0.5477	51.7594		Fejer-Korovkin	0.8697	15.8827
0.21	Conventional ED	0.4729	-	0.71	Conventional ED	0.8062	-
	Haar	0.6048	27.8917		Haar	0.8789	9.01761
	Daubechies	0.6556	38.6339		Daubechies	0.9043	12.1681
	BiorSplines	0.5875	24.2334		BiorSplines	0.8714	8.0873
	ReverseBior	0.6586	**39.2683**		**ReverseBior**	0.9053	**12.2922**
	Coiflets	0.5913	25.0370		Coiflets	0.8736	8.36020
	Fejer-Korovkin	0.6556	38.6339		Fejer-Korovkin	0.9041	12.1433
0.31	Conventional ED	0.5576	-	0.81	Conventional ED	0.8614	-
	Haar	0.6830	22.4892		Haar	0.9196	6.7564
	Daubechies	0.7298	30.8823		Daubechies	0.9359	8.6487
	BiorSplines	0.6660	19.4404		BiorSplines	0.9118	5.8509
	ReverseBior	0.7314	**31.1692**		**ReverseBior**	0.9367	**8.7415**
	Coiflets	0.6697	20.1040		Coiflets	0.9134	6.0366

	Fejer-Korovkin	0.7289	30.7209		Fejer-Korovkin	0.9356	8.6138
0.41	Conventional ED	0.6288	-	0.91	Conventional ED	0.9198	-
	Haar	0.7453	18.5273		Haar	0.9567	4.0117
	Daubechies	0.7851	24.8568		Daubechies	0.9665	5.0771
	BiorSplines	0.7287	15.8874		BiorSplines	0.9522	3.5225
	ReverseBior	0.7867	**25.1113**		**ReverseBior**	0.9668	**5.1098**
	Coiflets	0.7324	16.4758		Coiflets	0.9532	3.6312
	Fejer-Korovkin	0.7852	24.8727		Fejer-Korovkin	0.9662	5.0445

Table 4: CROC comparison of Wavelet based ED by using different Wavelet

P_f	Detection	P_m	Gain(%)	P_f	Detection	P_m	Gain(%)
0.01	Conventional ED	0.8356	-	0.51	Conventional ED	0.2668	-
	Haar	0.7047	15.6653		Haar	0.152	43.0284
	Daubechies	0.6469	22.5825		Daubechies	0.1199	55.0599
	BiorSplines	0.728	12.8769		BiorSplines	0.1672	37.3313
	ReverseBior	**0.6442**	**22.9056**		**ReverseBior**	**0.1183**	**55.6596**
	Coiflets	0.7239	13.3676		Coiflets	0.1641	38.4932
	Fejer-Korovkin	0.6474	22.5227		Fejer-Korovkin	0.1201	54.9850
0.11	Conventional ED	0.5905	-	0.61	Conventional ED	0.2132	-
	Haar	0.4289	27.3666		Haar	0.1172	45.0281
	Daubechies	0.3628	38.5605		Daubechies	0.0908	57.4108
	BiorSplines	0.4498	23.8272		BiorSplines	0.1295	39.2589
	ReverseBior	**0.359**	**39.2040**		**ReverseBior**	**0.0895**	**58.0206**
	Coiflets	0.4447	24.6909		Coiflets	0.1271	40.3846
	Fejer-Korovkin	0.3643	38.3065		Fejer-Korovkin	0.0909	57.3639
0.21	Conventional ED	0.4773	-	0.71	Conventional ED	0.1631	-
	Haar	0.3231	32.3067		Haar	0.0873	46.4745
	Daubechies	0.2642	44.6469		Daubechies	0.0648	60.2697
	BiorSplines	0.3416	28.4307		BiorSplines	0.0953	41.5695

	ReverseBior	**0.2631**	**44.8774**		**ReverseBior**	**0.0642**	**60.6376**
	Coiflets	0.338	29.1849		Coiflets	0.0938	42.4892
	Fejer-Korovkin	0.2643	44.6260		Fejer-Korovkin	0.0653	59.9632
0.31	Conventional ED	0.3943	-	0.81	Conventional ED	0.1146	-
	Haar	0.2533	35.7595		Haar	0.0552	51.8324
	Daubechies	0.2023	48.6938		Daubechies	0.0415	63.7870
	BiorSplines	0.2696	31.6256		BiorSplines	0.0626	45.3752
	ReverseBior	**0.2014**	**48.9221**		**ReverseBior**	**0.0407**	**64.4851**
	Coiflets	0.2654	32.6908		Coiflets	0.0612	46.5968
	Fejer-Korovkin	0.203	48.5163		Fejer-Korovkin	0.0417	63.6125
0.41	Conventional ED	0.3261	-	0.91	Conventional ED	0.0646	-
	Haar	0.1976	39.4050		Haar	0.0299	53.7151
	Daubechies	0.1576	51.6712		Daubechies	0.0214	66.8730
	BiorSplines	0.2133	34.5906		BiorSplines	0.0339	47.5232
	ReverseBior	**0.1551**	**52.4379**		**ReverseBior**	**0.021**	**67.4922**
	Coiflets	0.21	35.6025		Coiflets	0.0331	48.7616
	Fejer-Korovkin	0.1584	51.4259		Fejer-Korovkin	0.0216	66.5634