Chapter 1
INTRODUCTION

1.1 Introduction and Motivation

Wireless communication technology has made an incredible development in past few years, which provides various benefits to people all over the world in the form of web, voice and multimedia etc. All these applications demands high level of quality of service which leads to the allocated spectrum being overcrowded, results in obvious degradation of user satisfaction. With the further development and expansion of wireless applications and services spectrum resources are facing huge demands. Today, there is large number of new systems which are capable of using the 850-5800 MHz band which is suitable for broadband wireless access systems and for cellular communications as well as the frequency bands such as the very high frequency (VHF) and ultra-high frequency (UHF) bands. This shows that in next ten years, the majority of frequency bands used for mobile communication systems will be entirely engaged and new spectrum resources will be in demand in future. Most of the primary spectrum is previously assigned, so it becomes very difficult to find spectrum for either new services or expanding existing services. As available spectrum is limited but demands are increasing day by day, there's should be a way to solve this problem. An interesting study conducted by FCC pointed out that more than 70% of existing radio spectrums are not utilized properly in specific times and geographic locations [1]. This states that we have enough spectrum resources for our wireless application but we are lacking with proper utilization techniques. To overcome this problem "Cognitive Radio" technology is the one possible solution which is a radio or system that sense wireless environment and uses the best channels in its vicinity and is fully aware of its functioning situation and can regulate its radio operating parameters autonomously according to collaborating wired and wireless both type of system [2]. Cognitive radios can also be defined as "a software defined radio with an intelligent cognitive engine brain"[3]. At presently government policies do not allow the licensed spectrum access by unlicensed users but due to huge demand of spectrum, forced to adapt CR technology. Cognitive radio (CR) is actually dynamic spectrum utilization technology which improves the spectrum utilization efficiency [1]. The most important function of cognitive radio is to sensing the idle spectrum 'holes' which is not in use of primary users for a particular period of time and geographical area and make them available for secondary user. Several signal detection techniques have been proposed and are used usually in practice [4]–[7]. Energy based detection method is most frequently used spectrum sensing technique due to its low complexity nature and does not required any prior information of signals to be sensed. Generally, spectrum sensing for the detection of spectrum holes comes across low signal to noise ratio (SNR) signal detection problem. However, non-ideal noise in which we are not able to predict the exact model of that so noise uncertainty reduces the sensing performance. The main characteristic for any practical detection algorithm is robustness to modeling uncertainties. That is, the performance of a detector in the presence of uncertainty in environment must not be deviated significantly from the idealized (with no uncertainties) model. At high signal to noise ratios (SNRs) robustness to uncertainties is not hard to achieve as compared to low SNRs. The main reason behind this is, at high SNRs the nominal distributions under both the hypotheses (presence/absence of signals) are sufficiently far separated. So, although the uncertainties in the surroundings disturb the individual distributions but cannot mix the distributions completely. Hence, robustness could be achieved easily. In case very low SNRs, the total power measured (noise power or noise power + signal power) will be lie in the uncertainty range which lead to occurrence of large number of false alarms and missed detections which makes certainly reliable detection impossible [9]. This above, shows that in low SNRs spectrum sensing suffers from signal-to-noise ratio (SNR) wall, which states as a minimum SNR below which reliable detection is not possible or called, the probability of false alarm and/or probability of missed detection becomes more than half [8]. IEEE 802.22, which is a standard for CR wireless regional area network in television bands required at least SNR wall=-15dB for detection purpose but from existing literature, for practical uncertainty in noise, the SNR wall=-6dB. There's huge gap in between two cases. To solve this problem various sensing techniques already exist but with the cost of computational complexity and other conditions like for cyclostationary or matched filter method prior knowledge of signal is required. Therefore, in our proposed method we are using energy based detector for sensing purpose. Here in this project work we have worked on this limitation.

1.2 Objective

The main aim of this work is to explain the limitation (called SNR wall) of spectrum sensing under noise uncertainty and methods which can reduce this limitation. We are considering mainly energy detector spectrum sensing algorithm to analyses the SNR wall. To improve the performance of detector by reducing the SNR wall, we are introducing a new adaptive technique which is actually hybrid method of two different techniques. First, cross correlation and second method is adaptive threshold method. The contribution of this thesis work is mentioned below.

1. New SNR wall expression is formed which linked dynamic threshold factor (k) along with uncertainty parameter (U) and cross correlation factor (ε) for energy detection method.
2. It provides a comparison between improved SNR wall expressions generated in this work to the expression generated in some already mentioned method (cross-correlation method).
3. It provides tables of better result of improved SNR wall for various value of k under different value of U.

1.3 Thesis Layout

The thesis is organized as follows.

Chapter 2 describes an introduction to cognitive radio. This chapter discusses various stages of cognitive radio, its emergent behavior, applications, advantages/disadvantages, and various research organizations dealing with cognitive radio

Chapter 3 discusses the spectrum sensing and its challenges, overview of various spectrum sensing methods and the performance of energy detector spectrum sensing algorithm in cognitive radio.

Chapters 4 present SNR wall description.

Chapter 5 discusses the various methods to reduce SNR wall along with improved SNR wall derivation by using new technique that generate much better results as compare to others. Simulation analysis is also represents in this chapter.

The Final chapter of this thesis (Chapter 6) presents the conclusions and future aspects of this project.

Chapter-2
COGNITIVE RADIO

2.1 Introduction

Today, wireless based applications are rapidly growing. There are new radio technologies which are keep coming day by day, it includes Bluetooth, various digital services (TV, FM), Wi-Fi, satellite broadcast and WiMAX etc. Each technology has its own unique hardware structure and appropriate methods for transmitting and receiving the radio waves. Each radio based technology required its own spectrum for transmission/reception. Due to the huge demands of number of standards, availability of spectrum falls short and cause serious issue to concern. Regulations body imposed restriction on the usage of spectrum such that the users who does not possess license not allowed access the spectrum. These users are known as secondary users. On the other hand, the entire spectrum held by licensed users called primary users is not used efficiently and completely at all time and in all the places. This shows that there is miss management on spectrum usage. A proper management can make spectrum available for secondary users at a time when that spectrum is not in use of primary user at that time. This enhances the efficiency of spectrum usage. By considering this idea, a new technology is introduced called Cognitive Radio (CR). Therefore, this chapter concerns all the aspects related to cognitive radio like definition, its functioning, advantages/disadvantages, application and various standards using this technology.

2.2 Definitions of CR

The word “Cognitive Radio” is first introduced by Mitola in the wireless environment field. From then a number of definitions of Cognitive Radio have been introduced by various persons in different context. Table 2.1 representing the definitions of CR given by number of researchers.

	Definitions of Cognitive radio (CR)
Mitola [3]	The position at which wireless personal digital assistants (PDAs) and its associated networks are adequately computationally intelligent about radio resources and established computer-to-computer connections: • To sense user communications requirements. • To provide wireless services and radio resources properly to those who needs.
Simon Haykin [1]	Cognitive radio is a smart system in wireless communication which is aware of its neighboring environment and uses the techniques of understanding to learn from the surroundings and adjust its internal states and statistical variations for the received RF stimuli by creating consequent changes in particular operating parameters (for example carrier frequency, transmit power and modulation techniques) in real world.
FCC [11]	A transmitter or receiver of radio frequency which is designed to detect intelligently that a specific section of the radio spectrum is currently in use or not, and to hop into or out of the unused spectrum very fast, without causing interference with the transmissions/reception of authorized users.
SDR Forum [11]	An adaptive, multi-dimensionally and independent radio, that learns from its experiences to plan, reason and decide its future actions to achieve user needs.

Table 2.1 various definitions adopted for CR

2.3 Why Cognitive Radio is needed?

There are two main reasons for which CR is needed:

1. Two key problems can be solved by using CR [10].
    - Accessing the licensed spectrum
    - Interoperability for incompatible waveform.
2. CR helps in proper utilization of spectrum [12].

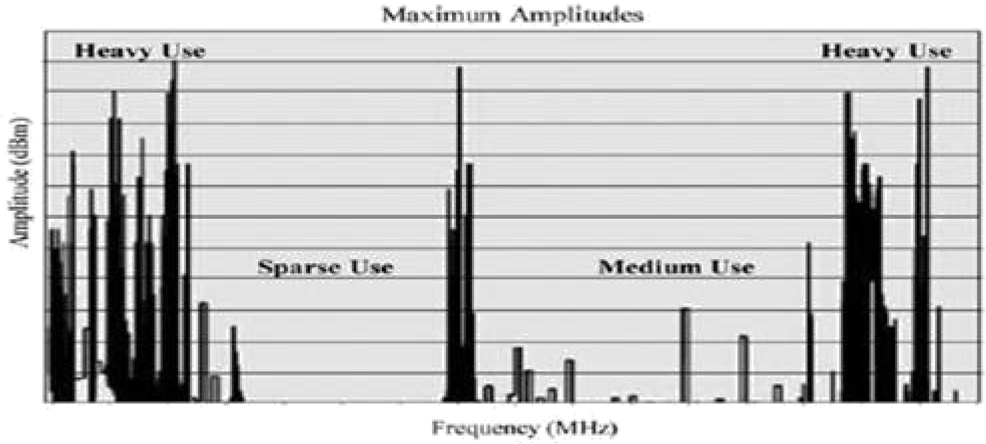


Figure 2.1 Utilization of Spectrum [12]

Figure 2.1 represents the actual utilization of spectrum [12]. From this figure we can observed that there are various section of band usage such as unused bands, medium used bands and heavily used bands in the spectrum. Figure shows that for a particular band there is variety in the usage. For particular number of frequencies band seems to be busy while for some other frequency the band is free. Therefore, improper usage leads to reduce the efficiency of spectrum. CR helps to manage the idle frequencies by allotting them to secondary user for particular time and space.

2.4 How is a Cognitive Radio Different from Other Radios?

The tables 2.2 shown below giving the points which show how cognitive radio in various scenarios (design, software and applications) is different as compare to others radios.

	Conventional Radio	Software Radio	Cognitive Radio
Design	1. Traditional RF design 2. Traditional baseband design	1. Conventional radio with software architecture 2. Reconfigurability 3. easy upgrades	1. SDR with intelligence 2. Observation, learning and adaptation
Software	1. Cannot be work for future purpose 2. Non-upgradeable	1. Future proof 2. several external mechanism available for upgradation	1. SDR upgrades 2. Various internal and cooperative upgrades available
Application	1. Fixed number of system supported 2. Reconfigurability is decided at installation time 3. Various services is chosen at time of design	1. Multiple system supported dynamically 2. Interface with diverse system 3. Multiple services are provided with Qos.	1. Can produce new waveform 2. Can cooperate with new interface 3. Adjust various parameters and operations to meet specified Qos.

Table 2.2 Comparison of Conventional radio, Software radio and Cognitive radio

2.5 CR Responsibilities

Figure 2.2 represents cognitive cycle which shows basic operations of cognitive radio [1]. A cognitive cycle is defined as the mean by which an interaction of cognitive radio with the environment is achieved. Cognitive cycle is divided into main three interconnected tasks. These three tasks are described below.

1. Analysis of radio environment, which incorporate following sub tasks:
   - Temperature of interference estimation in radio network.
   - White holes (vacant spectrum) detection.
2. Channel detection, which incorporate following sub tasks:
   - Channel-state information (CSI) estimation.
   - Calculation of channel capacity.
3. Dynamic spectrum management and controlling the transmit power.

Only Task 3 is carried out by transmitter section while other two tasks 1 and 2 are carried by receiver section. A cognitive cycle is formed by the interaction of these three tasks with the radio environment.

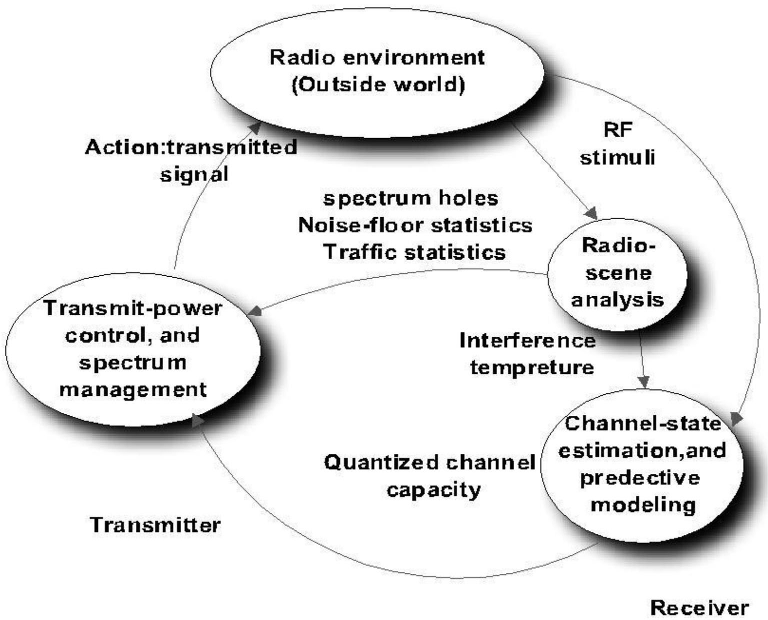


Figure 2.2 Cognitive Cycle of CR [1]

2.6 Advantages, Disadvantages and Applications of Cognitive Radio

As compare to conventional radio the cognitive radio possess more benefits. Due to presence of various advantages of CR, multiple application are followed the CR concepts. There are some disadvantages also which somewhere limits the performance of cognitive radio and further modification and adaptability in technology for cognitive radio is required. Table 2.3 given below represents the advantages, disadvantages and applications of cognitive radio.

Advantages	Disadvantages	Applications
1. Mitigate and solve the spectrum selective issues. 2. Improvement in current spectrum utilization. 3. Performance of wireless data is improved 4. Adaptability among the networks is more 5. Less coordination is required. 6. Spectrum utilization and efficiency improved 7. Link reliability improvement.	1. Software reliability. 2. Security. 3. Malware attack. 4. Fear of undesirable adaptations. 5. Regulatory concerns 6. Considerable research work is remained to be done for implementation of cognitive radio concept commercially. 7. Higher data rates are required. 8. Loss of control.	1. Advanced network topologies 2. Multimedia downloads. 3. SDR techniques enhanced 4. Emergency communication. 5. Automated radio source available 6. Broadband wireless services. 7. Less expensive radios. 8. Multimedia wireless networking.

Table 2.3 Advantages, Disadvantages and Applications of Cognitive Radio

2.7 Forums and Research Organization working on CR

Some of the forums, important institution and research organization where research in cognitive radio field is going on important institution are given below [9] [11].

IEEE: IEEE 1900 group has been started to study the issue related to cognitive radio and 802.22 type standards is giving.

FCC: FCC has started a workshop in 2003 to examine the impact of cognitive radio on utilization of spectrum and also to study the sensible regulatory issues that would arise due to cognitive radio.

SDR: This forum formed two groups in 2004 to investigate cognitive radio issues: these two groups are the CR Special Interest Group and the CR Working Group. Standardization of a definition of cognitive radio is performed by the working group and special interest group tasked to identifying the technologies enabling for cognitive radio.

Virginia Tech: Work is being performed exploring techniques to exploit collaborative radio to improve network performance.

Win Lab: A CR test bed is developing for disaster response by using components available commercially in Rutgers University.

E^2R: End-to-End Reconfigurability with various participating European companies and universities.

BWRC: A cognitive radio is currently developing in the Berkeley wireless research center for sensing or getting opportunity to access the available spectrum.

Chapter-3

SPECTRUM SENSING: CHALLENGES AND TECHNIQUES

3. 1 Introduction

One of the most important mechanism of cognitive radio model is the capability to measure the parameters of environment, sense the channels, study, and be awareness to the parameters related to the radio spectrum features, spectrum availability and their power, interference and noise temperature, radio's functioning environment, user needs and applications, available networks and nodes, local protocols and other operating limitations. In cognitive radio concepts, those users who have highest priority over others to use the particular part of spectrum are known as primary users. While secondary users have lower priority as compare to primary users, they can borrow the spectrum from primary users only when the spectrum is not in use of primary users at particular time and geographical are to avoid interference for primary users. Therefore, secondary users should have capabilities to sense the spectrum consistently to ensure that there's idle spectrum which is not in use of primary users for a particular time, and to utilize the unused part of the spectrum by changing the radio parameters. White holes are the unused/idle spectrum of primary users. Spectrum sensing includes various aspects such as awareness about the interference and noises, existence of primary users and to locate the white holes. In this chapter, mainly all the aspects of spectrum sensing which are performed by cognitive radios are introduced due to widely application areas while. Various aspects of spectrum sensing task are illustrated in Figure 3.1. The goal of this chapter is to mention numerous spectrum sensing aspects as shown in this figure. These aspects will be discussed in the rest of this chapter. We started with the description of multi-dimensionality that could be exploited in spectrum sensing in Section 3.2. We have introduced some challenges associated with spectrum sensing in Section 3.3. The cooperative sensing with its various types are introduced in Section 3.4. Section 3.5 explains the main spectrum sensing methods with some simulation performed in energy detection method. Finally, a comparison is shown in tabular form for various sensing techniques.

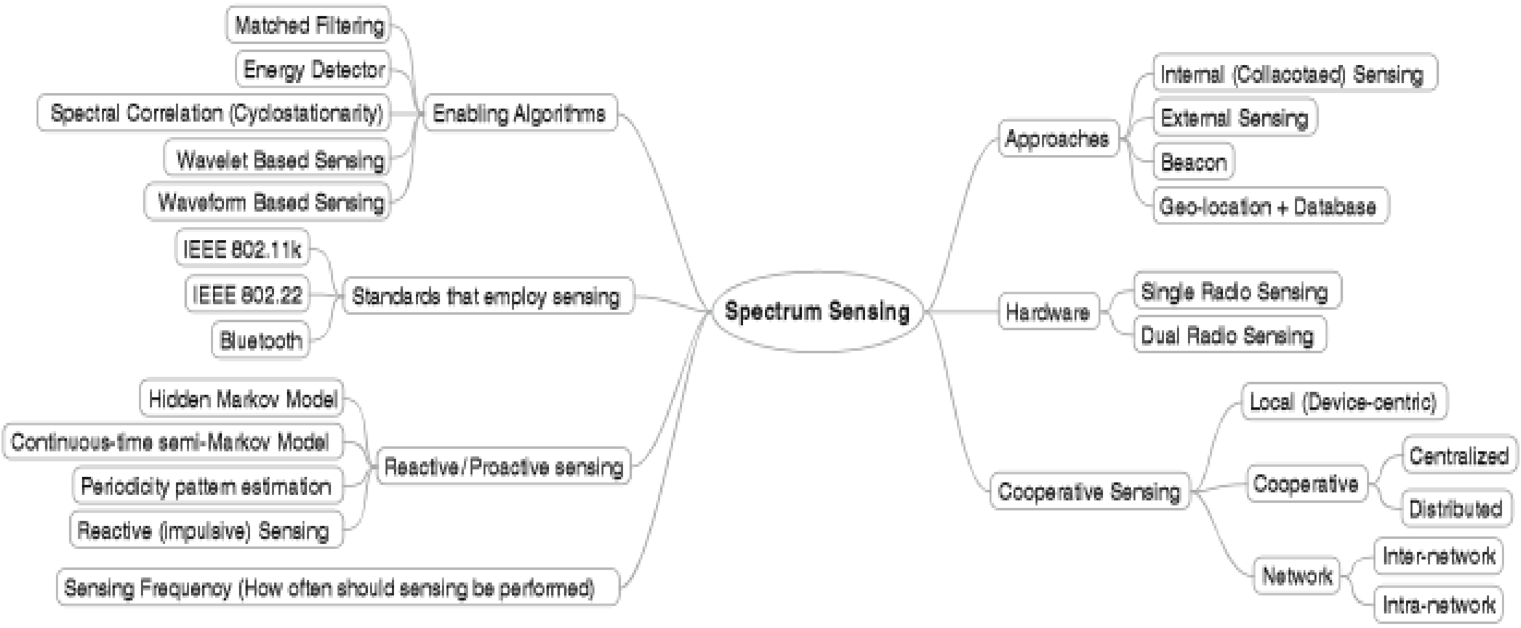


Figure 3.1 Aspects of spectrum sensing in the cognitive radio [13]

3. 2 Multi-Dimensional Spectrum Awareness

Opportunity defined as the ways of measuring and exploiting the spectrum space. The conventional definition of the spectrum opportunity, which is often, termed as "A spectrum of some particular frequencies which are not busy with the primary user at a specific time period in a specific geographic area", which mainly explore three dimensions in the spectrum space i.e. time, frequency, and space. Conventional sensing methods generally exploit these three dimensions. However, there are some other dimensions also available which can be explored to achieve spectrum opportunity. Some examples are, the code dimension of the spectrum space and angle dimension have not been explored well in the literature. If the code dimensions are used then more than a single message (in the form of different codes) can be transferred in a particular location at same. Similarly, by using the angle dimension, same channel can be used to multiplex multiple users' signals in the same geographical area simultaneously. In other words, other dimensions of spectral space can also be created as opportunity. By using these new dimensions, only usage of the frequency spectrum sensing reduced. Various dimensions of this space and corresponding measurement/sensing requirements are summarized in figure 3.2 below.

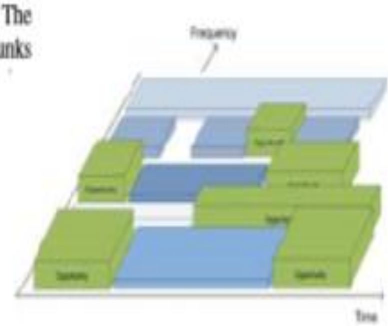
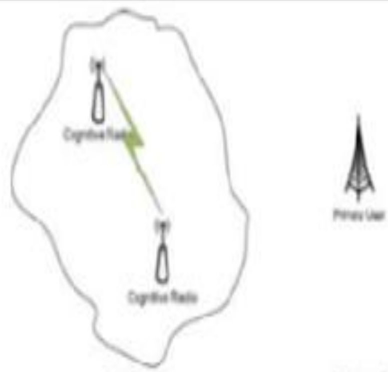
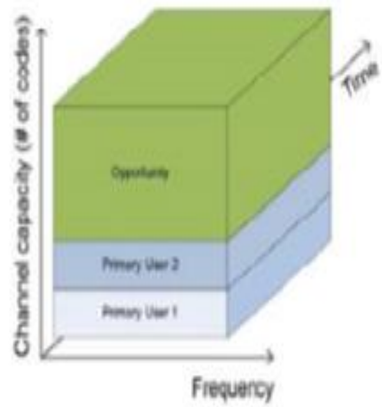
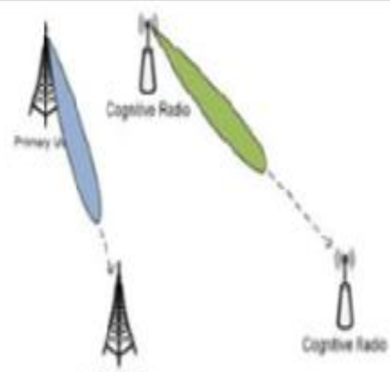
Dimension	What needs to be sensed?	Comments	Illustrations
Frequency	Opportunity in the frequency domain.	Availability in part of the frequency spectrum. The available spectrum is divided into narrower chunks of bands. Spectrum opportunity in this dimension means that all the bands are not used simultaneously at the same time, *i.e.* some bands might be available for opportunistic usage.	
Time	Opportunity of a specific band in time.	This involves the availability of a specific part of the spectrum in time. In other words, the band is not continuously used. There will be times where it will be available for opportunistic usage.	
Geographical space	Location (latitude, longitude, and elevation) and distance of primary users.	The spectrum can be available in some parts of the geographical area while it is occupied in some other parts at a given time. This takes advantage of the propagation loss (path loss) in space. These measurements can be avoided by simply looking at the interference level. No interference means no primary user transmission in a local area. However, one needs to be careful because of hidden terminal problem.	
Code	The spreading code, time hopping (TH), or frequency hopping (FH) sequences used by the primary users. Also, the timing information is needed so that secondary users can synchronize their transmissions w.r.t. primary users. The synchronization estimation can be avoided with long and random code usage. However, partial interference in this case is unavoidable.	The spectrum over a wideband might be used at a given time through spread spectrum or frequency hopping. This does not mean that there is no availability over this band. Simultaneous transmission without interfering with primary users would be possible in code domain with an orthogonal code with respect to codes that primary users are using. This requires the opportunity in code domain, *i.e.* not only detecting the usage of the spectrum, but also determining the used codes, and possibly multipath parameters as well.	
Angle	Directions of primary users' beam (azimuth and elevation angle) and locations of primary users.	Along with the knowledge of the location/position or direction of primary users, spectrum opportunities in angle dimension can be created. For example, if a primary user is transmitting in a specific direction, the secondary user can transmit in other directions without creating interference on the primary user.	

Figure 3.2 Multi-dimensionality present in the radio spectrum space with transmission opportunities [13]

3. 3 Challenges

The challenges related to the spectrum sensing in cognitive radio are mentioned below.

a. Hardware Requirements:

There are various hardware requirements which cause challenges to spectrum sensing for cognitive radio applications such as high sampling rate, high speed signal processors and high degree of resolution with large dynamic range in analog to digital converters (ADCs). Noise variance estimation techniques have been popularly used for designing the optimal receiver like soft information generation & channel estimation etc., also for power control, improved handoff and channel allocation techniques [15]. Cognitive radio should have capability to capture a relatively larger band and analyze it so that large numbers of spectrum opportunities can be finding. The Radio frequencies (RF) components like power amplifiers and antennas require large operating bandwidths which impose additional challenge to the system. Moreover, for the purpose of mathematical computation, high speed processing units (for example DSPs or FPGAs) are needed with relatively short delay.

Sensing can be performed by means of two different architectures termed as single-radio and dual-radio [16], [17]. In the architecture of single-radio, for spectrum sensing a definite time slot is allocated because of which, a limited sensing duration, and certain accuracy can be guaranteed in results whereas in the architecture of dual-radio sensing, one complete radio chain is allocated for spectrum monitoring, for data transmission and reception other chain is used. Advantages and Disadvantages comparison of both architectures are given in Table 3.1.

	Single-radio	Double-radio
Advantages	1. Simplicity 2. Lower cost	1. Higher spectrum efficiency 2. Better sensing accuracy
Disadvantages	1. Lower spectrum efficiency 2. Poor sensing accuracy	1. Higher cost 2. Higher power consumption 3. Higher complexity

Table 3.1 Advantages and Disadvantages of single-radio and dual-radio sensing schemes [13]

b. Hidden Primary User Problem:

When cognitive radio device causes undesirable interference to the receiving section of primary user therefore, the signal transmitted by the transmitting section of primary user could not be detected due to the locations of devices is termed as Hidden primary user problem. It can be caused by various factors including shadowing and severe multipath fading which is observed by secondary users while scanning the spectrum for primary users' transmissions. Figure 3.3 showing the hidden primary user problem where the operating ranges of the cognitive radio device and the primary are represented by the dashed circles in the figure.

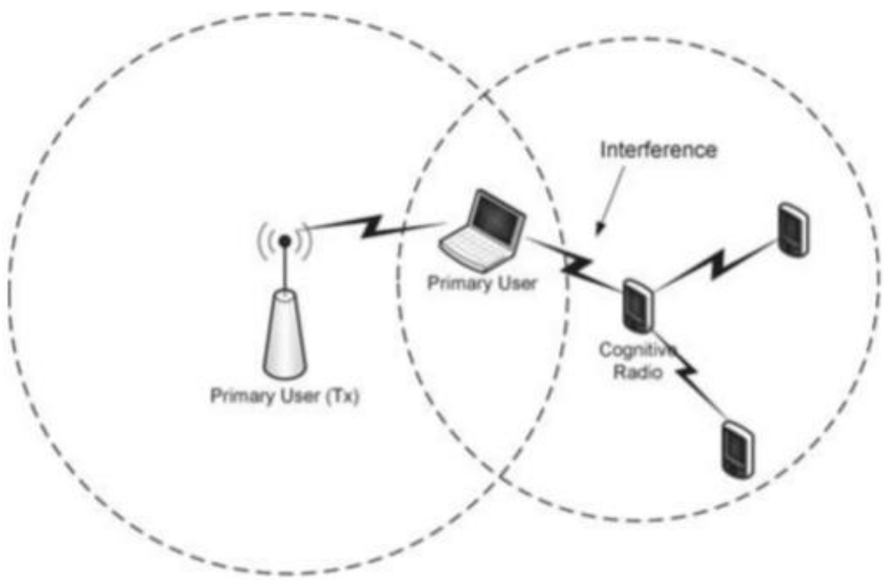


Figure 3.3 Hidden Primary User Problem in CR system [13]

c. Frequency and Sensing Time:

Primary users can use their frequency bands anytime while cognitive radio have to wait until primary user's bands become idle. In order to avoid interference for primary license owners, cognitive radio must be able to detect that primary users is present or not as fast as possible and at the time of primary user want the channel; cognitive radio should vacate it instantaneously. Hence, within limited period of time sensing methods should be able to detect the primary users. This requirement may impose a bound the performance of sensing algorithm which creates a challenge in proposing a design of cognitive radio. Selection of sensing parameters always creates a tradeoff between reliability of sensing and the sensing time.

d. Detecting Spread Spectrum Primary Users:

There are two main types of technologies available for commercially devices, spread spectrum and fixed frequency. Direct-sequence spread- spectrum (DSSS) and frequency-hopping spread-spectrum (FHSS) are the two major spread spectrum technologies. Devices using fixed frequency method are operated only at one frequency or channel. DSSS devices are analogous to FHSS devices; however, to spread their energy they use a single band. Primary users which use spread spectrum signalling are very difficult to detect because over a wide range of frequencies the power associated with the primary user is dispersed although the actual information is confined to much narrow bandwidth.

e. Security:

In cognitive radio, an unauthenticated or malicious user can alter its air interface to imitate a primary user. Therefore, unauthorized user can mislead the genuine primary users who performing the spectrum sensing. Such actions or attack is mentioned in [19] and it is named as primary user emulation (PUE) attack.

3. 4 Cooperative Sensing:

Noise uncertainty, shadowing and fading always creates problems in spectrum sensing. To avoid or mitigate this problem cooperation sensing is introduced. Cooperative sensing increases the probabilities of detection and decrease the probability of misdetection or false alarm simultaneously. In addition, cooperation can resolve the hidden primary user problem and it can also decrease sensing time as mentioned in challenges section above. A simple listen-before-talk (LBT) based scheme is proposed in [20] which employed in the interference caused by cognitive radio devices for primary users. Analytically and numerically results shows that the collaborative sensing schemes provides significantly more spectrum capacity efficiency than local sensing. Algorithms for developing efficient information sharing and increased complexity are the Challenges for cooperative sensing concept. By using different methodologies, the control (or pilot) channel can be implemented in cooperative sensing architectures. Control channel can also be used for sharing channel allocation information and sharing spectrum sensing results among different cognitive users. Time division multiple access (TDMA) based method is one from various architecture for control channels in which exchange of data during sensing are proposed in [21]. In this method, cognitive radios are divided into number of groups and scanned statistics are sent to the group head in slots of frames which is assigned to a particular cluster. In this scheme the coordination algorithm is required which introduce a small delay between subsequent frames. This sensing method is most efficient for those collaborating cognitive radios which have independent shadowing or fading observation [18]. Correlated shadowing limits the performance of collaborative sharing spectrum sensing in terms of missing the opportunities. Cooperation sensing can be implemented in two forms: centralized or distributed. Both methods are discussed in the sections below.

a. Centralized Sensing :

In centralized cooperative sensing, a central unit also called decision fusion center collects all sensing information from various cognitive devices and locate the available spectrum, then this information is broadcasted to other cognitive radios or controls the traffic of cognitive radio directly. Bandwidth requirement for reporting becomes huge when users become large in number. Cognitive radios are quantized to one bit in order to reduce the sharing bandwidth. Furthermore, only the reliable information from cognitive radios is allowed to account their decisions to the decision fusion unit. Therefore, some sensors are censored. Two threshold values method is used instead of one to censoring the sensors. Figure 3.4 is represented centralized sensing in which decision fusion center receives the information from other cognitive radios i.e. CR1, CR2, CR3 and CR4.

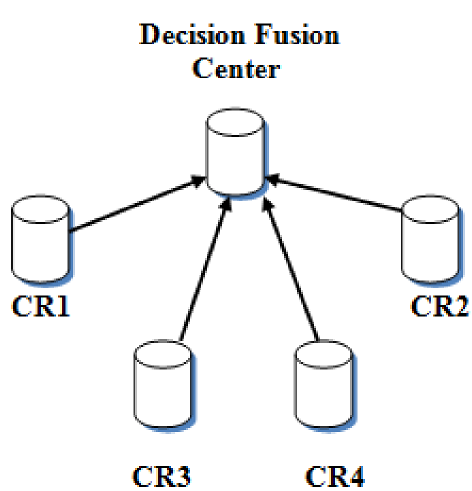


Figure 3.4 Centralized Cooperative Sensing

b. <u>Distributed Sensing</u>:

In the case of distributed cooperative sensing, each cognitive node share its information to every other cognitive nodes but which part of the spectrum will used by them, this decisions is make by them own. Since in distributed sensing there is no backbone infrastructure required as in centralizes sensing required therefore, distributed sensing is considered more beneficial than centralized sensing which also reduced the overall cost.

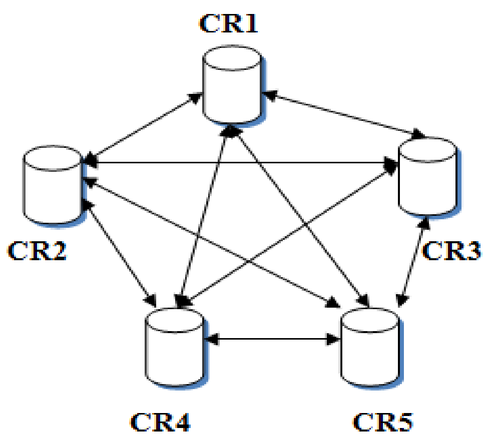


Figure 3.5 Distributed Cooperative Sensing

Figure 3.5 is showing the distributed cooperative sensing above .There's Collaboration performed between two secondary users. The user which are closer to a primary transmitter and which has a better chance of detecting the transmission of primary section, cooperates with user situated far away. Sharing of features among cognitive users improves the detection ability.

3. 5 Spectrum Sensing Methods For Cognitive Radio:

Spectrum sensing refers to detecting the white holes or unused spectrum (spectrum holes) and sharing it without harmful interference with other secondary users. In cognitive radio technology, the main tasks is spectrum sensing in which secondary users (cognitive radio) sense for the white holes that are not being held by primary users at particular time and space. Secondary users should have performed this task without causing any interference to the primary users. A number of various methods have proposed for identifying the presence of signal in transmissions. In some another approaches, various features of the known transmission are explored for taking decision that whether the signal is transmitting or not as well as identifying which type of signal is this[13]. The well known spectrum sensing techniques used are energy detection, covariance detection, matched filter detection, wavelet detection and cyclostationary detection etc.

3. 5.1 Spectrum Sensing Problem

In CR networks, the spectrum sensing always follows a binary hypothesis testing in which two hypotheses are considered:

H_0 : Primary user is absent

H_1 : Primary user is present (3.1)

In spectrum sensing, the key metric are the probability of detection of correct signal (P_d) with the two types of error caused by spectrum sensor, the first error occurs when in actual the channel is vacant (H_0) but the spectrum sensor can make a decision that channel is occupied, this event is the termed as probability of false alarm(P_f), the second error occurred when in actual channel is occupied (H_1) but the spectrum sensor decide that channel is unoccupied, this event is termed as probability of misdetection (P_m) [22]

P_d = prob {Decision= H_1/ H_1 }

P_f = prob {Decision= H_1/ H_0 }

P_m = prob {Decision= H_0/ H_1 } (3.2)

3.5.2 Cyclostationary Detection

Cyclostationary feature detection is a method in which the cyclostationary features of the received signals are exploited for detecting primary user transmissions. Cyclostationary features are caused due to presence of periodicity in the signal or having statistics mean and autocorrelation or they can be purposely induced to support spectrum sensing. Cyclic correlation function is used instead of power spectral density (PSD) for detection of signals in a given spectrum. As the noise is a wide-sense stationary (WSS) signal with no correlation while modulated signals correlation due to the redundancy of signal periodicity are cyclostationary with spectral. The cyclostationary based detection algorithms can distinguish noise from primary user’s signals. Moreover, cyclostationary can also be used for distinguish different types of primary users and transmissions [23].

For a received signal, the cyclic spectral density (CSD) function can be computed as

$$S(f, \alpha) = \sum_{r=-\infty}^{\infty} R_{\alpha}^{y}(\tau) e^{-j2\pi f\tau} \quad (3.3)$$

$$R_{\alpha}^{y}(\tau) = E\left[y(n+\tau)y^{*}(n-\tau)e^{j2\pi\alpha n}\right] \quad (3.4)$$

$R_{\alpha}^{y}(\tau)$ is the cyclic autocorrelation function (CAF) whereas α is the cyclic frequency. When the fundamental frequencies of transmitted signal $x(n)$ and cyclic frequency becomes equal the CSD function gives outputs peak values. Cyclic frequencies can be considered as known also can be extracted and then used as features of transmitted signals to identifying the signal.

3.5.3 Waveform-Based Sensing

Generally, known patterns are utilized to assist synchronization or for other purposes in wireless systems. Such patterns include preambles, midambles, and synchronized symbols and regularly transmitted pilot patterns etc. Sequence transmitted before each burst is known as preambles while sequence transmitted in the between of a burst is known as midambles. This method is applicable only for the known pattern, where sensing can be performed by performing correlation between the received signal and its known copy. This method is also defined as coherent sensing. In terms of reliability and convergence time t, waveform based sensing performs well as compare to energy detector based sensing. Moreover, it is shown that as the known signal pattern length increases the performance of the sensing algorithm increases.

We assumed that the received signal can be represented as the following simple form

$$y(n) = s(n) + w(n) \quad (3.5)$$

Where, $y(n)$ is received signal

,$s(n)$ is transmitted signal

,$w(n)$ is AWGN (Additive white Gaussian noise)

Sensing metric for the waveform based method can be obtained as:

$$M = Re[\sum_{n=1}^{N} y(n)s*(n)] \quad (3.6)$$

Where,'*' represents the conjugation operation. The metric value for the absence of the primary user represented as:

$$M = Re[\sum_{n=1}^{N} w(n)s*(n)] \quad (3.7)$$

Similarly, in the presence of a primary user's signal, the sensing metric becomes

$$M = \sum_{n=1}^{N} |s(n)|^2 + Re[\sum_{n=1}^{N} w(n)s*(n)] \quad (3.8)$$

3.5.4 Matched Filtering

When the transmitted signal is known Matched-filtering is considered as the desirable method for primary users' detection [24]. The main advantage of matched filtering is to achieve a certain probability of misdetection or probability of false alarm in the short time as compared to other conventional methods that are discussed in this section. However, matched filtering method requires to performed demodulation of received signal by cognitive radio. Hence, there must be perfect knowledge of the primary users signalling features like bandwidth, pulse shaping, operating frequency, order, modulation type and frame format. In addition, the implementation complexity of sensing unit is very large because of cognitive radio requires receivers for all signal types. Consumption of large power is another disadvantage of matched filtering as compare to other various receiver algorithms.

The matched filter perform a correlation between the known signal s(n) and the unknown received signal x(n), and the decision is made through

$$T(x) \triangleq \sum_{n=1}^{N} x(n)s*(n) \frac{>^{H_1}}{<_{H_0}} \gamma \quad (3.9)$$

The test statistic T(x) is normally distributed under both hypotheses,

$$T(x) \sim \begin{cases} N\left(0, N_{p_s}\sigma^2{}_v\right) \, under \;\; H_0 \\ N\left(N_{p_s}, N_{p_s}\sigma^2{}_v\right) \, under \;\; H_1 \end{cases} \quad (3.10)$$

The probabilities of false alarm and detection are now given as

$$P_f = Q\left[\frac{\gamma}{\sigma_v \sqrt{N_{p_s}}}\right] \quad (3.11)$$

$$P_d = Q\left[\frac{\gamma - N_{p_s}}{\sigma_v \sqrt{N_{p_s}}}\right] \tag{3.12}$$

Where N is the number of samples and σ_v is the noise variance p_s is the average primary signal power.

It is well known that in the presence of additive noise if the transmitted signal known the matched filter structure is considered as the most favorable detection method that maximizes the SNR. However, in very low SNR regions the matched filter is not suitable for spectrum sensing since synchronization is difficult to achieve.

3.5.5 Energy Detector Based Sensing

Energy detector based method is also known as periodogram or radiometry, is the most general mean of spectrum sensing because of its small implementation and computational complexities. Furthermore, it is more common (as compared to other methods described above) since receivers do not require any knowledge on the primary users signal. In this method, the signal is detected by perform a comparison of energy detector output with a prescribed threshold which depends on the noise floor. There are some limitations with energy detection method which include inability to make a distinction for the interference caused from primary users and noise, fixed threshold selection for detecting primary users under noise uncertainty and poor performance for low SNR values. Moreover, for detecting spread spectrum signals energy detection scheme does not perform efficiently [25].

Energy detector is composed of five main blocks as shown in Figure 3.6

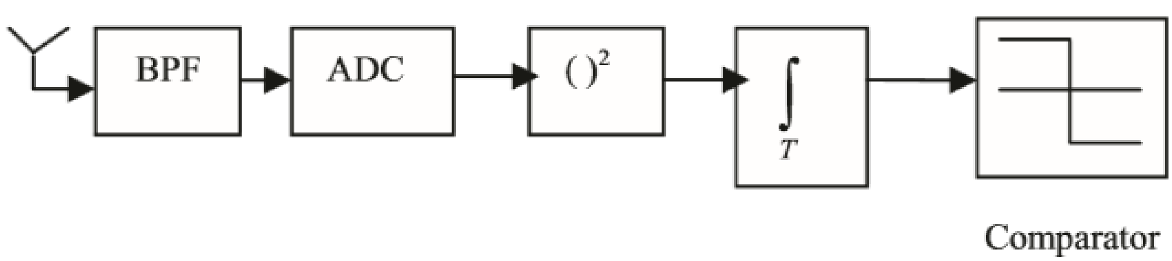


Figure 3.6 Block diagram of energy detector in time domain

The output that comes out of the integrator is the filtered received signal in the form of energy over the time interval of T and this output is compared with prescribed threshold and considered the test statistic for the testing of two hypotheses H_0 and H_1. H_0: corresponds to the absence of the signal and presence of only noise. H_1: corresponds to the presence of both signal and noise.

a. Decision Statistic :

Considering the following notations: $x(t)$ is the transmitted signal waveform, $y(t)$ is the received signal waveform, $w_i(t)$ is in-phase noise component, $w_q(t)$ is quadrature phase component, BN is Noise bandwidth, N_0 is power-spectral density (two-sided), N is power spectral density (one-sided), T is the sampling interval, E_s is the signal energy, Λ is decision threshold.

The received signal y (t) is filtered by a pre-filter which is a band-pass filter. The filtered signal is then passed through A/D converter i.e. converted to samples. Decision statistic can be Y or any quantity which is monotonic with Y. Taking Y' as decision statistic.

$$Y' = \frac{1}{N_0} \int_0^T y^2(t) dt \tag{3.13}$$

Decision statistic Y' under H_1 has a non-central chi- square distributed with 2BNT degrees of freedom and non-centrality parameter λ given by $\frac{E_s}{N_0}$ Now, defining Signal to Noise Ratio (SNR), λ in terms of non-centrality parameter as in

$$\lambda = \frac{E_s}{N} = \frac{E_s}{2N_0} = \frac{\gamma}{2} \tag{3.14}$$

This energy value has a central or non-central chi-square distribution. The final result is compared with threshold λ and the decision is made, the probability of false alarm or misdetection and detection can be generally solved by [26]

b. Probability of detection for AWGN Channel:

Probability of detection Pd and false alarm Pf can be evaluated respectively by,

$$P_d = P\left[Y' > \frac{\Lambda}{H_1}\right] \tag{3.15}$$

$$P_{fa} = P\left[Y' > \frac{\Lambda}{H_0}\right] \tag{3.16}$$

Where Λ is decision threshold, also, P_f can be written in terms of Probability density function as

$$P_{fa} = \int_{\Lambda}^{\infty} f_{Y'}(y)dy \tag{3.17}$$

From (3.10), we get:

$$P_{fa} = \frac{1}{2^d\Gamma(d)} \int_{\Lambda}^{\infty} (y)^{d-1} e^{\left(\frac{-y}{2}\right)} dy \tag{3.18}$$

Dividing and multiplying the RHS of above equation by 2d-1, we get,

$$P_{fa} = \frac{1}{2\Gamma(d)} \int_{\Lambda}^{\infty} \left(\frac{y}{2}\right)^{d-1} e^{\left(\frac{-y}{2}\right)} dy \tag{3.19}$$

Substituting, $\frac{y}{2} = t, \frac{dy}{2} = dt$ and changing the limits of integration to ($\frac{\Lambda}{2}, \infty$), we get,

$$P_{fa} = \frac{1}{2\Gamma(d)} \int_{\frac{\Lambda}{2}}^{\infty} t^{d-1} e^{-t} \, dt \tag{3.20}$$

$$\text{Or, } P_{fa} = \frac{\Gamma\left(d, \frac{\Lambda}{2}\right)}{\Gamma(d)} \tag{3.21}$$

Where, Γ (.) is the incomplete gamma function. Now, probability of detection can be written by making use of cumulative distribution function.

$$P_d = 1 - F_{Y'}(\Lambda) \tag{3.22}$$

The cumulative distribution function (CDF) of Y' can be obtained (for an even number of degrees of freedom which is 2d in this case) as

$$F_{Y'}(\Lambda) = 1 - Q_d\left(\sqrt{\gamma}, \sqrt{\Lambda}\right) \tag{3.23}$$

Therefore using (3.22) and (3.23), probability of detection Pd for AWGN channel is

$$P_d = Q_d\left(\sqrt{\gamma}, \sqrt{\Lambda}\right) \tag{3.24}$$

Using (3.14),

$$P_d = Q_d\left(\sqrt{2\lambda}, \sqrt{\Lambda}\right) \tag{3.25}$$

Where, $Q_d(\dots)$ is the generalized Marcum-Q function and thus, probability of detection for AWGN channel can be evaluated using above expressions. [27]

3.5.6 Simulation

All simulation performed on MATLAB version R2011a. We have used receiver characteristics (ROC) analysis to study the energy detector performances under Additive White Gaussian noise. The ROC curves for different SNR under AWGN channel is represented in Figure 3.7. The simulation carried out for the analysis of P_d for different number of SNR where P_{fa}=0.01 and time bandwidth factor N=100 are taken. Figure 3.7 shows that performance of detection varies with the function of SNR. It also shows that P_d is almost zero before 15dB and increasing as the SNR (from 0dB to 25dB) increased and finally get P_d is almost 1 at SNR is 25dB.

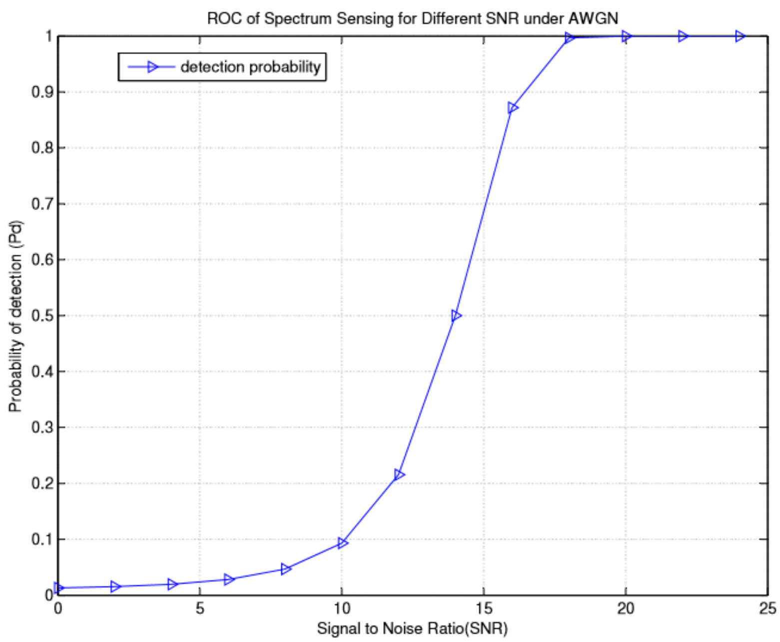


Figure 3.7 ROC of Spectrum Sensing for Different SNR

Figure 3.8 plotted the ROC curve at different SNR and time bandwidth factor N under AWGN channel. From figure 3.8 we have seen that P_d is best for the SNR from 22dB to 24dB and becomes 1 for 25dB. For this simulation P_{fa}=0.01 and time bandwidth factor N is changed to 100, 500, 1000 and 2000 are taken.

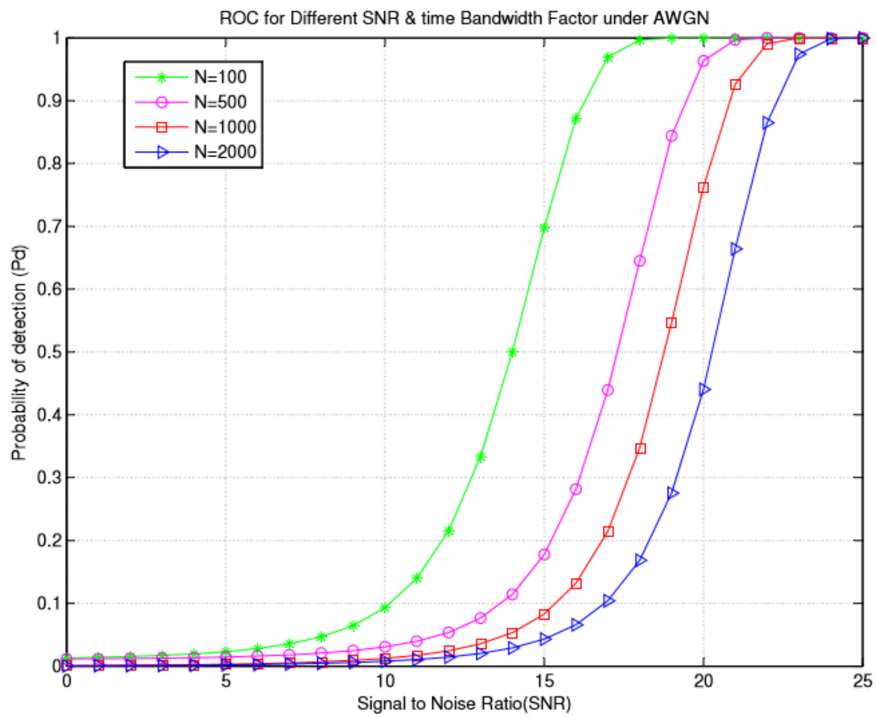


Figure 3.8 ROC for Different SNR & time Bandwidth Factor (N)

Figure 3.9 represents the ROC of spectrum sensing for varying P_{fa} under AWGN channel where time bandwidth factor is taken 1000. P_d plotted in this figure is the function of probability of false alarm. It shows that P_d is also varies based on SNR. Here P_{fa} is used from 0.01 to 1 by increasing 0.01 for each step. From the simulation result we have seen P_d is increasing for large value of SNR and at SNR=21, P_d is approximately equal to unity.

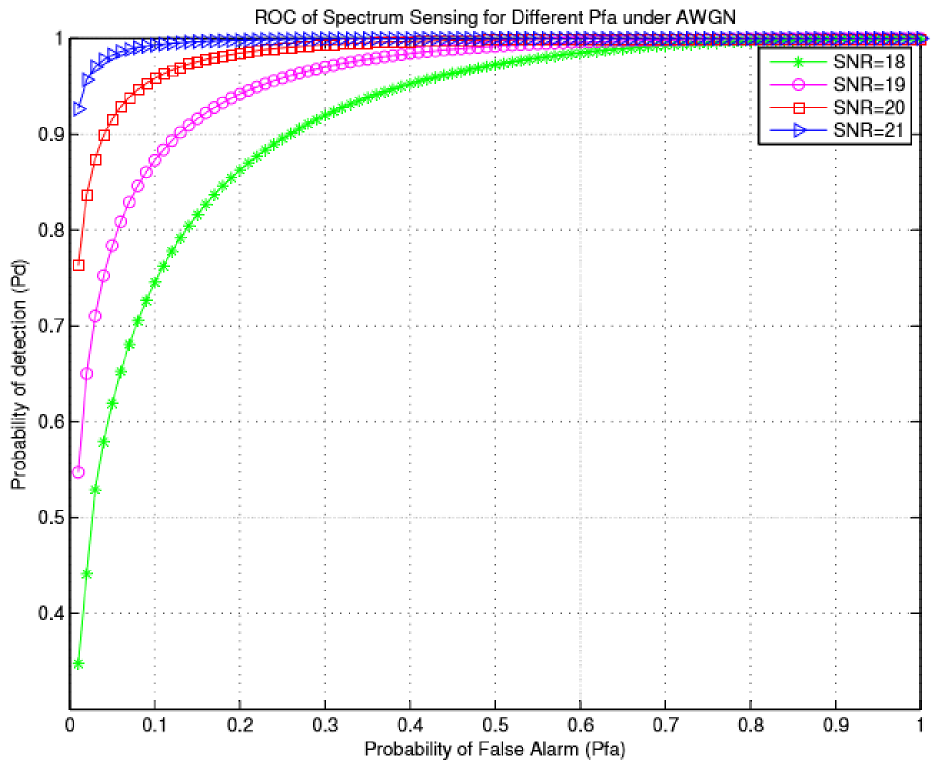


Figure 3.9 ROC of Spectrum Sensing for Different SNR values

3.5.7 Comparison among all sensing techniques:

Table 3.2 has shown the overall summary of advantages and disadvantages of all the spectrum sensing techniques for.

Spectrum sensing Techniques	Advantages	Disadvantages
Energy detection	1. Does not need any prior information 2. Low computation	1. Cannot work in low SNR 2. Cannot distinguish users 3. Sharing the same channel
Matched filter	1. Optimal detection performance 2. Low computational cost	1. Require prior knowledge of primary users
Cyclostationary detection	1. Robust in low SNR 2. Robust to interference	1. Requires partial information of primary users 2. High computational cost
Waveform based detection	1. Effective for wideband signal	1. High computational cost 2. Does not work for spread spectrum signals

Table 3.2 Advantages and Disadvantages of spectrum sensing techniques [28]

Chapter-4
SNR WALLS FOR SIGNAL DETECTION

4.1 Introduction

Parameters of physical system in a real world cannot be compute perfectly with infinite precision. Some examples are environmental noise to the wireless system which is neither perfectly Gaussian nor stationary and white in the real world, practical filters which response never comes ideal, channel fading never exist flat and constant over time. Analog-to-digital converters have only finite precisions and no infinite long précised results obtained. Similarly, signal processed in a receiver path never perfectly matched with original signal and sinusoidal waveform generated from local oscillators have always some phase difference with original one. Uncertainties in the wireless channel limit the detection performance such that the probability of false alarm/ probability of misdetection increase with function of uncertainty factor. Energy detection is considered as most popular spectrum sensing technique, however, the impact of noise uncertainty in wireless environment lead to fundamental limit on the sensitivity of energy based detector, and it generally suffers from the "**SNR Walls**" [8]. Only increasing the sensing time cannot solve the limitations occurred due to uncertainties. Therefore, some serious steps need to be taken regarding this issue. This chapter focus on the issues that how these uncertainties inflict the fundamental restrictions on performance of detection during spectrum sensing in cognitive radio. Section 4.2 defines the SNR wall in cognitive radio. In section 4.3 the basic limits on signal detection due to the presence of noise uncertainty are analyzed by considering the energy detection method. Finally, SNR wall mathematical expression is given in the end of 4.3.

4.2 Definition of SNR wall

SNR (signal-to-noise ratio) wall is defined as the minimum signal-to-noise ratio (SNRs) below which a robust detection is not possible or below a minimum SNRs for which performance of detection is not reliable is called SNR wall.

SNR wall is also defined as below a certain SNR threshold for which at least one of the error probabilities i.e. probability of false alarm/ probability of misdetection can become worse than half. This situation is sort of robustness failure in the detector. This phenomenon is known as **SNR wall** for the radio detector.

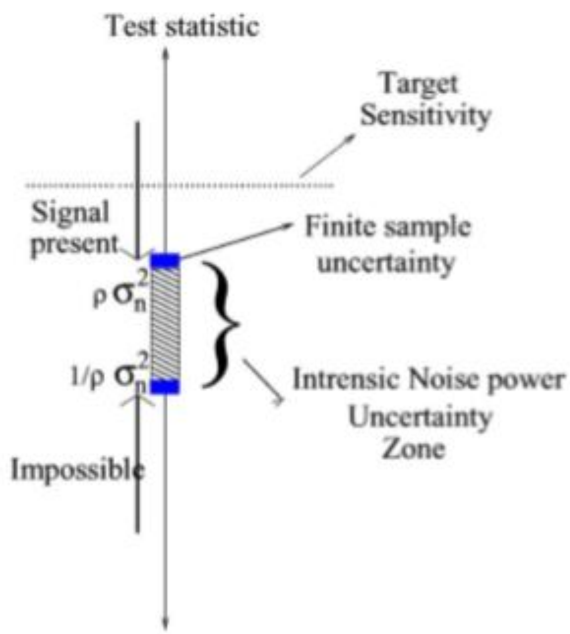


Figure 4.1 Presence of noise uncertainty in the radio detector [8]

Figure 4.1 showing how the presence of uncertainty in noise may affect the robust detection. As from the figure it is seen that the grey shaded area representing the uncertainty present in the noise power. It is clear from the figure that if the test statistic falls inside the region of grey shades, then there is no means to differentiate between the two hypotheses that signal is present or absent. In the next section 4.3 the performance of energy detection is formulate in the absence and presence of noise uncertainty.

4.3 Detector Robustness

Consider a scenario where sensor of the spectrum having very less knowledge about the primary signal. Also the primary signalling method is not known, except idea of power within the band of interest. This gives freedom to a primary licensee to choose its signalling strategy with only specified power and the bandwidth in the license. To robustly detection of such a primary user, a cognitive radio (secondary user) must be able to sense any possible primary signal presence which satisfies bandwidth and power constriction. By considering only this limited information, analysis will be done by taking the optimal detector is energy detector or radiometer can be represented as [30].

For analysis the robustness of detector two cases are considered i.e. absence of uncertainty in noise and presence of uncertainty in noise.

a. Uncertainty Absent: If the noise variance is known completely and there is no uncertainty, the CLT (central limit theorem) (see [8]) represents the following approximations can be made.

$$\text{D(Y/H0)} \sim \mathcal{N}(\sigma_n^2, 2\sigma_n^4/\text{N})$$

$$\text{D(Y/H1)} \sim \mathcal{N}(\text{P}+\sigma_n^2, 2(P+\sigma_n^2)^2/\text{N}) \quad (4.1)$$

The probability expressions are

$$P_{FA} = P_r(\text{D}(\text{Y}/\text{H0})) > \gamma = Q\left(\frac{\gamma-\sigma_n^2}{\sqrt{2\sigma_n^4/N}}\right) \quad (4.2)$$

$$P_D = Q\left(\frac{\gamma-(P+\sigma_n^2)}{\sqrt{2(P+\sigma_n^2)^2/N}}\right) \quad (4.3)$$

Where D(Y) is the decision statistic and γ is the decision threshold, N is the number of samples. $Q(..)$ is the standard Gaussian complementary cumulative distribution function and $Q^{-1}(..)$ is the inverse standard Gaussian complementary CDF.

From equation (4.2), (4.3) eliminating threshold

$$Q^{-1}(P_{FA}) = \frac{\gamma-\sigma_n^2}{\sqrt{2\sigma_n^4/N}} \quad (4.4)$$

$$Q^{-1}(P_D) = \frac{\gamma-(P+\sigma_n^2)}{\sqrt{2(P+\sigma_n^2)^2/N}} \quad (4.5)$$

Substituting (4.4) in (4.5) and eliminate γ, we get

$$\text{SNR} = \sqrt{\frac{2}{N}}\left(Q^{-1}(P_{FA}) - \left(Q^{-1}(P_D) * (1+\text{SNR})\right)\right) \quad (4.6)$$

Also, put $P_{MD} = 1 - P_D$

Approximate the above equation by considering $(1 + SNR \approx 1)$ by this we get the relationship for N, SNR, P_{FA} and P_{MD}

$$N = 2[Q^{-1}(P_{FA}) - Q^{-1}(P_{MD})]^2 * SNR^{-2} \tag{4.7}$$

This above relation shows that if we have complete knowledge of noise power (certainty in noise) then at random low SNRs signals could be detected only by increasing the sensing duration N.

b. Uncertainty Present:

We have discussed and analyzed by considering the case of no noise uncertainty. Now, we are considering the case when uncertainty is present in the noise model [28], let the distribution of uncertainty in noise is represented as

$$\sigma_n^2 \epsilon \left[\frac{\sigma_n^2}{\rho}, \qquad \rho\sigma_n^2\right]$$

ρ is the noise uncertainty coefficients, $\rho > 1$

Now (4.2) and (4.3) are modified as

$$P_{FA} = P_r(\mathrm{D(Y/H0)}) > \gamma = Q\left(\frac{\gamma - \rho\sigma_n^2}{\rho\sqrt{2\sigma_n^4/N}}\right) \tag{4.8}$$

$$P_D = Q\left(\frac{\gamma - (P + \sigma_n^2/\rho)}{\sqrt{2(P + \sigma_n^2/\rho)^2/N}}\right) \tag{4.9}$$

$$P_{MD} = 1 - Q\left(\frac{\gamma - (P + \sigma_n^2/\rho)}{\sqrt{2(P + \sigma_n^2/\rho)^2/N}}\right) \tag{4.10}$$

From equation (4.8), (4.9)

$$Q^{-1}(P_{FA}) = \frac{\gamma - \rho\sigma_n^2}{\rho\sigma_n^2\sqrt{2/N}} \tag{4.11}$$

$$Q^{-1}(1 - P_{MD}) = \frac{\gamma - (P + \sigma_n^2/\rho)}{(P + \sigma_n^2/\rho)\sqrt{2/N}} \tag{4.12}$$

Approximate the equation (4.12) by considering $(1 + SNR \approx 1)$ and eliminating γ gives result,

$$N = 2[Q^{-1}(P_{FA}) - Q^{-1}(1 - P_{MD})]^2 * (SNR - (\rho - \frac{1}{\rho}))^{-2} \qquad (4.13)$$

From the above expression in equation (4.13) it is clear that as SNR↓ $(\rho - \frac{1}{\rho})$ N tends to infinity (N→ ∞) and this is illustrated in Figure 4.2. It is clear from the figure that why we term it "SNR Wall."

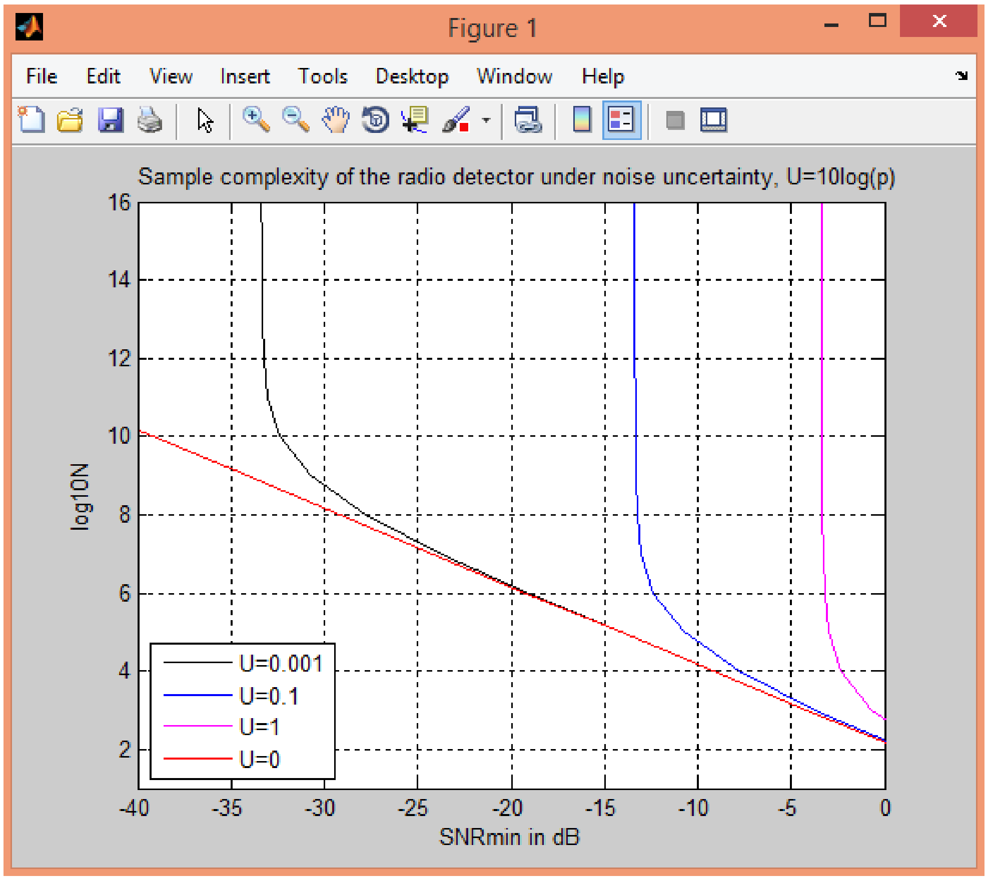


Figure 4.2 SNR approaches to SNR wall as sample complexity N varies to infinity

Figure 4.2 shows as SNR tends to approach SNR wall, the sample complexity of radio detector varies to infinity. Signal presence becomes indistinguishable as there's a slightly larger noise value in environment. Due to this reason threshold should be prevented to setting it within the noise uncertainty zone Therefore, from equation (4.13) and figure 4.2 we can extract the SNR wall i.e. is represented as,

$$SNR_{wall}^{energy} = \frac{\rho^2 - 1}{\rho} \qquad (4.14)$$

$$U = 10\ log_{10}\rho \ \ \text{dB} \tag{4.15}$$

Figure 4.3 plots equation (4.14) for SNR wall that is the function of uncertainty present in the noise, which is expressed in dB form in equation (4.15).

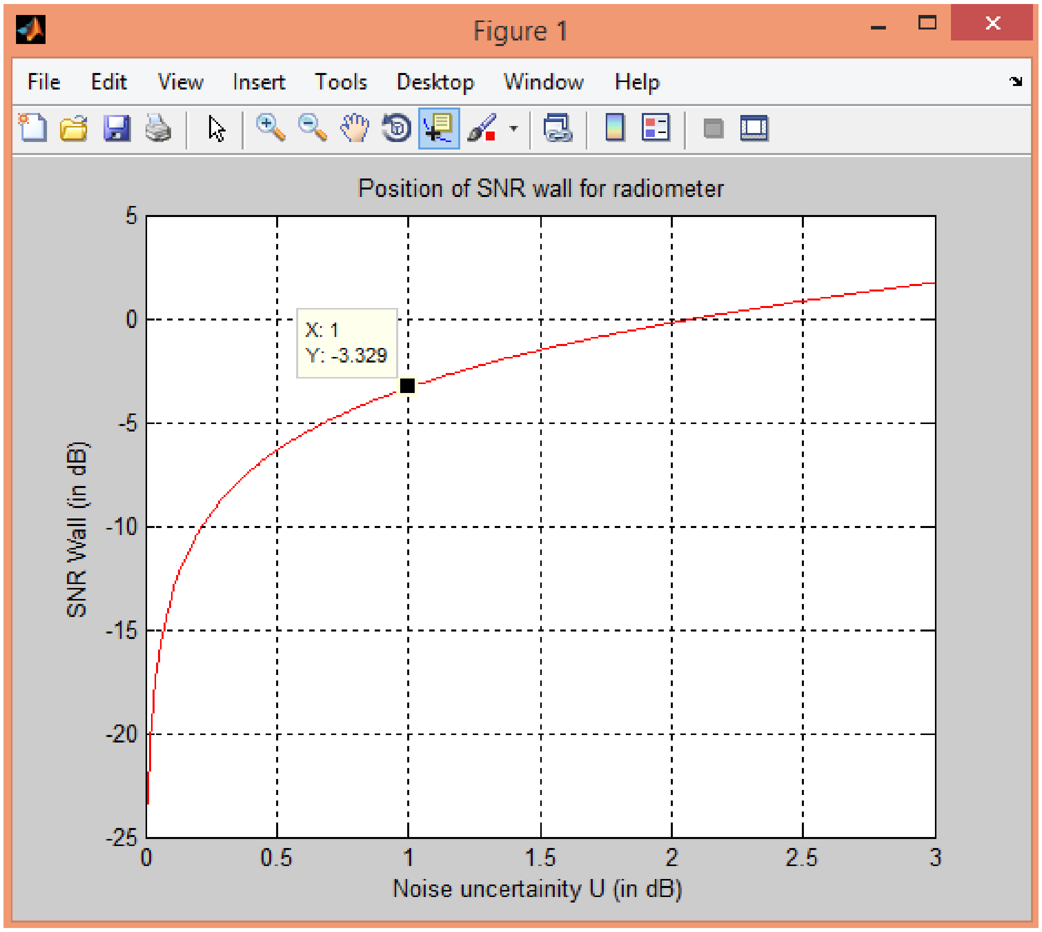


Figure 4.3 SNR wall with respect to noise uncertainty

Figure 4.3 illustrates for the particular value of noise uncertainty in wireless environment a particular value of SNR wall generated such as, in figure at U=1dB the value of SNR wall becomes -3.329dB.

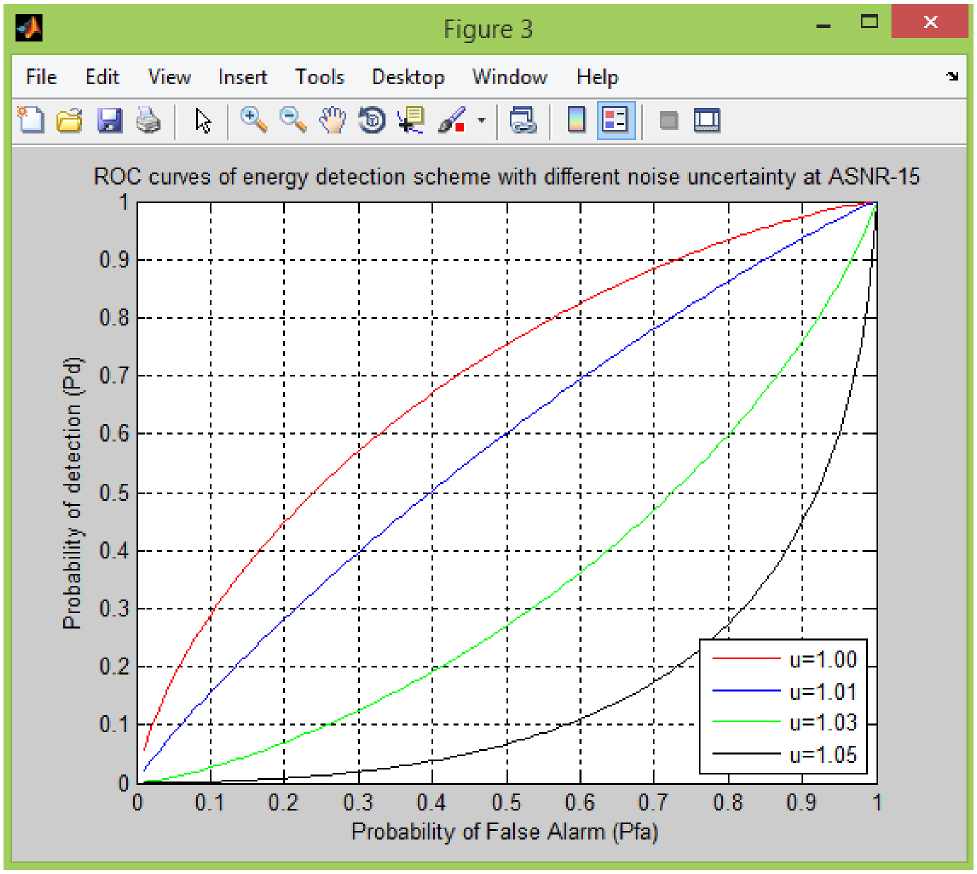


Figure 4.4 ROC Curves of Energy detection scheme with different noise uncertainty at SNR=-15dB

Figure 4.4 plot equation (4.9) for a given SNR=-15dB, $P_{FA} \epsilon$ (0,1) and N=1000 with different values of noise uncertainty u = [1, 1.01, 1.03, 1.05]. This plot is showing that how the uncertainty in the system degrades the performance of detection as uncertainty factor increasing from 1 to 1.05. To combat this problem a new adaptive technique is described in next chapter along with some previous available methods to reduce the SNR wall in the presence of uncertainty.

Chapter 5
SNR WALL REDUCTION METHOD

5.1 Introduction

Energy detection is considered as most popular spectrum sensing technique, however, the impact of noise uncertainty in wireless environment lead to fundamental limit on the sensitivity of energy based detector, and it generally suffers from the “SNR walls”, which defines as the minimum SNR below which robust detection is not possible. To address this issue, an adaptive technique is proposed in this chapter. By adopting the method which combines cross correlation scheme and dynamic threshold method, an analytical expression of SNR wall is derived which decrease the SNR wall in the conventional energy detector. Theoretical analyses and simulations validate the effectiveness of proposed method under the noise uncertainty environment. Specifically, this chapter shows that the proposed adaptive technique gives better results than the cross correlation scheme to reduce SNR wall under same conditions.

This chapter is organized as follows. An overview of alternative techniques used for lowering the SNR wall is presented in section 5.2. Section 5.3 represents problem formulation. Section 5.4 described the complete proposed method and its derivation for SNR wall is represented in section 5.5. In section 5.6, performance analyses and simulation results are discussed.

5.2 Related Work

The detection of signals for low SNRs under uncertainty wireless channel imposed limit on sensing techniques which is termed as “SNR wall,” [28]. To solve the SNR wall problem various method already proposed in past. Some examples are, in [36] oversampling method is introduced in which over sampled signals and their successive samples becomes highly correlated while noise signal will be highly uncorrelated so SNR improved. Another method for lowering the SNR wall is described in [37] in which improved energy detection (IED) based on non-linear stochastic resonance (SR) is proposed. In this scheme the resonance frequency of the SR system matching the received PU signal’s frequency, resonance occurred and at the resonant frequency corresponding signal will be significantly enhanced, thus improving the SNR of the received PU signal and lowering the SNR wall for traditional energy detection.

Adaptive threshold method is another approach to reduce SNR wall. This method used to change the threshold adaptively which depends upon the environmental conditions of channel to improve the performance of detection or lower the probability of false alarm. Various algorithms have been proposed already to estimate threshold values. The method mentioned in [31], calculate the required threshold as a linear function of recorded signal's standard deviation and mean. This method does not require the calculation of SNR and/or noise variance. Another threshold adaptation scheme for energy detection is represented in [32] in which spectrum sensing error $(\epsilon[\gamma(n)] = (1-\delta)P_{MD}[\gamma(n)] + \delta P_{FA}[\gamma(n)]$, where $0 < \delta < 1$ is a given constant weighting the probability of misdetection relative to that of probability of false alarm) is minimized under constraint imposed on $P_{MD}$and P_{FA}. In paper [33], the estimation of threshold depends upon SNR of the channel. Estimation of SNR can be performed by method like maximum likelihood estimator or second and fourth order moment estimator [34].

In [35] for spectrum sensing, energy detection by cross correlation technique is used. This method is basically use concept of two paths which process same input, such that the noise entered in both path are highly uncorrelated therefore, at the receiving end, only correlated noise remained which improves the SNRs and reduce the SNR wall. The limitation of this method is, if the correlation between two noises high then the desired results could not be achieved and SNR wall will start to seem a problem again. Therefore, some improvement is required in this method so that in presence of high correlated noises we can still improve the SNR wall value.

5.3 Problem Formulation

In CR networks, the spectrum sensing using energy detection follows a binary hypothesis testing in which two hypothesis are considered [28].

H_0 : Primary user is absent
H_1 : Primary user is present

$$D(Y) = \frac{1}{N}\sum_{n=0}^{N-1} Y(n)Y(n) \begin{array}{ll} >\gamma & : H1 \\ <\gamma & : H0 \end{array} \tag{5.1}$$

Let us assume that the received signal has the following simple form

$$y(n) = s(n) + w(n) \tag{5.2}$$

Where, $y(n)$ is received signal

, $s(n)$ is transmitted signal

, w(n) is AWGN (additive white Gaussian noise)

If the noise variance is completely known, then from the central limit theorem the following approximations can be made [28]

$$D(Y/H0) \sim N\ (\sigma_n^2,\ 2\sigma_n^4/N) \tag{5.3}$$

$$D(Y/H1) \sim N\ (P+\sigma_n^2,\ 2(P+\sigma_n^2)^2/N) \tag{5.4}$$

$$N = 2[Q^{-1}(P_{FA}) - Q^{-1}(P_D)]^2 * SNR^{-2} \tag{5.5}$$

However, if the noise power is estimated with distributional uncertainty in a single interval $\sigma_n^2 \ \epsilon \ [\frac{\sigma_n^2}{\mu},\ \mu\sigma_n^2]$

Where, μ is the noise uncertainty coefficient ($\mu > 1$)

Also, U = 10 $log_{10}\mu$

$$N = 2\left[\mu Q^{-1}(P_{FA}) - \left(\frac{1}{\mu} + SNR\right) Q^{-1}(P_D)\right]^2 * \left(SNR - \left(\mu - \frac{1}{\mu}\right)\right)^{-2} \tag{5.6}$$

Equation (7) shows that when N tends to infinity, SNR approaches $\frac{\mu^2 - 1}{\mu}$, which is called SNR wall [32]

$$SNR_{wall}^{energy} = \frac{\mu^2 - 1}{\mu} \tag{5.7}$$

For SNR less than SNR_{wall}^{energy}, a signal cannot be reliably detected.

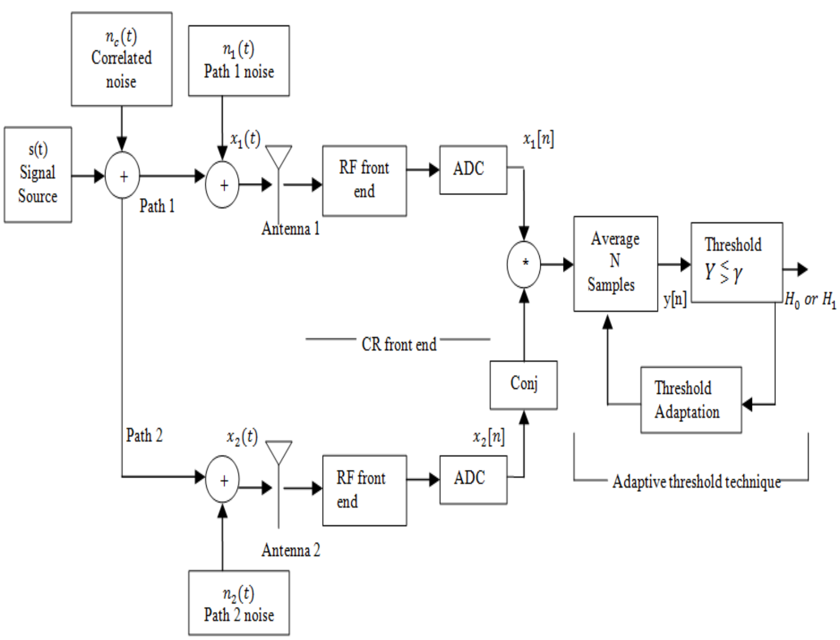


Figure 5.1 Block diagram of proposed system model

5.4 System Model

The system model shown in figure 5.1 is based upon the adaptive technique method which is basically a hybrid method of two. First, method is based upon cross-correlation system model mentioned in [35]. Second method is dynamic threshold method [29] which change its parameter that is, dynamic threshold factor depend upon the received SNR.

From the figure 5.1, the first part of proposed model consists of cross-correlation model. This part is basically consists of two path receiver system where same signal $s(t)$ is received by two receivers. Since, two different paths are given to same signal then there will be two different noises $n_1(t)$ and $n_2(t)$ interference to same signal. There must also be third noise $n_c(t)$ source available for signal which is due to the correlation present in the noise in wireless channel. Receiver part is a simple energy based detector which typically includes a low-noise amplifier (LNA) followed by amplifiers and then prefilters, and an analog to digital converter (ADC). Due to presence of two paths for this model, complete receiver chain is duplicated. After the cross-correlation part $y[n]$ is collected as an average of N samples. Now, adaptive threshold technique is combined with previous part and by using threshold adaptation method, appropriate threshold is estimated. Depend upon new threshold, signal is assumed to be present or absent. In this way, complete system model will work. Mathematical analysis for this model is expressed in next section.

5.5 Mathematical Analysis

The mathematical analysis of the model mentioned in above section is discussed in this section. Here, the SNR wall is derived for a signal source $s(t)$ with power P_s and the noise sources which are considered as independent complex zero-mean white Gaussian noise. The power spectral density (PSD) of noise is $N_o = \sigma_n^2$. It is assumed that the average power of real and imaginary parts of each process is same and independent also PSD of $n_1(t)$ and $n_2(t)$ are equal. For further evaluation we are taking some expressions from [35].

Let, ε represents the noise correlation between two receivers. Such that,

PSD of $n_c(t)$= $\varepsilon * N_o$

PSD of $n_1(t)$= PSD of $n_2(t)$= $(1-\varepsilon) * N_o$

At the output, SNR= P_s / N_oW

Where, (N_oW is the noise within band of interest).

From the figure 5.1,

$$Y=Y_{re} + Y_{im}$$

Where, (Y_{re} and Y_{im} are the real and imaginary parts of the sample respectively). Since, all the samples are independent and identically distributed (iid), then according to the central limit theorem (CLT), for a large number of samples, their average converges to a normal distribution.

Here, we are assuming that both receivers in the figure 5.1 are perfectly in phase i.e. $\Delta\emptyset = 0$. therefore, imaginary parts can be assumed as zero. For simplicity purpose, we are taking $N_o = 1$.

a) For H_0 (signal absent) i.e. SNR=0

$$\mu_0 = \varepsilon$$

$$\sigma_0^2 = \frac{1+\varepsilon^2}{2N} \qquad (5.8)$$

b) For H_1 (signal present) i.e. SNR>0

$$\mu_1 = \varepsilon + SNR$$

$$\sigma_1^2 = \frac{(2SNR^2 + (2+2\varepsilon)SNR + 1 + \varepsilon^2)}{2N} \qquad (5.9)$$

For fixed threshold model γ,

$$P_{FA} = Q\left(\frac{\gamma-\mu_0}{\sigma_0}\right) \qquad (5.10)$$

$$P_D = Q\left(\frac{\gamma-\mu_1}{\sigma_1}\right) \qquad (5.11)$$

Now, introducing noise uncertainty in the channel, say, U is peak-to-peak uncertainty which limit the performance of energy detection.

To improve the performance of the system, instead of fixed threshold, dynamic threshold is considered. Let'd' is a dynamic threshold factor also (d>1), so that, new threshold varies in the interval of $\gamma' \in (\frac{\gamma}{d}, \gamma d)$.

Equations (5.10) & (5.11) are modified as,

$$P_{FA} = Q\left(\frac{\gamma'-\mu_0}{\sigma_0}\right) = Q\left(\frac{\gamma d-\mu_0}{\sigma_0}\right) \qquad (5.12)$$

$$P_D = Q\left(\frac{\gamma' - \mu_1}{\sigma_1}\right) = Q\left(\frac{\frac{\gamma}{d} - \mu_1}{\sigma_1}\right) \tag{5.13}$$

From equation (5.12), for desired value of P_{FA}, setting the value of γ and multiplying with U factor for the evaluation under noise uncertainty condition.

$$\gamma = U\,\frac{\left[\mu_0 + \sigma_0 Q^{-1}(P_{FA,des})\right]}{d} \tag{5.14}$$

Putting value of γ in equation (5.13),

$$P_D = Q(\frac{\left\{\frac{\left[\mu_0 + \sigma_0 Q^{-1}(P_{FA,des})\right]}{d}\right\}/d - \mu_1}{\sigma_1} \tag{5.15}$$

From equations (5.8) & (5.9), putting values of μ_0,μ_1 σ_0& $\sigma_1$in equation (5.15).

$$P_D \approx Q\left[\frac{\left(\varepsilon\left(U - d^2\right) - d^2 SNR\right)\sqrt{N} + U\sqrt{p}\,Q^{-1}(P_{FA,des})}{d^2\sqrt{\gamma + (\epsilon + 1)SNR}}\right] \tag{5.16}$$

Here,$\left(p \equiv \frac{1}{2} + \frac{\varepsilon^2}{2}\right)$ (SNR$\ll$ 1) and (N$\gg$ 1).

For SNR_{min} expression, approximate equation (17) for (N$\gg$ 1), desired P_D and P_{FA} such that, $(P_D \geq P_{D,des})$ & $(P_{FA} \leq P_{FA,des})$.

$$SNR_{min} \approx \frac{\varepsilon(U - d^2)}{d^2} + \frac{X^2(\varepsilon + 1)}{2N} + \frac{UpY}{d^2\sqrt{N}} - \frac{X\sqrt{Nd^6\left(pd^2 + (U - d^2)(\varepsilon + \varepsilon^2)\right) + Z}}{N} \tag{5.17}$$

Where, X$\equiv Q^{-1}(P_{D,des})$, Y$\equiv Q^{-1}(P_{FA,des})$, Z$\equiv X^2(\varepsilon + 1)^2 d^8 + pUY(\varepsilon + 1)\sqrt{N} d^6$

Above expression can be simplified by using $(N \gg 1)$ and$|X|$, $|Y|$fairly small such that,

$$(|X|.|Y| \leq 10), P_{FA} = P_{MD} \geq 10^{-23}$$

$$SNR_{min} \approx \frac{\varepsilon(U - d^2)}{d^2} + \frac{UpY - Xd^5\sqrt{pd^2 + (U - d^2)(\varepsilon + \varepsilon^2)}}{d^2\sqrt{N}} \tag{5.18}$$

Since, SNR wall is defined as a minimum SNR for infinitely long averaging, below which a signal cannot be detect. Therefore, SNR wall expressed as,

$$SNR_{wall} = \lim_{N \to \infty} SNR_{min} = \frac{\varepsilon(U - d^2)}{d^2} \tag{5.19}$$

For, fixed threshold model (d=1), the above expression becomes,

$$SNR_{wall} = \varepsilon(U - 1) \tag{5.20}$$

The mathematical expression given in equation (20) represents the SNR wall for proposed system model which depends upon three factors,

1. Uncertainty factor (U).
2. Cross-correlation between two paths (ε).
3. Dynamic threshold factor (d).

As value of U increases the SNR wall increase, to compensate the effect of U, value of ε should maintain low, also for better result value of d should be greater than 1. SNR wall for d=1, shown in equation (21) which represents for fixed threshold energy detection method.

5.6 Performance Analysis And Results

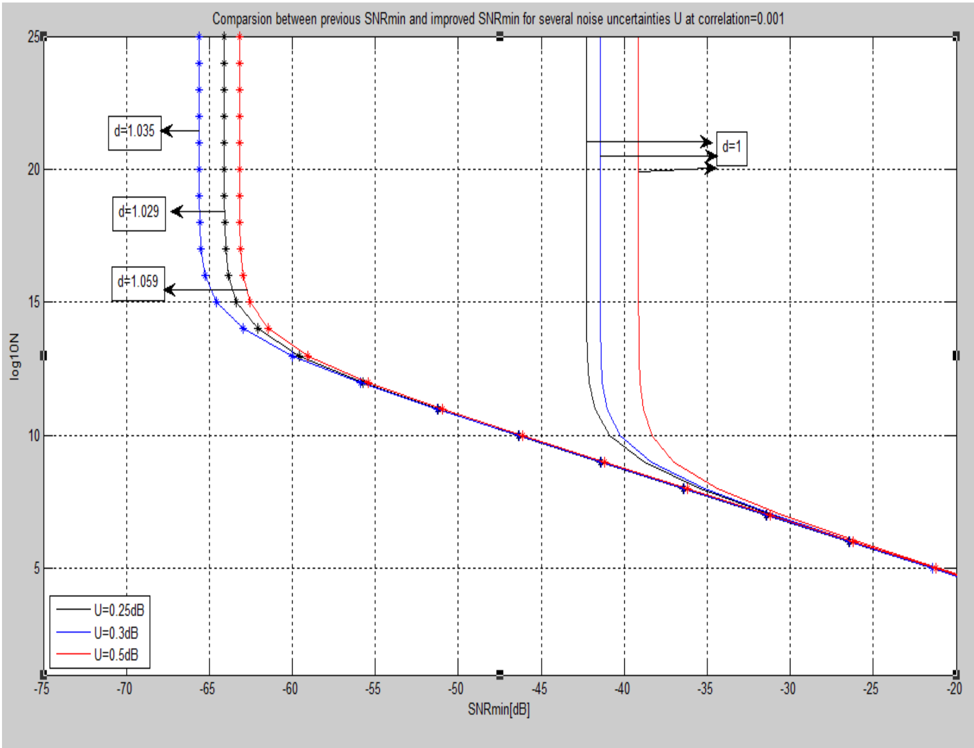


Figure 5.2 Comparison of the Previous SNR_{min} and the Improved SNR_{min} for several noise uncertainties U at $\varepsilon = 0.001$

In this section, results obtained from cross-correlation scheme with static threshold and proposed adaptive technique is compared. The simulation parameters are set for reasonable detection probabilities. The values of P_{MD} and P_{FA} used are 10^{-5} for analysis the performance of SNR_{min} according to (5.18) under the noise uncertainty environment.

Equation (5.18) is plotted in figure 5.2 i.e. SNR_{min} with respect to number of samples for various U (0.25dB, 0.3dB, 0.5dB) and($\varepsilon = 0.001$). In this figure, a comparison is shown between SNR_{min} at d=1 and improved SNR_{min} for different value of d. we can see from figure that at U=0.25dB and $\varepsilon = 0.001$ SNR_{min} at d=1 is -42dB while for same condition SNR_{min} at d=1.029 is -64dB. This shows that improved SNR_{min} gives better results as compared to previous one. Similarly, for U=0.3dB and U=0.5dB improved SNR_{min} is received.

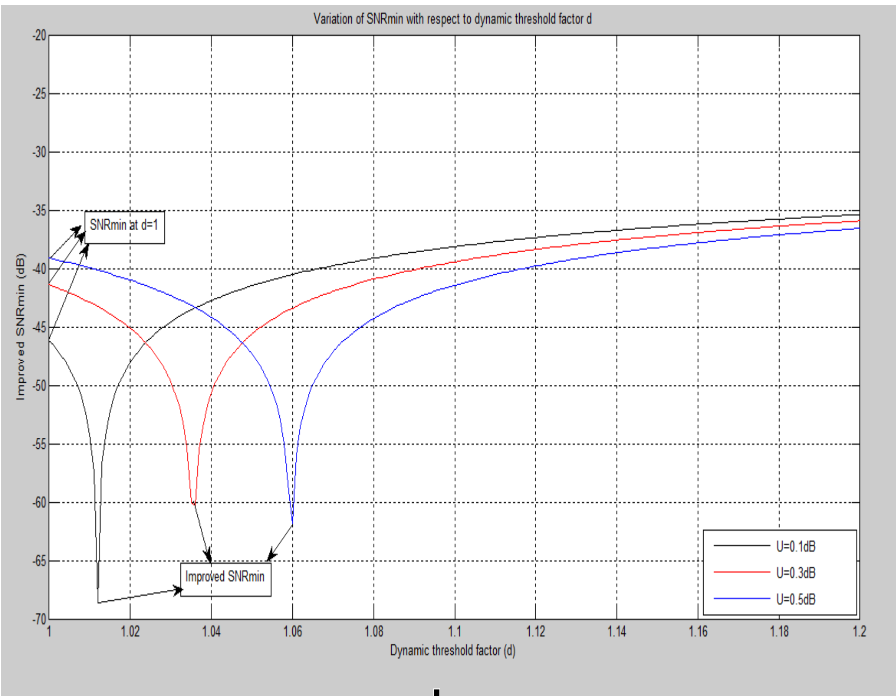


Figure 5.3 Variation of SNR_{min} (dB) with respect to the dynamic threshold (d)

In figure 5.3 $SNR_{min}$is plotted with respect to several values of dynamic threshold (d). A range of dynamic threshold factor represents for which SNR_{min} gives improved results as compared to SNR_{min} at d=1. From this figure, one can easily calculate the value of d for which SNR_{min} is lowest. For example, for the value of U=0.5dB at d=1.06, SNR_{min} becomes lowest (i.e. -62dB). The variation of $SNR_{min}$with varying value of d and percentage of improvement with respect to

SNR_{min}at d=1 is given in table 5.1, 5.2, 5.3 for value of U=0.1dB, 0.3dB, 0.5dB respectively. The results are analyzed by consideration of correlation present in noise is $\varepsilon = 0.001$ and number of samples are N=10^{20}.

S.No.	SNR_{min}at d=1	Value of 'd'	Improved SNR_{min}	%age of Improvement
1.	-46.327	1.008	-51.478	11.11
2.	-46.327	1.009	-52.907	14.20
3.	-46.327	1.010	-55.044	18.81
4.	-46.327	1.011	-59.404	28.22

Table5.1 Improved SNR_{min} and Percentage of improvement for different values of d at U=0.1dB.

S.No.	SNR_{min}at d=1	Value of 'd'	Improved SNR_{min}	%age of Improvement
1.	-41.455	1.02	-45.241	9.13
2.	-41.455	1.03	-49.995	20.60
3.	-41.455	1.04	-50.305	21.35
4.	-41.455	1.05	-45.512	9.79

Table 5.2 Improved SNR_{min} and Percentage of improvement for different values of d at U=0.3dB.

S.No.	SNR_{min}at d=1	Value of 'd'	Improved SNR_{min}	%age of Improvement
1.	-39.135	1.03	-42.395	8.33
2.	-39.135	1.07	-46.992	20.08
3.	-39.135	1.08	-44.196	12.93
4.	-39.135	1.09	-42.547	8.72

Table5.3 Improved SNR_{min} and Percentage of improvement for different values of d at U=0.5dB.

Figure 5.4 plotted the probability of misdetection ($P_{MD} = 1 - P_D$) for U=0dB and SNR=-10dB. This is showing that how the performance of P_{MD} degrade as noise correlation between the noise ε increases from 0 to 1. As from figure we can see that at($\varepsilon = 1$), P_{MD} is nearby 1 which means that the number of miss detection of actual signals are increased and P_D decreased simultaneously.

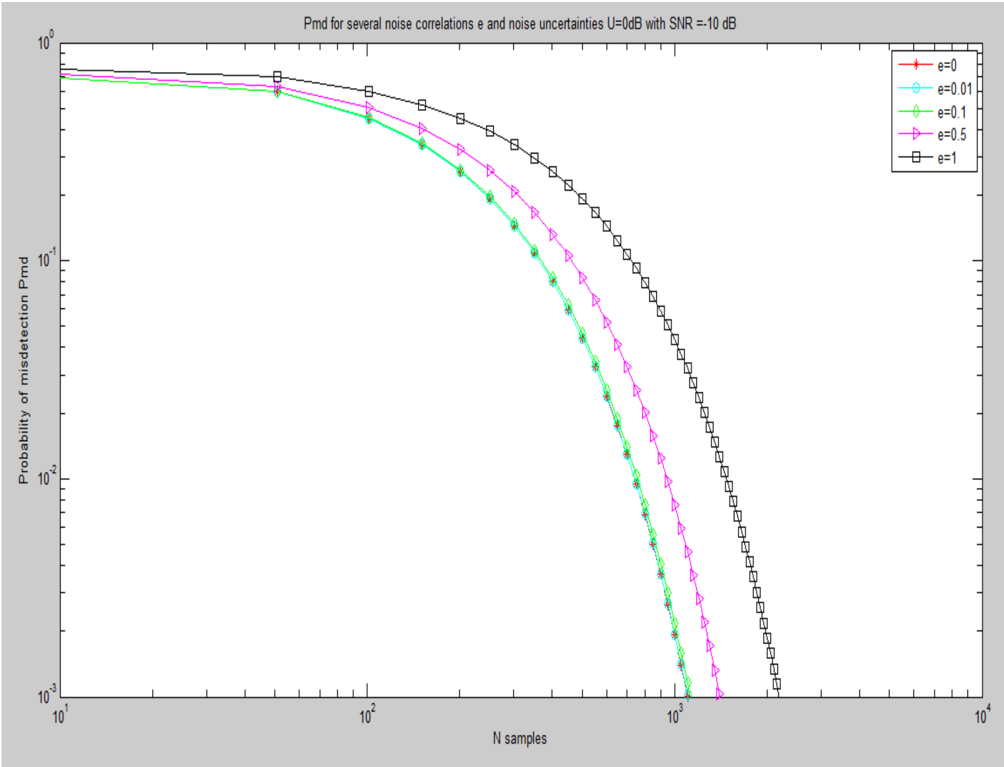


Figure 5.4 Probability of misdetection (P_{MD}) with respect to samples (N) for the different values ε

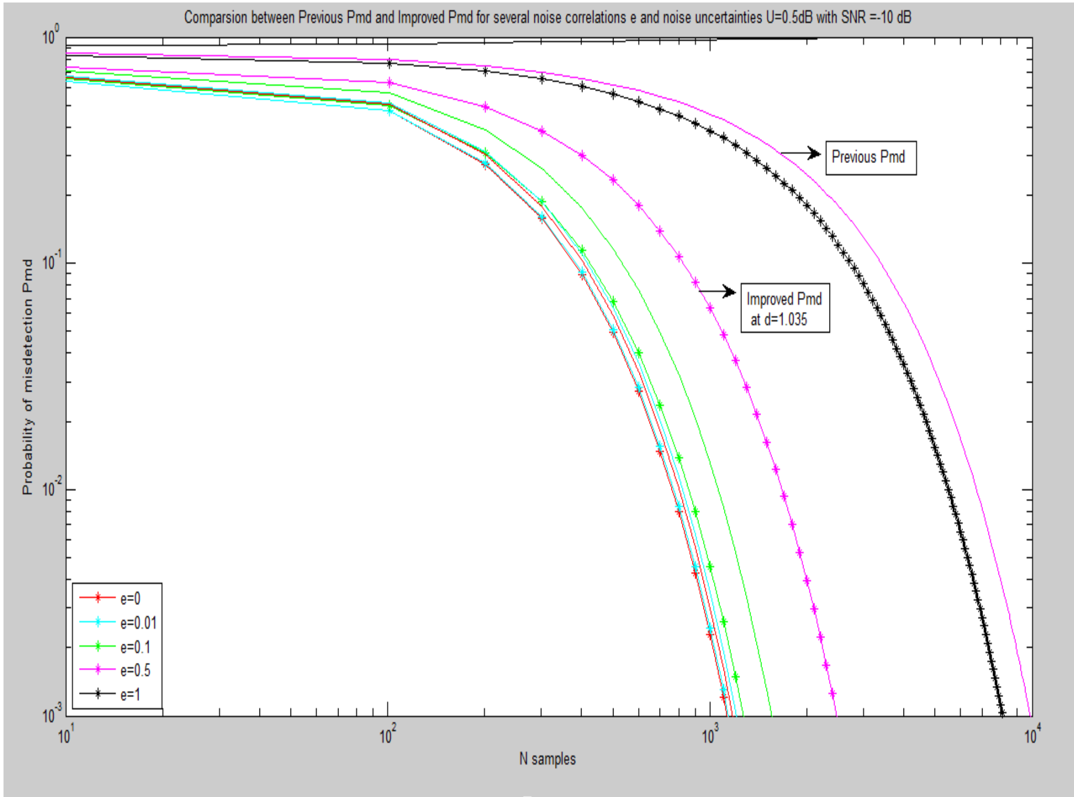


Figure 5.5 Improved P_{MD} (at d=1.035) & Previous P_{MD} with U=0.5dB, SNR=-10dB

In fig.5 and fig.6 improved P_{MD} is plotted for different values of ε and U (i.e. 0.5dB and 5dB) with different value of d (i.e. 1.035 and 1.7). For the simulation purpose $P_{FA,des} = 0.1$ and SNR=-10dB taken. From figure 5 & 6, we can see clearly that, lower ε is required for higher U for robust detection. Also, as the d factor introduced in the simulation, at the particular value of d, performance of P_{MD} (improvedP_{MD}) shows much better result as compared to previous one.

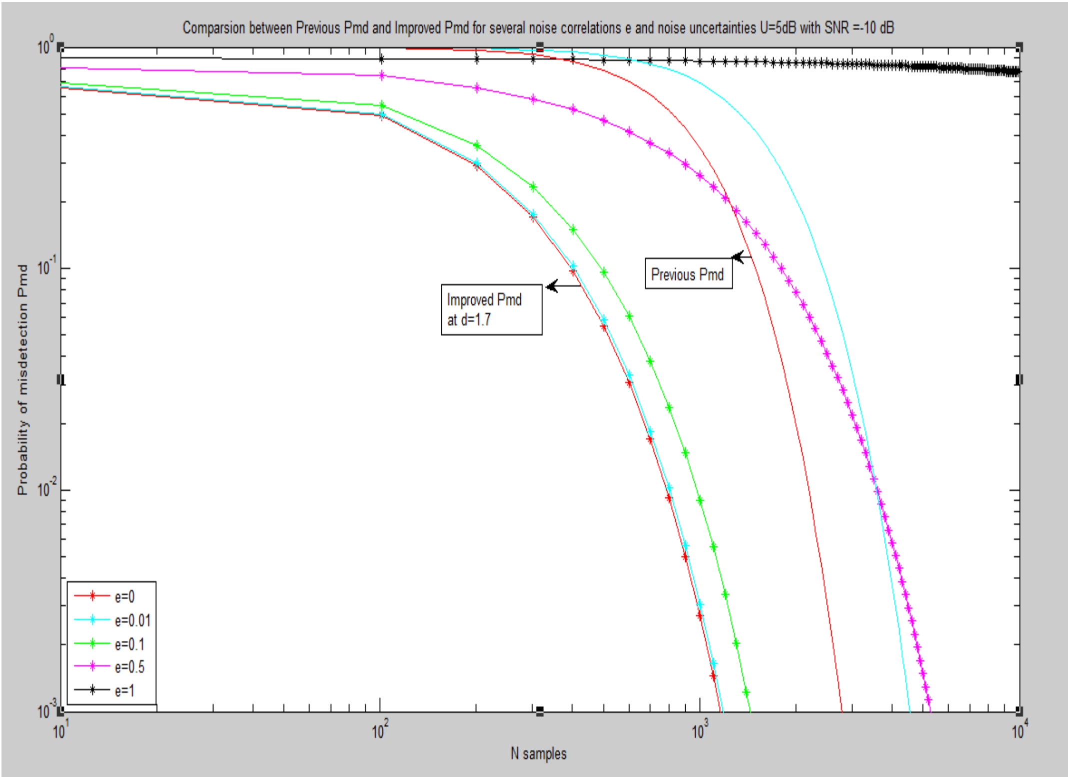


Figure 5.6 Improved P_{MD} (at d=1.7) & Previous P_{MD} with U=5dB, SNR=-10dB

Chapter 6
CONCLUSION

6.1 Conclusion

Energy detection method does not perform well in the presence of uncertainty in environment. SNR wall is the limitation causes due to presence of uncertainty in wireless environment which degrade performance of radio detector. Cross-correlation method is one of the available methods in which same signal passed to two different paths which introduce two uncorrelated noises. At the output, uncorrelated noises eliminated and only correlated noise remained. Therefore, SNRs is improved and so that SNR wall. But, this method can give better results only when the correlation between two noises is less. For less uncorrelated noises, the performance of P_{MD} degrade.

In this thesis work, we introduced an adaptive technique in which two different method are combined to enhance the results as compare to previous results. These two methods are cross-correlation method and adaptive threshold method. An expression is derived for SNR wall that relate the various parameters, such as correlation ε, uncertainty U and dynamic threshold factor d. Simulations showed that new derived SNR wall and detection performance gives better result than from previous method. In this work a range of the dynamic threshold factor (d) is also defined for which enhanced results are obtained.

6.2 Future work

For implementing the design of cognitive radio for spectrum sensing under above mentioned conditions following work can be extend for future purpose

1. Here, in thesis the performance of energy based detector is observed by computer simulation. In future, a practical method can be adapted to show how performances improved.
2. A comparatively study of performances of detector can be done by approaching various algorithms for dynamic threshold setting phenomena.

6.3 Limitations

Below some limitations are mentioned associated with this thesis work. Some of the limits can be solve by taking suitable steps in future.

1. All the simulation results are performed by only computer based simulations; these results are not verified yet in real environment.
2. High detection probability and low probability of false alarm are needed to achieve desired outputs in cognitive radio at all channel condition.
3. A fast processing unit of such devices is required so that capability of decision making can be fast.

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