PERFORMANCE ANALYSIS OF ENERGY DETECTION ALGORITHM IN COGNITIVE RADIO

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIRMENTS FOR THE DEGREE OF

MASTER OF TECHNOLOGY

IN

TELEMATICS AND SIGNAL PROCESSING

By

V.V.SATYANARAYANA EERLA

Roll No: 209EC1101

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY

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UNDER THE GUIDANCE OF

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CERTIFICATE

This is to certify that the thesis entitled," **PERFORMANCE ANALYSIS OF ENERGY DETECTION ALGORITHM IN COGNITIVE RADIO"** submitted by **V.V.SATYANARAYANA EERLA** in partial fulfillment of the requirements for the award of Master of Technology Degree in **Electronics & Communication Engineering** with specialization in **Telematics and Signal Processing** during 2010-2011 at the National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by him under my supervision and guidance. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

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V.V.Satyanarayana Eerla

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List of Acronyms

AWGN	Additive White Gaussian Noise
CAV	Covariance Absolute Value
CDF	Cumulative Distribution Function
CDMA	Code Division Multiple Access
CFN	Covariance Frobenius Norm
CR	Cognitive Radio
CSI	Channel State Information
DAB	Digital Audio Broadcast
DARPA	Defense Advanced Research Projects Agency
DFT	Discrete Fourier Transform
DSP	Digital Signal Processing
DVB	Digital Video Broadcast
FCC	Federal Communication Commission
FER	Frame Error Rate
HDTV	High-Definition Television
OFDM	Orthogonal Frequency Division Multiplexing
PDA	Personal Digital Assistants
PSD	Power Spectral Density
RF	Radio Frequency
RKRL	Radio Knowledge Representation Language
ROC	Receiver Operating Characteristics
SCF	Spectrum Correlation Function

SDR	Software Defined Radio
SPTF	Spectrum Policy Task Force
SNR	Signal to Noise Ratio
TRAI	Telecom Regulation Authority of India
UHF	Ultra High Frequency
WLAN	Wireless Local Area Network
WRAN	Wireless Regional Area Network

ABSTRCT:

Rapid growth of wireless applications and services has made it essential to address spectrum scarcity problem. if we were scan a portion of radio spectrum including revenue-rich urban areas, we find that some frequency bands in the spectrum are largely unoccupied most of the time, some other frequency bands are partially occupied and the remaining frequency bands are heavily used. This leads to a underutilization of radio spectrum, Cognitive radio (CR) technology attempts alleviate this problem through improved utilization of radio spectrum.

Cognitive radio is a form of wireless communication in which a transceiver can intelligently detect which RF communication channels are in use and which are not, and instantly move into vacant channels while avoiding occupied ones. This optimizes the use of available radio-frequency (RF) spectrum while minimizing interference to other users. There two types of cognitive radio, full cognitive radio and spectrum-sensing cognitive radio. Full cognitive radio takes into account all parameters that a wireless node or network can be aware of. Spectrum-sensing cognitive radio is used to detect channels in the radio frequency spectrum. Spectrum sensing is a fundamental requirement in cognitive radio network. Many signal detection techniques can be used in spectrum sensing so as to enhance the detection probability.

In this thesis we analyze the performance of energy detector spectrum sensing algorithm in cognitive radio. By increasing the some parameters, the performance of algorithm can be improved as shown in the simulation results**.** In cognitive radio systems, secondary users should determine correctly whether the primary user is absent or not in a certain spectrum within a short detection period. Spectrum detection schemes based on fixed threshold are sensitive to noise uncertainty, the energy detection based on dynamic threshold can improve the antagonism of noise uncertainty; get a good performance of detection while without increasing the computer complexity uncertainty and improves detection performance for schemes are sensitive to noise uncertainty in lower signal-to-noise and large noise uncertainty environments.

CHAPTER 1

1.1 Introduction. and Motivation

With the development of a host of new and ever expanding wireless applications and services, spectrum resources are facing huge demands. Currently, spectrum allotment is done by providing each new service with its own fixed frequency block. As day passes demand for spectrum are expected to increasing rapidly and it would get in future. As more and more technologies are moving towards fully wireless, demand for spectrum is enhancing. Some of recent services like Digital video broadcast (DVB), Digital audio broadcast (DAB), Internet, WiMAX etc current are on unlicensed based.

As Most of the primary spectrum is already assigned, so it becomes very difficult to find spectrum for either new services or expanding existing services. At Presently government policies do not allow the access of licensed spectrum by unlicensed users, constraining them instead to use several heavily populated, interference-prone frequency bands. As the result there is huge spectrum scarcity problem in certain bands. In particular, if we were to scan the radio spectrum, including the revenue-rich urban areas, we find that some frequency bands in the spectrum are unoccupied for some of the time, and many frequency bands are only partially occupied, whereas the remaining frequency bands are heavily used [1].The radio spectrum is limited resource and is regulated by government agencies such as Telecom Regulation Authority of India (TRAI) in India, Federal Communications Commission (FCC) in the United States.

Within the current spectrum regulatory framework, all the frequency bands are exclusively allocated to specific services and no violation from unlicensed users is allowed. The spectrum scarcity problem is getting worse due to the emergence of new wireless services. Fortunately, the worries about spectrum scarcity are being shattered by a recent survey made by Spectrum Policy Task Force (SPTF) within FCC. It indicates that the actual licensed spectrum is largely under-utilized in vast temporal and geographic dimensions [2].A remedy to spectrum scarcity is to improve spectrum utilization by allowing secondary users to access under-utilized licensed bands dynamically when/where licensed users are absent.

Cognitive radio is a novel technology which improves the spectrum utilization by allowing secondary users to borrow unused radio spectrum from primary licensed users or to share the spectrum with the primary users. As an intelligent wireless communication system, cognitive radio is aware of the radio frequency environment, selects the communication parameters (such as carrier frequency, modulation type, bandwidth and transmission power) to optimize the spectrum usage and adapts its transmission and reception accordingly. By sensing and adapting to the environment, a cognitive radio is able to able to fill in the spectrum holes and serve its users without causing harmful interference to the licensed user. To do so, the cognitive radio must continuously sense the spectrum it is using in order to detect the re-appearance of the primary user [3]. Once the primary user is detected, the cognitive radio should withdraw from the spectrum instantly so as to minimize the interference. This is very difficult task as the various primary users will be employing different modulation schemes, data rates and transmission powers in the presence of variable propagation environments and interference generated by other secondary users [1].

1.2 Objective

The main aim of this work is to explain the problem of spectrum sensing, various spectrum sensing methods, such as cyclostationary detection, covariance detection, wavelet based detection, matched filter detection, energy detection. We are mainly focusing on energy detector spectrum sensing algorithm, the performance of energy detection algorithm by varying some parameters and the performance of dynamic threshold on spectrum sensing algorithms (Matched filter detection and Energy detection).

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, standards, and various research organizations dealing with cognitive radio. Chapter 3 discuss the spectrum sensing problem, overview of various spectrum sensing methods and the performance of energy dector spectrum sensing algorithm in cognitive radio. Chapter 4 discusses the performance of dynamic threshold based spectrum detection in cognitive radio systems. Chapter 5 discusses the conclusion and future in this field of study.

CHAPTER 2

Cognitive radio-An Introduction

2.1 Introduction

Today wireless field is rapidly evolving. This started with Guglielmo Marconi first radio broadcast from England to one person in Nova Scotia. It was the radio equivalent of flying an airline's passengers across the Atlantic one at a time [4]. Today, we pack radio waves into the air as tightly as economy seats on a 747. New radio technologies keep coming along Wi-Fi, WiMAX, Bluetooth, ZigBee, the growing panoply of cellular voice and digital services, broadcast satellite, and more. Each requires a unique hardware appropriate to its special way of sending and receiving radio waves. Due to the large number of standards, spectrum availability has become an important issue. Spectrum usage regulations not allowing unlicensed users to operate in a licensed spectrum. However, it has been observed that the entire licensed spectrum is not used at all places all the time. An unlicensed user can take advantage of such a situation to communicate thereby increasing spectrum efficiency. This is the basic idea behind Cognitive Radio (CR) [1].This chapter presents a brief history, definition, functionality and applications of CR.

2.2 Brief history of CR

The Cognitive radios do not have the history of a century; rather the development of cognitive radio is still at a conceptual stage. The Cognitive Radio is an emerging technology, for the efficient use of the limited spectrum available. Nevertheless, as we look to the future, we see that cognitive radio has the capability to make a significant difference to the way the radio spectrum can be accessed, with much improved utilization. Indeed, given its potential, the cognitive radio can rightly be described as a "disruptive, but unobtrusive technology". Disruptive as it can make a great difference in the technology. Unobtrusive as it attracts with its solution for utilization of the already licensed frequency bands efficiently. It all started when [3] Joseph Mitola III coined word "Cognitive Radio" in his doctoral dissertation. He described, the way a cognitive radio could enhance the flexibility of personal wireless services, through a new language called the "Radio Knowledge Representation Language" (RKRL) [5]. The idea of RKRL was further expanded in Mitola's doctoral dissertation, presented at the Royal Institute of Technology in May 2000 [3] at Sweden. This dissertation presents a conceptual overview of CR as an exciting multidisciplinary subject.

Cognitive radio is not a single technology to be very precisely and clearly. It resulted from many technologies coming together to result in the Cognitive Radio technologies, due the fact that exists among its applications. For example, the development of digital signal processing (DSP), development of signal processing, math tools and source coding of data, voice and image etc..It is technology which is built on Software defined Radio which is brain child of Defense Advanced Research Projects Agency (DARPA). Later, DARPA launched the next Generation program (XG) that focused on "the enabling technologies and system concepts to dynamically redistribute allocated spectrum." [6] The successful conclusion of the XG project, the FCC realized that CR was the answer to stimulate growth of open spectrum.

2.3 Definitions of CR

After Mitola coined the word "Cognitive radio" its definition is also growing as research interest in CR is increasing. Regulatory bodies, prominent researchers and forums define it in different ways.

According to Mitola [3], CR is defined as The point in which wireless personal digital assistants (PDAs) and the related networks are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to: (a) detect user communications needs as a function of use context, and (b) to provide radio resources and wireless services most appropriate to those needs. However the concept of CR is not limited strictly to wireless devices such as PDAs.

Simon Haykin defines Cognitive Radio, it as follows [1]: "Cognitive radio is 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 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.

The regulatory bodies focus on the operation of transmitter like FCC defines the cognitive radio as: A radio that can change its transmitter parameters based on interaction with the environment in which it operates [7].

While assisting the FCC in its efforts to define cognitive radio, IEEE USA offered the following definition [8].A radio frequency transmitter or 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.

SDR forum which is mostly associated with CR and SDR , that works on CR [8] application defines CR as: An adaptive, autonomous radio, multi-dimensionally aware (system) that learns from its experiences to reason, plan, and decide future actions to meet user needs.

So among all definitions it is found that following terminologies are common "**Observation", "Adaptability"** and **"Intelligence".** Using following terminologies CR is defined as [8]

"Radio whose control processes permit the radio to leverage situational knowledge and intelligent processing to autonomously adapt towards some goal.

2.4 Why Cognitive Radio

Cognitive radio is a excellent tool for solving two major problems [7]**.**

- Accessing the spectrum (finding an open frequency and using it)
- Interoperability (talking to legacy radios using a variety of incompatible waveforms)

The following Figure 2.1 shows the utilization of spectrum [9]. From this it is observed that heavily used bands, medium used bands and unused bands in the spectrum.

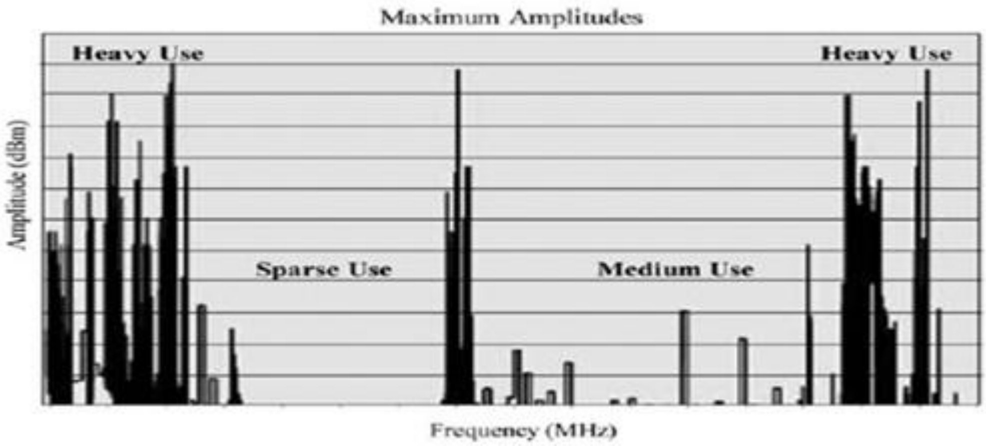

Figure 2.1 Spectrum utilization

2.5 How is a Cognitive Radio Different from Other Radios?

2.5.1. Application

Table 1 Comparison of cognitive radio with conventional radio and software radio in application point of view

Conventional Radio	Software Radio	Cognitive Radio
1.Supports a fixed number of Systems	1.Dynamically support multiple variable systems, protocols and interfaces	1.Can create new waveforms on its own
2.Reconfigurability decided at the time of design	2.Interface with diverse systems	2.Can negotiate new interfaces
3. May support multiple services, but chosen at the time of design	3.Provide a wide range of services with variable QoS	3.Adjusts operations to meet the QoS required by the application for the signal environment

2.5.2 Design

Table 2 Comparison of cognitive radio with conventional radio and software radio in design point of view

Conventional Radio	Software Radio	Cognitive Radio
1. Traditional RF design	1.Conventional Radio + Software Architecture	1.SDR + Intelligence
2.Traditional baseband design	2 .Reconfigurability	+ Awareness
	3.Provisions for easy upgrades	+Learning Observations

2.5.3 Software

Table 3 Comparison of cognitive radio with conventional radio and software radio in software point of view

Conventional Radio	Software Radio	Cognitive Radio
1. Cannot be made as future proof	1. Ideally software radios could be future proof	1. SDR upgrade mechanisms
2. Typically radios „ are not upgradeable	2. Many different external upgrade mechanisms	2. Internal upgrades & Collaborative upgrades

From the above tables it is observed that how a cognitive radio is different from other radios in the scenario application, design and software. From this it is observed that cognitive radio is most suitable for upcoming new wireless communications because of its intelligence, awareness, learning observations and up gradation mechanisms.

2.6 CR Tasks

In [1], a typical cognitive radio operation is representated as a simplification to the cognition cycle. A cognitive cycle by which a cognitive radio interact with environment is described in [3] [5] and can be divided into three, tightly interconnected tasks see in Figure 2.2.which shows the basic cognition cycle which includes the following three tasks.

1) **Radio-scene analysis, which encompasses the following**:

• Estimation of interference temperature of the radio environment;

• Detection of spectrum holes.

2) Channel identification, which encompasses the following:

• Estimation of channel-state information (CSI)

• Prediction of channel capacity for use by the transmitter.

3) Transmit-power control and dynamic spectrum management

Tasks 1) and 2) are carried out in the receiver, and task 3) is carried out in the transmitter. Through interaction with the RF environment, these three tasks form a cognitive cycle, which is presented in its most basic form in Figure 2.2.

2.6.1 Radio-scene analysis

During Radio-scene analysis different radio configurations are probed to estimate interference temperature of the radio environment and detection of spectrum holes. Interference temperature and spectrum holes are defined as under.

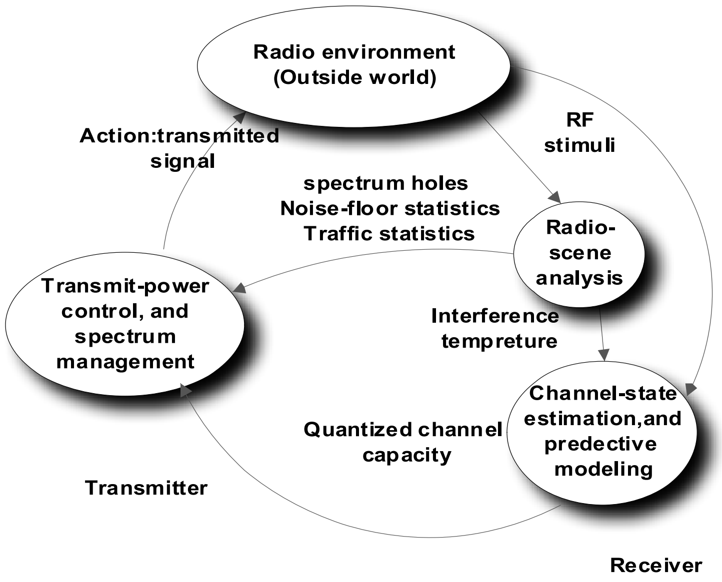

Figure 2.2 Basic cognitive cycle. (The figure focuses on three fundamental cognitive tasks.)

Interference Temperature

The interference temperature is a measure of the sensed power in a certain frequency band. Thus, by obtaining this measure, two important limits can be identified:

• The maximum level where any signal exceeds threshold level.

• The minimum level where any signal below it can be neglected and thus that certain band can be considered as empty or unused, and can be used by other users.

Spectrum Hole

A spectrum hole is a band of frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not utilized by that user. Primary users are those who hold the licensed channels or primary bands.

As said above radio scene analysis includes two functionality. These two stages are performed periodically. The interference temperature is suggested to be estimated for the whole targeted frequency ranges. Then depending on the current interference and the interference temperature on the previous iterations all channels can be classified into three types of spectrum holes:

• White spectrum holes, which are fully not used.

• Gray spectrum holes, which are partially used.

• Black spectrum holes, which are fully used.

After the sensing operation is completed, the users are allowed to access freely the white holes and partially use the gray holes in such a way that does not disturb the primary user. But they will not use the black holes, because the black holes are assumed to be fully used and any extra use will interfere with the ongoing communication in them. In general, there are two sensing modes, reactive sensing and proactive sensing, depending on the way to initiate the sensing. These two modes are defined as under.

Reactive sensing: The sensing is initiated only when the user has data to send, thus it is called on-demand sensing. If no usable channel is found, the user will wait for a predefined time and then restart sensing again until the user send all data that is available to be send.

This technique reduces the sensing overhead. And its disadvantage is that, data is delayed until the sensing is performed with a good accuracy.

Proactive sensing: The sensing is done periodically even when the user is not intending to send any data. The time between the sensing iterations is called the sensing period. These sensing periods may differ between channels since each channel has its own unique characteristics. The sensing periods should be optimized separately for each channel to compensate for the unique traffic pattern on that channel. Following are some of the advantages and disadvantages.

Advantage: The delay is decreased since the users will know the holes even before they need them.

Disadvantage: A lot of time and effort is wasted on sensing even when it is not needed, thus increasing the sensing overhead.

Each one of those two modes has their advantages and disadvantages, thus both of these might be used depending on the application and the environmental conditions.

2.6.2 Channel-state estimation

Channel estimation [1] was also proposed to be part of the cognitive radio. This operation aims in analyzing the channel behavior and its effects on the transmitted signal and estimating the impulse response of the channel. By observing the channel impulse response, information is used by the receiver for an equalizer design or the transmitter by transmitting a signal that can absorb those effects.

2.6.3 Distributed transmit-power control

Like the spectrum allocation, this process is done centrally in conventional radios [1]. Thus, in cognitive radio each user should take care of it is own transmission power control and gives some feedbacks related to the signals that it received. As a result, the power control process is done in a distributed manner. In other words, each user must make sure that the signal that it transmits reaches the receiver in a certain level higher by the receiver and low enough to avoid interfering with other users. At the same time each user has to inform other users, which are transmitting to it, about the reception signal level. The power control operation plays a crucial part in minimizing the interference and in insuring the needed quality of service in many communication systems.

2.6.4 Dynamic spectrum management

As with transmit-power control, dynamic spectrum management [1] (also referred to as dynamic frequency-allocation) is performed in the transmitter. These two tasks are intimately related to each other, and hence have been included inside a single functional module. It performs the role of multiple-access control in basic cognitive cycle as in Figure 2.2 simply replace, the primary purpose of spectrum management with an adaptive strategy for the efficient and effective utilization of the RF spectrum. Particularly, the spectrum-management algorithm is designed to do the following. Building on the spectrum holes detected by the radio-scene analyzer and the output of transmit-power controller, select a modulation strategy that adapts to the time-varying conditions of the radio environment, all the time assuring reliable communication across the channel. Communication reliability is assured by choosing the SNR gap large enough as a design parameter.

- **Modulation considerations**

A modulation strategy that commends itself to CR is the OFDM by advantage of its flexibility and computational efficiency. For its operation, OFDM uses a set of carrier frequencies bring together on a corresponding set of narrow channel bandwidths. Most important, the availability of rate feedback (by the use of a feedback channel) permits the use of bit loading, whereby the number of bits per symbol for each channel is optimized for the SNR characterizing that channel; As time progress and spectrum holes come and go, the bandwidth-carrier frequency implementation of OFDM is dynamically modified. This is illustrated in the time-frequency picture in Figure.2.3 for the case of four carrier frequencies. The picture illustrated in Figure 2.3. This describes a distinctive feature of cognitive radio: The dynamic spectrum-sharing process, which evolves with time.

In effect, the spectrum-sharing process fulfills the constraint imposed on cognitive radio by the availability of spectrum holes at a particular geographic location and their possible variation with time. Throughout the spectrum-sharing process, the transmit-power controller keeps detail information of the bit-loading across the spectrum holes in use. In effect, the dynamic spectrum manager and the transmit-power controller work in concert together, thereby fulfilling the multiple-access control requirement. Starting with a set of spectrum holes, it is possible for the dynamic spectrum management algorithm to accost a situation where the prescribed frame-error rate (FER) cannot be satisfied. In situations of this kind, the algorithm can do one of two things:

i) Work with a more spectrally efficient modulation strategy, or else;

ii) Incorporate the use of another spectrum hole, assuming availability.

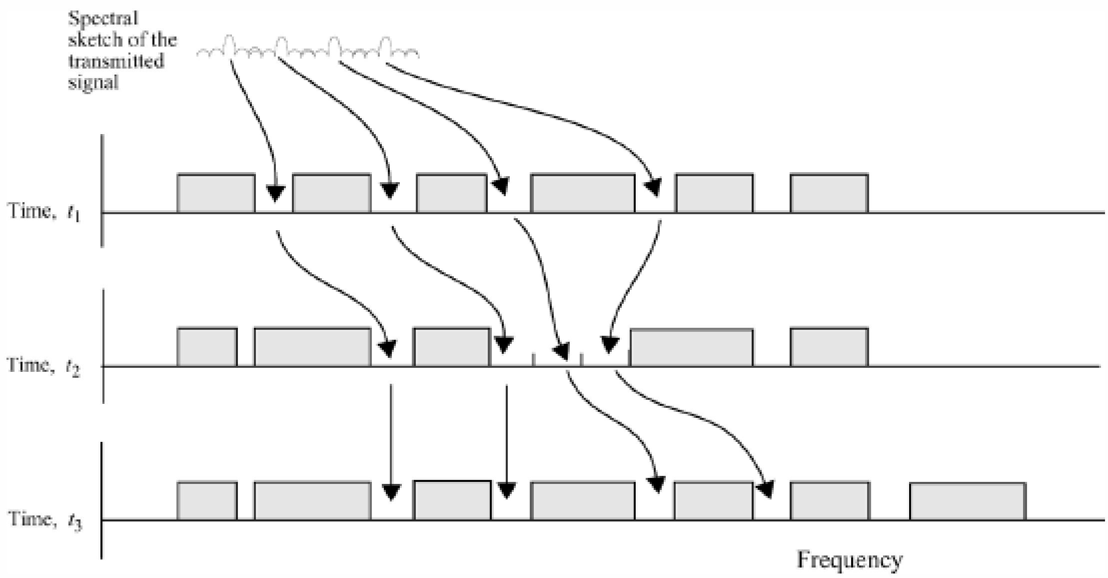

Figure 2.3 Illustrating the notion of dynamic spectrum-sharing for OFDM based on four channels

And the way in which the spectrum manager allocates the requisite channel bandwidths at different time instants $t_1 < t_2 < t_3$, depends on the availability of spectrum holes. This is also presented in Figure.2.3

In approach i), the algorithm recourse to increased computational complexity, and in approach ii), it recourse to increased channel bandwidth so as to maintain communication reliability.

- **Traffic considerations**

In a code division multiple access system (CDMA), like the IS-95, there is a phenomenon called cell breathing; the cells in the system effectively condense and grow over time. Particularly, if a cell has more users, then the interference level tends to increase, which is opposed by allocating a new incoming user to another cell; that is, the cell coverage is shrunk. On the other hand, if a cell has fewer users, then the interference level is correspondingly lowered, in this case the cell coverage is allowed to become larger by accommodating new users. So in a CDMA system, the interference and traffic levels are associated together. In a cognitive radio based on CDMA system, the dynamic spectrum management algorithm generally focuses on the allocation of users, first preference to white spaces with low interference levels, and then to grey spaces with higher interference levels. When using other multiple-access techniques, such as co-channel interference, OFDM has to be avoided. To satisfy this requirement, the dynamic-spectrum management algorithm must contain traffic model of the primary user occupying a black space. The traffic model, built on historical data, provides the means for predicting the future traffic patterns in that space [1]. This in turn, makes it possible to predict the duration for which the spectrum hole vacated by the occupant primary user is probably to be available for use by a cognitive radio operator. In a wireless environment, traffic data patterns are of two classes distinguished. This is summarized here.

1) *Deterministic patterns*: In this class of traffic data, the primary user (e.g., Radar transmitter, TV transmitter) is assigned a fixed time slot for transmission of signals. When it is switched OFF, the frequency band is vacated and can be used by a cognitive radio operator.

2) *Stochastic patterns*. In this class, the traffic data can only be described in statistical terms. Usually, data packets arrival times are modeled as a Poisson process; while the service times of data packets are modeled as exponentially distributed, depending on whether the data are of circuit-switched kind or packet-switched, respectively. In any occurrence, the model parameters of stochastic traffic data vary slowly and, as a result, lend themselves to on-line estimation using historical data. Furthermore, by building a tracking strategy into design of predictive model. The accuracy of the model can be further improved.

2.7 Emergent behaviors of cognitive radio

Considering the complex situations that should normally happens in a cognitive radio system, the rapidly varying configurations of the radios my lead the system to a new mysterious state. Since radios may compete or cooperate in cognitive radio system, their benefits can normally oppose each other. Thus there is no simple way to ensure agreeing on an acceptable solution for all sides. The states can be categorized into two main types [1]:

Positive state: where the overall system performance is improving and the radio resources are used efficiently.

Negative state: where the overall system performance is degrading and some of the radio resources are not used or are used inefficiently.

Thus, it is very important to develop a way to ensure the system convergence to a positive state and avoid approaching a negative state. This can be done by developing models that can foresee the system development. This kind of a system can be handled by one of these two models, self organizing system or evolutionary game. The self organizing system model views the system as a group of players, each player actions are influenced by the others and therefore every action is reflected back to its originator. If these reflections continue in a pattern that amplifies their effects they may lead to instability in the system. Thus, the system reflections and their effects need to be checked in order to protect the system from the negative states.

The evolutionary game model views the system as a group of animals every one of them has its own instincts and intentions which lead to behaviors that looks very stochastic. Using those two models the system behaviors can be predicted. From these predictions, further investigations can be made to find the parameters that will likely lead to positive state and use them and find the ones that will probably lead to negative state and avoid them. It is also possible to find simple rules that can ensure the system stability.

2.8 Emerging Cognitive Radio Standards and Deployments

The IEEE 802 community is currently developing two standards that directly relate to cognitive radio – IEEE 802.22 also called standard for cognitive wireless regional area networks (WRANs) and 802.11h. Additionally, 802.11k is developing techniques for incorporating radio resource management information into WLAN operation – in effect incorporating knowledge about the environment and the radios [8] [10].

2.8.1 IEEE 802.22

There are three applications typically discussed for coexistence with initial trial deployments of cognitive radios: television, microwave point-to-point links, and land mobile radio. Each of these applications has been seen to dramatically underutilize spectrum on average. However, only television signals have the advantage of incumbent signals that are easy to detect (as opposed to a microwave point-to-point links) and not involved in life-critical applications (as would be the case for many land mobile radio systems). Throughout its history, the UHF bands were under-allocated as regulators underestimated the cost-effectiveness of establishing new TV towers in these bands. It was not until the advent of cable TV that smaller TV stations were capable of cost-effective operation. Now with the introduction of HDTV technology, regulators in the US plan to force a nation-wide switch to this more efficient modulation by 2009[9] accompanied by a completion of a de-allocation from analog TV of 108 MHz of high quality spectrum. With these bands in mind, the 802.22 working group is pursuing the development of a waveform intended to provide high bandwidth access in rural areas using cognitive radio techniques. In a report [10] presented at DySPAN, it is stated that the 802.22 standard intends to achieve spectral efficiencies of up to 3 bits/sec/Hz corresponding to peak download rates at coverage edge at 1.5 Mbps. Simultaneously, the 802.22 system hopes to achieve up to 100 km of coverage. Currently only 2×85MHz of spectrum has been assigned on average to mobile operators in India, while state broadcaster Doordarshan uses 112MHz of UHF spectrum for analogue terrestrial broadcasting alone, and a further 116MHz has been earmarked for digital broadcasting

2.8.2 IEEE 802.11h

Unlike 802.22, 802.11h is not formulated as a cognitive radio standard. However, the World Wireless Research Forum has noted that a key portion of the 802.11h protocol – dynamic frequency selection – has been termed a "cognitive function". Reasons for 802.11h WLAN might be considered as CR based on following tasks.

Observation – It requires WLANs to estimate channel characteristics such as path loss and link margin and further requires the radios estimate channel characteristics such as path loss and link margin.

Orientation – Based on these observations, the WLAN has to determine if it is operating in the presence of a radar installation, in a bad channel, in band with satellites, or in the presence of other WLANs.

Decision – Based on the situation that the WLAN is encountering, the WLAN has to decide to change its frequency of operation (Dynamic Frequency Selection), adjust the transmit power (Transmit Power Control), or both.

Action – The WLAN has to then implement this decision.

Reviewing most of the definitions from before, only learning or "recalling and correlating past actions, environments and performance" is not required as part of the standard. However, if we move beyond the requirements of the standard to expected implementations, it seems reasonable that many vendors will include and leverage some memory of past observations (useful for detecting intermittent transmitters) which implies that both cognitive radio definitions will be satisfied.

2.9 Cognitive Radio Applications, Advantages and Drawbacks

The cognitive radio does the same advantages and disadvantages of SDR. The cognitive has the more benefits than a conventional radio. The following are the applications, advantages and disadvantages of cognitive radio.

Some of the important applications of CR are as follows:

- Improving spectrum utilization & efficiency
- Improving link reliability
- Less expensive radios
- Advanced network topologies
- Enhancing SDR techniques
- Automated radio resource management
- Four most promising applications are
  1. Multimedia downloads
  2. Emergency communications (with priority flag)
  3. Broadband wireless services
  4. Multimedia wireless networking.

Advantages of CR:

- Cognitive radios are expected to be powerful tools for mitigating and solving general and selective spectrum access issues
- Improves current spectrum utilization (Fill in unused spectrum and move away from occupied spectrum)
- Improves wireless data network performance through increased user throughput and system reliability
- More adaptability and less coordination required between wireless network.

Drawbacks of CR:

- Security
- Software reliability
- Keeping up with higher data rates

- Loss of control
- Regulatory concerns
- Fear of undesirable adaptations
- Significant research remains to be done to realize commercially practical cognitive radio.

2.10 Important Institution and forums working on CR

Some of the important institution, forums and research organization where extensive research is going on are listed below [6] [8].

DARPA- is exploring many different aspects of cognitive radio as part of the XG program and other ongoing programs. Unfortunately, many of the results of the DARPA programs are not currently in the public domain

IEEE- has started the IEEE 1900 group to study the issue of cognitive radio and giving standard like 802.22

SDR Forum- chartered two groups in 2004 to explore cognitive radio issues: the Cognitive Radio Working Group and the Cognitive Radio Special Interest Group. The working group is tasked with standardizing a definition of cognitive radio and identifying the enabling technologies for cognitive radio.

FCC- On May 19, 2003, the FCC convened a workshop to examine the impact that cognitive radio could have on spectrum utilization and to study the practical regulatory issues that cognitive radio would raise.

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

Win lab Rutgers University is developing a cognitive radio test bed for disaster response using commercially available components.

E^2R-European initiative into supporting End-to-End Reconfigurability with numerous participating European universities and companies.

BWRC-Berkeley wireless research center is currently developing a cognitive radio for sensing and opportunistically using the spectrum.

CHAPTER 3

Energy detector spectrum sensing algorithm in Cognitive Radio

Spectrum sensing refers to detecting the unused spectrum (spectrum holes) and sharing it without harmful interference with other secondary users. In cognitive radio technology, primary users(can be defined as the users who have the highest priority on the usage of a specific part of the spectrum. Secondary users have lower priority, and should not cause any interference to the primary users when using the channel. Spectrum sensing is still in its early stages of development. A number of various methods are proposed for identifying the presence signal in transmissions. In some another approaches, characteristics of the identified transmission are detected for deciding the signal transmission as well as identifying the type of signal [11]. The well known spectrum sensing techniques used are matched filter detection, energy detection, cyclostationary detection, wavelet detection and covariance detection.

3.1 Spectrum sensing problem

Spectrum sensing is a key element in cognitive radio communications as it must be performed before allowing unlicensed users to access a vacant licensed band. The essence of spectrum sensing is a binary hypothesis-testing problem:

$$\mathrm{H_0} : \text{Primary user is absent}$$

$$\mathrm{H_1} : \text{Primary user is present} \qquad (1)$$

The key metric in spectrum sensing are the probability of correct detection ($\mathrm{P_d}$) and two types of error in spectrum sensor, the first error occurs when the channel is vacant (H_0) but the spectrum sensor can decide the channel is occupied, the probability of this event is the probability of false alarm($\mathrm{P_f}$), the second error when channel is occupied (H_1) the spectrum sensor can decide the channel is unoccupied, the probability of this event is probability of misdetection ($\mathrm{P_m}$) [12].

$$\mathrm{P_d} = \mathrm{prob}\{\text{Decision=}\mathrm{H_1}/\mathrm{H_1}\}$$

$$\mathrm{P_f} = \mathrm{prob}\{\text{Decision=}\mathrm{H_1}/\mathrm{H_0}\}$$

$$\mathrm{P_m} = \mathrm{prob}\{\text{Decision=}\mathrm{H_0}/\mathrm{H_1}\} \qquad (2)$$

3.1.1 Cyclostationary detection

Cyclostationary detection is more robust to noise uncertainty than energy detection. If the signal of the PU exhibits strong cyclostationary properties, it can be detected at very low SNR values by exploiting the information (cyclostationary feature) embedded in the received signal. A signal is said to be cyclostationary (in the wide sense) if its mean and autocorrelation are a periodic function of time with some period (eqn 3). Modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading, hoping sequences, or cyclic prefixes which result in built-in periodicity. Even though the data is a wide-sense stationary random process, these modulated signals are characterized as cyclostationary, since their statistics, mean and autocorrelation, exhibit periodicity. This periodicity is introduced intentionally in the signal format so that a receiver can exploit for estimation such as carrier phase and pulse timing [13].

$$R_x\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)=R_x\left(t+T_0+\frac{\tau}{2},t+T_0-\frac{\tau}{2}\right) \tag{3}$$

for some period $T_0 \neq 0$ where

$$R_x\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)=E\left\{x(t+\frac{\tau}{2})x(t-\frac{\tau}{2})\right\} \tag{4}$$

Where E[.] is expectation operation. Since R_x is periodic, it can be represented as a Fourier series as

$$R_x\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)= \sum_\alpha R_x^\alpha(\tau)e^{j2\pi\alpha t} \tag{5}$$

Where the sum over α includes all integer multiples of the reciprocal of the fundamental period T_0. The Fourier coefficient $R_x^\alpha(\tau)$ also known as cyclic autocorrelation is given by

$$R_x^\alpha(\tau)=\frac{1}{T0}\int_{-T0/2}^{T0/2}R_x\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)e^{-j2\pi\alpha t}dt \tag{6}$$

Cyclostationary signals exhibit correlation between widely separated spectral components due to spectral redundancy caused by periodicity. The Fourier transform of the cyclic autocorrelation is spectral correlation function and is given by,

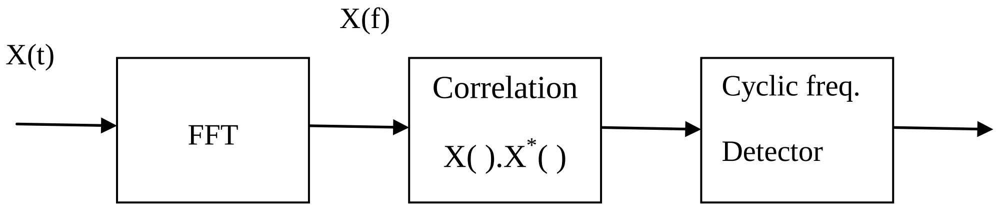

Figure 3.1 Block diagram of cyclostationary detection

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-j2\pi f\tau}\, d\tau \qquad (7)$$

Unlike power spectrum density, which is real-valued one dimensional transform, the spectral correlation function in (7) is a two dimensional transform. In general it is complex-valued and the parameter α is called cycle frequency. Power spectral density is a special case of a spectral correlation function for α = 0. Different types of modulated signals (such as BPSK, QPSK, SQPSK) that have identical power spectral density functions can have highly distinct spectral correlation functions. Furthermore, stationary noise and interference exhibit no spectral correlation.

Given N samples, the spectral correlation function $S_x^{\alpha}(f)$ (SCF) is estimated as [14]

$$S_x^{\alpha}(f) = \frac{1}{N}\sum_{n=1}^{N} X_L(n, k + \frac{k_\alpha}{2}) X_L^*(n, f - \frac{k_\alpha}{2}) \qquad (8)$$

$$\text{where } X_L(n,k) = \frac{1}{\sqrt{L}} \sum_{l=n-\frac{L}{2}}^{n+\frac{L}{2}-1} x(l) e^{-\frac{j2\pi kl}{L}} \qquad (9)$$

is the *L*-point discrete Fourier transform (DFT) around the *n*th sample of the received signal, and $k_\alpha = \alpha\, L/Fs$ is the index of the frequency bin corresponding to the cyclic frequency α. The SCF of received signal is then correlated with the SCF of the signal (known priori) and then compared to a threshold to detect if the primary signal is present.

3.1.2 Wavelet detection

For signal detection over wideband channels, the wavelet approach offers advantages in terms of both implementation cost and flexibility in adapting to the dynamic spectrum as opposed to conventional use of multiple narrowband band pass filters

(BPF)[15]. Unlike the Fourier transform, using sine's and cosines as basic functions, the wavelet transforms use irregularly shaped wavelets as basic functions and thus offer better tools to represent sharp changes and local features. In order to identify the locations of vacant frequency bands, the entire wide-band is modeled as a train of consecutive frequency sub bands where the power spectral characteristic is smooth within each sub band but changes abruptly on the border of two neighboring sub bands. By employing a wavelet transform of the power spectral density (PSD) of the observed signal x(t), the singularities of the PSD can be located and thus the vacant frequency bands can be found. One critical challenge of implementing the wavelet approach in practice is the high sampling rates for characterizing the large bandwidth.

3.1.3 Covariance detection

Since the statistical covariance matrices or autocorrelations of the signal and noise are generally different, covariance-based signal detection methods can be used for spectrum sensing By observing the fact that off diagonal elements of the covariance matrix of the received signal are zero when the primary user signal is not present and nonzero when it is present, two detection methods are possible: covariance absolute value detection and covariance Frobenius norm detection. The methods can be used for various signal detection and applications without knowledge of the signal, channel, and noise power. The received signal samples under the two hypotheses are therefore respectively as follows [16]

$$\begin{aligned} H0 &: x(n) = \eta(n) \\ H1 &: x(n) = s(n) + \eta(n) \end{aligned} \tag{10}$$

Let f(k), k = 0, 1, · · · ,K be normalized bandpass filter applied to the signal. Let $x'(n) = x(n)*f(n)$,$s'(n) = s(n)*f(n)$ and $\eta'(n) = \eta(n)*f(n)$. Then,

$$\begin{aligned} H0 &: x'(n) = \eta'(n) \\ H1 &: x'(n) = s'(n) + \eta'(n) \end{aligned} \tag{11}$$

Consider L samples and let

$$\mathbf{X}(n) = [x'(n), x'(n-1), \ldots\ldots x'(n-L+1)]^T$$
$$\mathbf{S}(n) = [s'(n), s'(n-1), \ldots\ldots s'(n-L+1)]^T$$
$$\boldsymbol{\eta}(n) = [\eta'(n), \eta'(n-1), \ldots\ldots \eta'(n-L+1)]^T$$

Define a L x (L+K) matrix

$$H = \begin{bmatrix} f(0) & f(1) & \cdots & f(K) & 0 & \cdots & 0 \\ 0 & f(0) & \cdots & f(K-1) & f(K) & \cdots & 0 \\ & \ddots & & & & \ddots & \\ 0 & 0 & \ldots & f(0) & f(1) & \ldots & 0 \end{bmatrix} \tag{12}$$

If $G = H(H^*)^H = Q^2$ then define $R'_x = Q^{-1} R_x Q^{-1}$.(R_x is the correlation matrix of x(n)). If there is no signal, then $R'_x = 0$. Hence the off diagonal elements of R'_x are all zeros. If there is signal and the signal samples are correlated, R'_x is not a diagonal matrix. Let r_{nm} be the elements of R'_x. Let

$$K_1 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}| \tag{13}$$

$$K_2 = \frac{1}{L}\sum_{n=1}^{L}|\, r_{nn}| \tag{14}$$

$$K_3 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}|^2 \tag{15}$$

$$K_4 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}|^2 \tag{16}$$

The primary signal is considered to be present if $K_1 > \gamma\ K_2$. Covariance absolute value (CAV) detection or if $K3 > \gamma K4$. Covariance Frobenius norm (CFN) detection where γ is an appropriate value based on P_f.

The spectrum sensing can also be done using max-min eigenvalue detection and max-eigenvalue detection methods. The essence of the eigen detection methods lies in the significant difference of the eigenvalue of the received signal covariance matrix when the primary user signal is present or not.

3.1.4 Matched filter detection

The coherent detector also referred to as a matched filter, can improve detection performance if the primary transmitted signal's, is deterministic and known a priori [14].

The matched filter correlates the known signal s(n) with the unknown received signal x(n), and the decision is made through

$$T(x) \triangleq \sum_{n=1}^{N} x(n)s^*(n) \underset{H0}{\overset{H1}{\gtrless}} \gamma \tag{17}$$

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

$$T(x) \sim \begin{cases} N(0, Np_s\sigma_v^2) & under\ H0 \\ N(Np_s, Np_s\sigma_v^2) & under\ H1 \end{cases} \tag{18}$$

The probabilities of false alarm and detection are now given by

$$P_f = Q\left[\frac{\gamma}{\sigma_v\sqrt{Np_s}}\right] \tag{19}$$

$$P_d = Q\left[\frac{\gamma - Np_s}{\sigma_v\sqrt{Np_s}}\right] \tag{20}$$

Where N is the number of samples and σ_v^2 is the noise variance p_s is the average primary signal power.

It is well known that the matched filter structure is the optimal detector that maximizes the SNR in the presence of additive noise if the transmitted signal, s, is known a priori. However, the matched filter is not suitable for spectrum sensing in very low SNR regions since synchronization is difficult to achieve.

3.1.5 Energy detection

To enhance the detection probability, many signal detection techniques such as matched filter, wavelet detection, cyclostationary detection and energy detection are there. Matched filter is the optimal detection technique which requires a prior knowledge of the primary user and has low computational cost. Wavelet detection is effective for wideband signal, does not work for spread spectrum signals demanding high computational cost. Cyclostationary detection requires partial information of the primary user requires high computational cost.

Energy detector is also known as radiometry and it is most common method of spectrum sensing because of its low computational and implementation complexities. Moreover, the cognitive user's receivers do not need any knowledge of the primary user's signal. The signal is detected by comparing the output of energy detector with threshold which depends on noise floor [17].

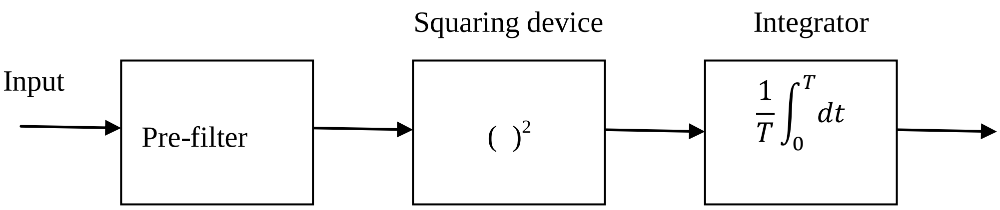

Figure 3. 2 Block diagram of energy detector in time domain

The binary hypotheses problem can be formulated by

$$X\ (N) = W\ (N) \qquad H_0(\text{absent})$$

$$= S\ (N) + W\ (N), \quad H_1(\text{present}) \qquad (21)$$

Where N is the number of samples, N=2TW, T is duration interval ,W is bandwidth, S (N) is the primary user's signal, W (N) is the noise and X (N) is the received signal. The noise is assumed to be additive white Gaussian noise (AWGN) with zero mean and is a random process. The signal to noise ratio is defined as the ratio of signal power to noise power

$$\gamma = P_s/N_0 \qquad (22)$$

where P_s and N_0 are the average power of signal and noise.

The decision parameter is as follows

$$\Delta = \frac{1}{N_0}\sum_0^{2TW}|X\ (N)|\text{^}2 \qquad (23)$$

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 detection and false alarm can be generally computed by [18]

$$P_f = \frac{\Gamma(N/2,\lambda/2)}{\Gamma(N/2)} \tag{24}$$

Where Γ (.,.) is the incomplete gamma function and Γ (.) is the complete gamma function

$$P_d = Q_{\frac{N}{2}}(\sqrt{2\gamma}, \sqrt{\lambda}) \tag{25}$$

Where $Q_{\frac{N}{2}}(\sqrt{a}, \sqrt{b})$ is generalized Marcum Q-function [19].

Simulation results

With a view to verify the hypothesis simulation was made. In the simulation study input random bit stream is multiplied by 1 MHz sinusoidal carrier signal to get 1 MHz BPSK modulated signal, which is transmitted in AWGN channel. The detection performance can be performed by varying the probability of false alarm from 0 to 1 and finding the probability of detection by using Monte Carlo simulation for each case, theoretically as shown in Figure 3.3. Here the number of sample points taken is N=2000(N=2TW) and SNR is -30dB.

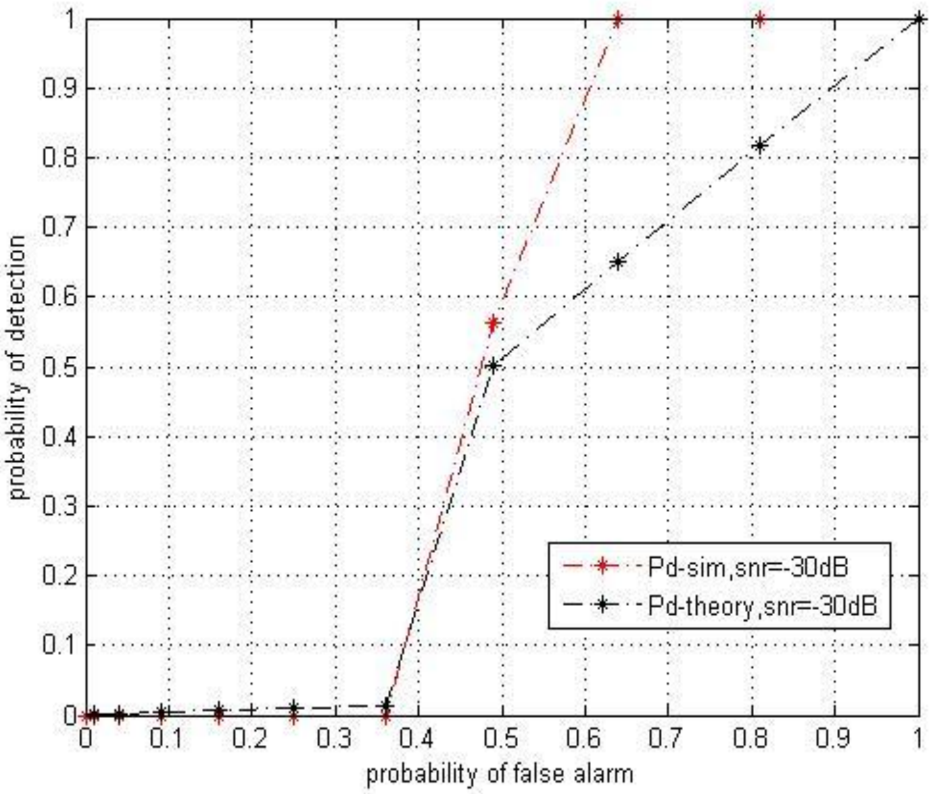

Figure 3.3 The graph of probability of detection Vs probability of false alarm

The graph probability of false alarm on X-axis and probability of detection on Y-axis as shown in Figure 3.4. Here we have taken probability of false alarm is (0,1), N=2000 and the SNR at three different values -30dB ,-20dB,-10dB.from the figure it is observed that detection performance improved by increasing SNR value.

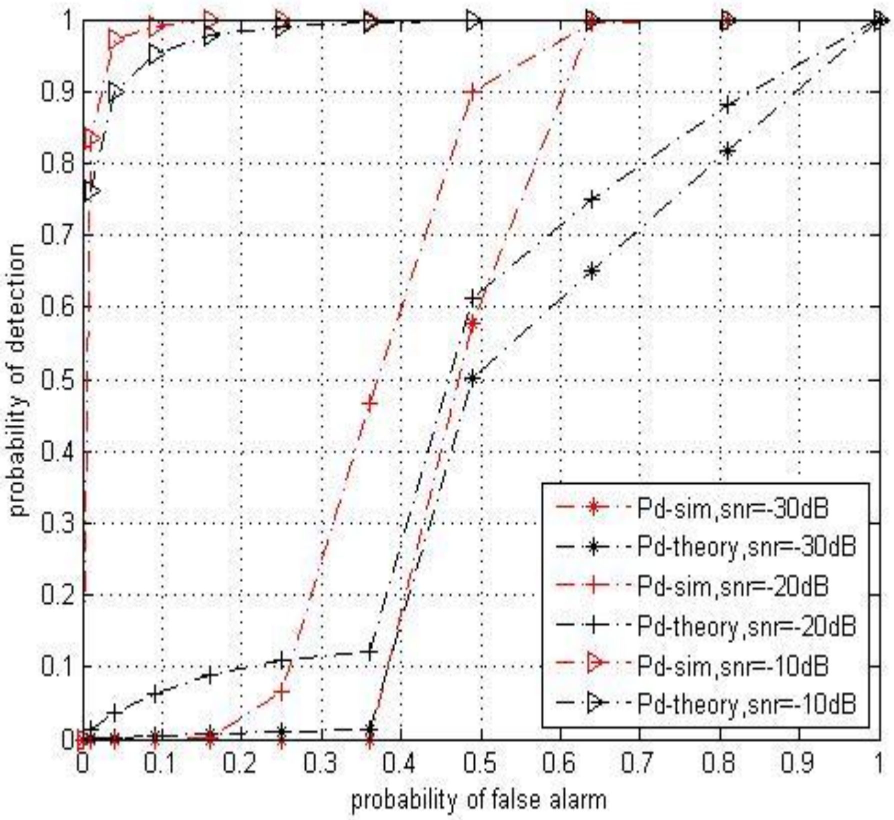

Figure 3.4 The graph of probability of detection Vs probability of false alarm for varying SNR

Next energy detection mechanism was analyzed. The graph of SNR values on X-axis and probability of detection on Y-axis shown in the Figure 3.5.The graph shows that simulation and theoretically values of probability of detection for different values of SNR curves. Here we have taken probability of false alarm is 0.1 and number of sample points N=2000.from the figure it is observed that performance is better at higher SNR values and the simulation and theoretical values matches at higher SNR values.

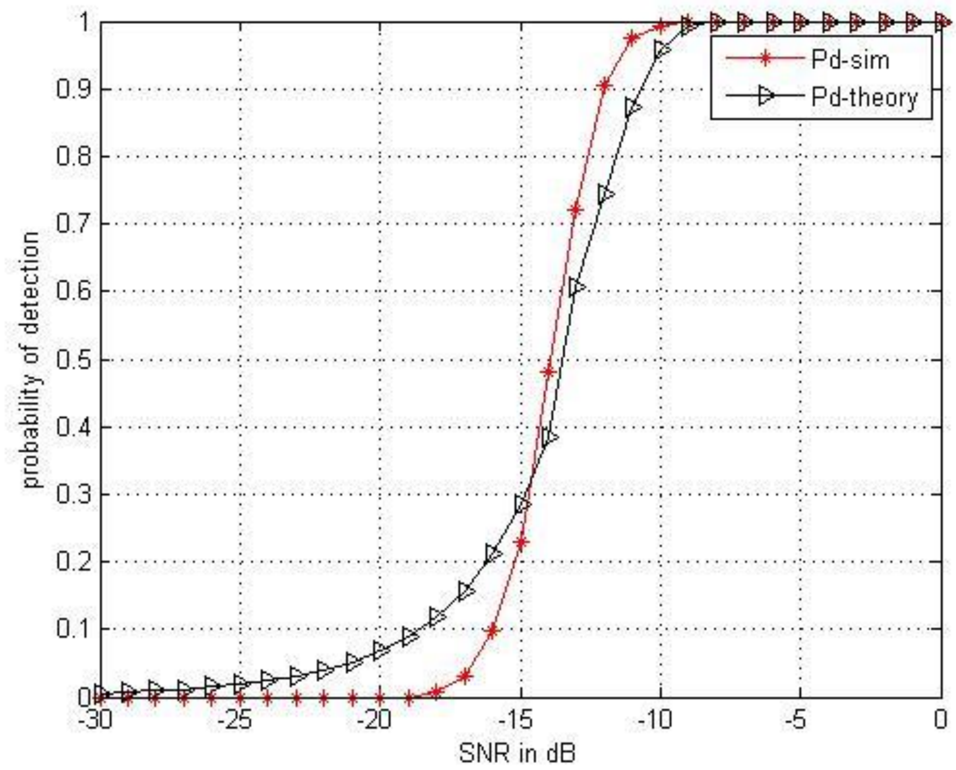

Figure 3.5 The graph of probability of detection Vs SNR Values

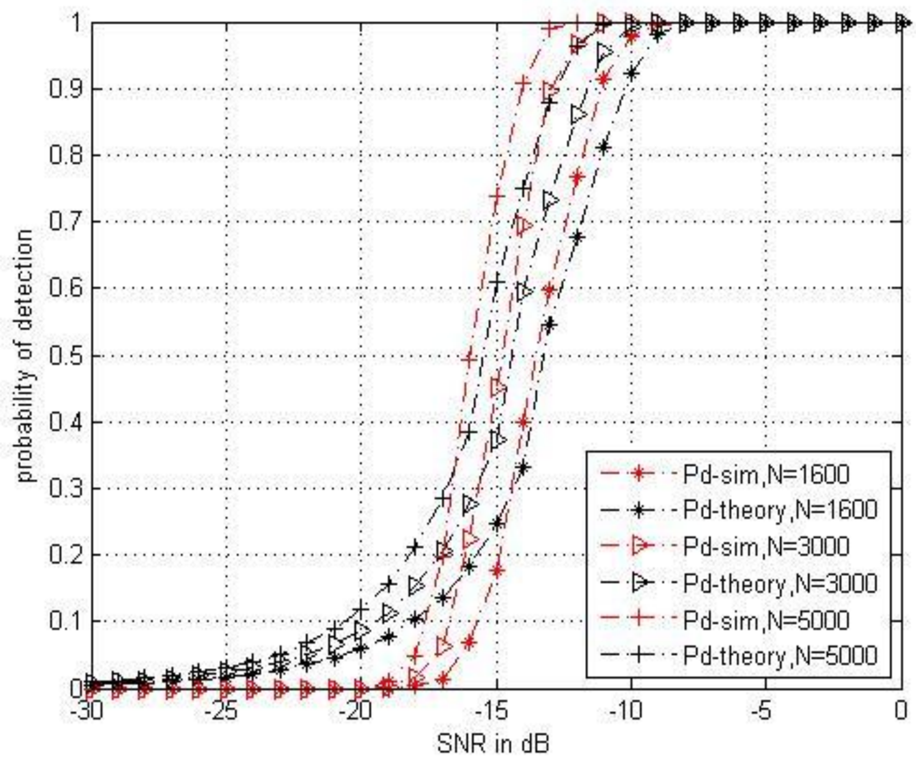

Figure 3.6 The graph of probability of detection Vs SNR Values by varying N values

The Figure 3.6 shows the graph of SNR values on X-axis and probability of detection on Y-axis for different number of sample points. Here the number of sample points taken as three different values N=1600, N=3000 and N=5000. It is observed that by increasing the number of sample points the detection performance can be improved at lower SNR values

CHAPTER 4

Dynamic threshold based spectrum detection in CR systems

In this chapter we formulate the problem of signal detection in additive noise and explain the spectrum detection schemes which include Energy detection and Matched filter detection. Noise uncertainty effects on spectrum detection performance of matched filter,[20] new algorithm applying dynamic threshold for anti-noise uncertainty and analyze noise uncertainty effects on energy detection and dynamic threshold in energy detection is also analyzed.

4.1Problem formulation

The problem of signal detection in additive noise can be formulated as a binary hypothesis testing problem with the following hypotheses

$$\mathrm{H0{:}\,Y(n) = W(n)} \qquad ,\mathrm{n} = 1,2,\dots\dots,\mathrm{N}$$

$$\mathrm{H1{:}\,Y(n) = X(n) + W(n)} \qquad ,\mathrm{n} = 1,2,\dots\dots,\mathrm{N} \qquad (1)$$

Where Y(n),X(n) and W(n) are the received signals at CR nodes, transmitted signals at primary nodes and white noise samples respectively. It is assumed that both signals and noise are independent each other. Noise samples W (n) are from a White Gaussian noise process with power spectral density σ_n^2 , i.e.W (n)~ N $(0, \sigma_n^2)$ and its statistics are completely known to the receiver.

4.2 Matched filter detection

When the signal X(n) is completely known to the receiver, the optimal detector is the matched filter detector or the correlation detector [22]. The decision model is

$$D(Y) = \frac{1}{N}\sum_{n=0}^{N-1} Y(n)X(n) > \gamma \quad H1$$

$$< \gamma \quad H0 \qquad (2)$$

Where D(Y) is the decision variable and γ is the decision threshold, N is the number of samples. If the noise variance is completely known, from the central limit theorem the following approximations can be made [22]

$$D(Y|H0) \sim N(0, P\sigma_n^2/N)$$

$$D(Y|H1) \sim N(0, P\sigma_n^2/N) \tag{3}$$

Where P is the average signal power and σ_n^2 is the noise variance. Using these approximations

The following probability expressions are

$$\mathrm{P_{FA}} = \mathrm{P_r}(\mathrm{D(Y/H0)} > \gamma = \mathrm{Q}(\frac{\gamma}{\sqrt{\mathrm{p}\sigma_\mathrm{n}^2/\mathrm{N}}}) \tag{4}$$

$$\mathrm{P_D} = 1 - \mathrm{P_{Md}} = \mathrm{Q}(\frac{\gamma - \mathrm{P}}{\sqrt{\mathrm{p}\sigma_\mathrm{n}^2/\mathrm{N}}}\ ) \tag{5}$$

Where Q(.) is the standard gaussian complementary cumulative distribution function and $Q^{-1}(.)$is the inverse standard gaussian complementary CDF.

From (4) and (5) eliminating threshold γ

From (4) we are getting

$$Q^{-1}\,(\mathrm{P_{FA}}) = \frac{\gamma}{\sqrt{\mathrm{p}\sigma_\mathrm{n}^2/\mathrm{N}}} \tag{6}$$

From (5) we are getting

$$Q^{-1}\,(\mathrm{P_D}) = \frac{\gamma - \mathrm{P}}{\sqrt{\mathrm{p}\sigma_\mathrm{n}^2/\mathrm{N}}} \tag{7}$$

Substituting (6) in (7) we are getting

$$\frac{P}{\sqrt{\mathrm{p}\sigma_\mathrm{n}^2/\mathrm{N}}} = Q^{-1}\,(\mathrm{P_{FA}}) - Q^{-1}\,(\mathrm{P_D})$$

With this

$$\mathrm{N} = [\,Q^{-1}\,(\mathrm{P_{FA}}) - \ Q^{-1}\,(\mathrm{P_D})]^2\,(\mathrm{SNR})^{-1} \tag{8}$$

Where $\mathrm{SNR} = \frac{\mathrm{P}}{\sigma_\mathrm{n}^2}$, σ_n^2 is the normalized noise power.

The Figure 4.1 shows the performance of matched filter detection at different SNR conditions (SNR=-20dB, SNR=-15dB and SNR=-10dB) for a given $P_{FA}(0,0.5)$, N=100. From the figure it is observed that the performance can be improved by increasing the SNR values.

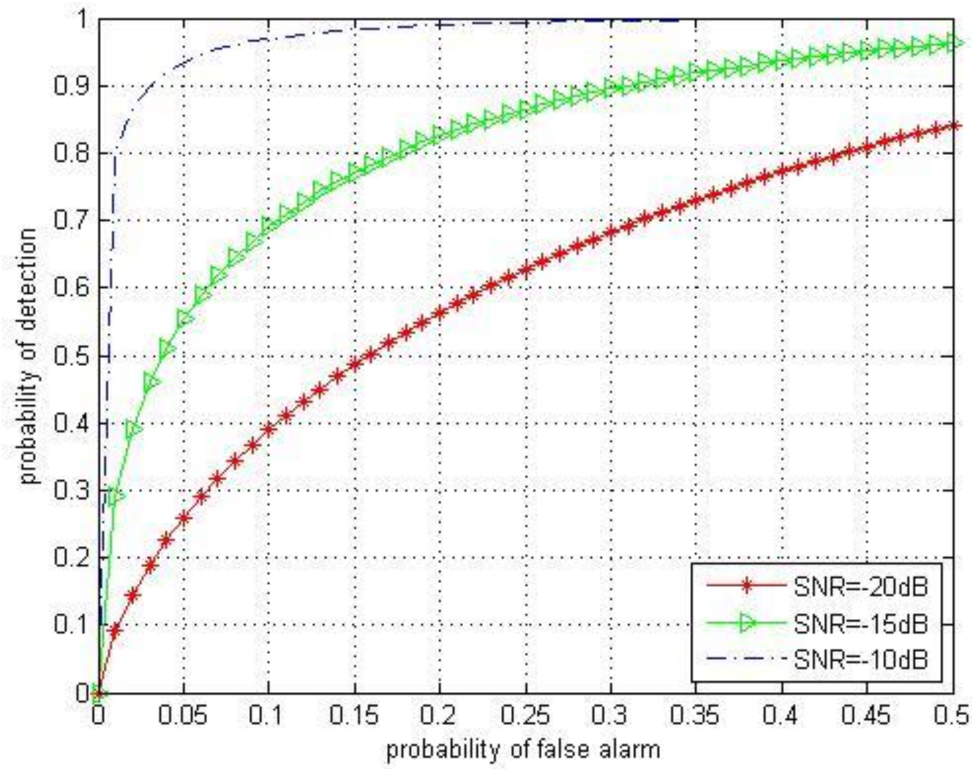

Figure 4.1 Matched filter detection by varying SNR

Figure 4.2 shows the performance of matched filter detection at different N values for a given $P_{FA}(0,0.5)$, SNR=-15dB. From the graph we observed that the performance can be improved by varying N value

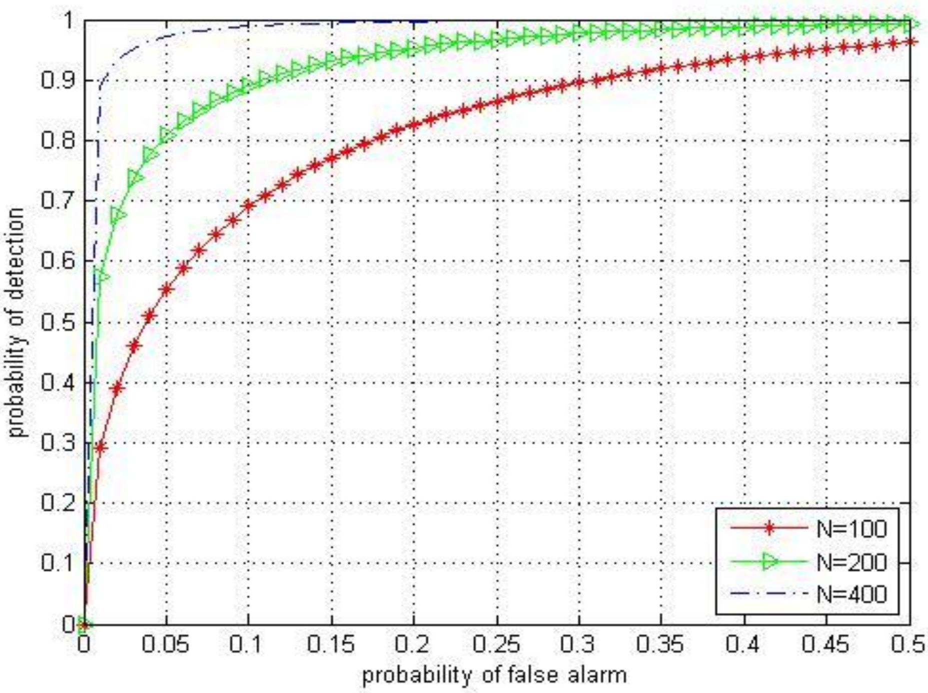

Figure 4.2 Matched filter detection by varying N

4.3 Matched filter detection based on dynamic threshold

4.3.1. Noise uncertainty

In the previous analysis it was assumed that there is no noise uncertainty, if there is uncertainty in the noise model [21] [20]. The distributional uncertainty of noise is in the interval

$$\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]$$

ρ as the noise uncertainty coefficient and $\rho > 1$. For probability of false alarm chosen maximum value in the above interval and for the probability of detection chosen minimum value. Now the probability equations are modified as [22]

$$P_{FA} = Q\left(\frac{\gamma}{\sqrt{\rho p \sigma_n^2/N}}\right) \tag{9}$$

$$P_D = Q\left(\frac{\gamma - P}{\sqrt{p\sigma_n^2/\rho N}}\right) \tag{10}$$

Eliminating threshold γ from (9) and (10)

From (9) we get

$$Q^{-1}\,(\mathrm{P_{FA}}) = \frac{\gamma}{\sqrt{\rho p \sigma_n^2/N}} \tag{11}$$

From (10) we get

$$Q^{-1}\,(\mathrm{P_D}) = \frac{\gamma - P}{\sqrt{p\sigma_n^2/\rho N}} \tag{12}$$

$$\mathrm{Q}^{-1}\,(\mathrm{P_D}) = \frac{\gamma\rho}{\sqrt{p\sigma_n^2/\rho N}} - (\sqrt{\mathrm{SNR}} \times \sqrt{\mathrm{N}} \times \sqrt{\rho}\,)$$

Substituting (11) in (12) we get

$$\mathrm{Q}^{-1}\,(\mathrm{P_D}) = \rho Q^{-1}\,(\mathrm{P_{FA}}) - (\sqrt{\mathrm{SNR}} \times \sqrt{\mathrm{N}} \times \sqrt{\rho})$$

With this

$$\mathrm{N} = \rho[\mathrm{Q}^{-1}(\mathrm{P_{FA}}) - (\mathrm{Q}^{-1}(\mathrm{P_D})/\rho)]^2(\mathrm{SNR})^{-1} \tag{13}$$

Figure 4.3 shows the response of probability of false alarm on X-axis and probability of detection on Y-axis for different values of uncertainties as shows in Here the probability of false alarm is varied from 0 to 1, N=150, SNR=-15dB.From the figure it is observed that as the noise uncertainty value increases the performance is slightly decreases.

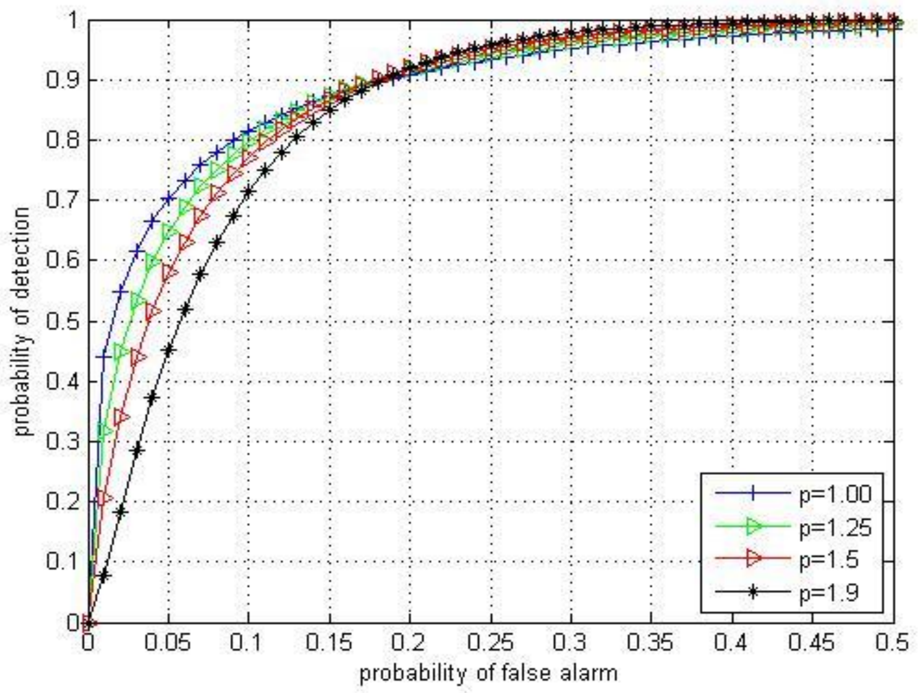

Figure 4.3 Matched filter detection by varying noise uncertainty values

4.3.2. Dynamic threshold

Assume that the dynamic threshold factor ρ' which is greater than one.

$$\rho' > 1$$

The distributional of dynamic threshold in the interval

$$\gamma' \in [\gamma/\rho', \rho'\gamma]$$

Then the probability equations are

$$P_{FA} = Q\left(\frac{\rho'\gamma}{\sqrt{\rho'\sigma_n^2/N}}\right) \tag{14}$$

$$P_D = Q\left(\frac{\frac{\gamma}{\rho} - P}{\sqrt{\frac{p\sigma_n^2}{N}}}\right) \tag{15}$$

From (14) and (15) Eliminating threshold γ ,with this we get the relationship of number of samples N, SNR, P_{FA} , P_D

$$N = [\,(\frac{Q^{-1}\,(P_{FA})}{\rho'^2}) - Q^{-1}\,(P_D)]^2\,(SNR)^{-1} \qquad (17)$$

4.3.3Noise uncertainty and dynamic threshold

Now considering noise uncertainty and dynamic threshold jointly

The noise variance is in the interval as follows

$$\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]$$

The threshold value is in the interval as follows

$$\gamma\,' \in [\,\gamma/\rho', \rho'\,\gamma]$$

Now the probability relationship can be modified as

$$P_{FA} = Q(\frac{\rho'\gamma}{\sqrt{\rho' P\sigma_n^2/N}}) \qquad (18)$$

$$P_D = Q(\frac{\frac{\gamma}{\rho'} - P}{\sqrt{p\sigma_n^2/N\rho}}\,) \qquad (19)$$

Removing the parameter γ ,we get

$$N = \frac{1}{\rho}\left[\frac{\rho}{\rho'^2}Q^{-1}(P_{FA}) - Q^{-1}(P_D)\right]^2 (SNR)^{-1} \qquad (20)$$

Figure 4.4.shows the performance of matched filter detection by various parameters for a given $P_{FA}(0,0.5)$, SNR=-15dB, N=150, noise uncertainty $\rho = 1.5$ and dynamic threshold factor $\rho' = 1.9$.From figure it is observed that with noise uncertainty the detection performance slightly decreases, in other words, matched filter detection scheme is sensitive to noise uncertainty at lower SNR values. By considering the dynamic threshold the performance is improved even in the case of noise uncertainty.

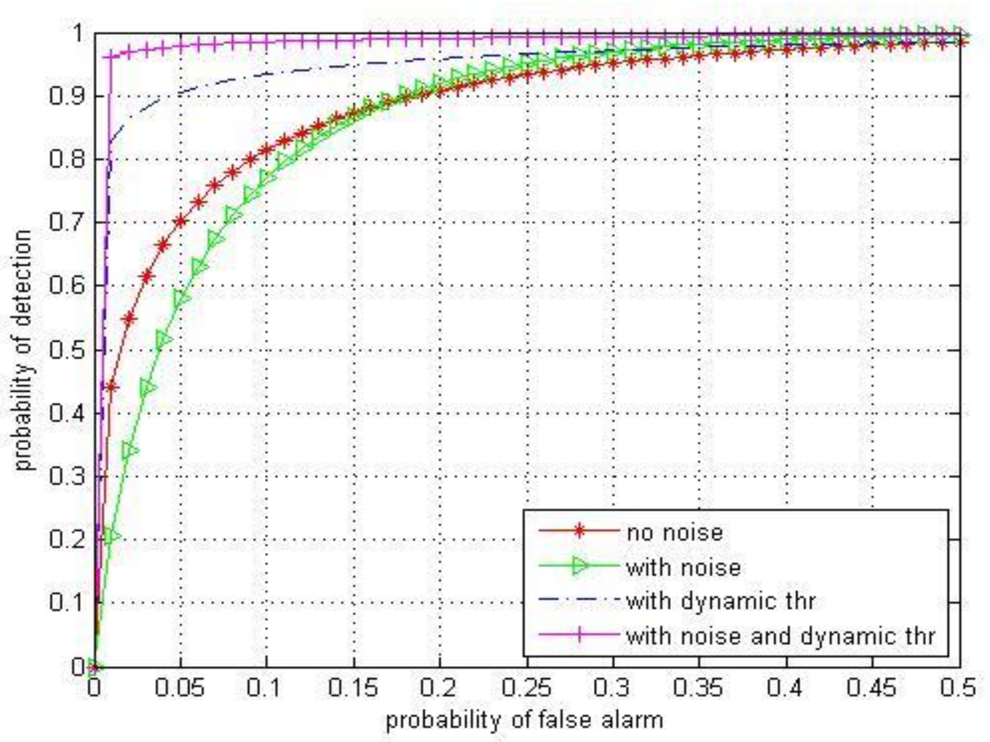

Figure 4.4 The performance of Matched Filter detection by various parameters

4.4 Energy detection

Under the assumption of absolutely no deterministic knowledge about the signal X(n), i.e., we assume that we know only the average power in the signal. In this case the optimal detector is energy detector or radiometer can be represented as [23]

$$D(Y) = \frac{1}{N}\sum_{n=0}^{N-1} Y(n)Y(n) \begin{array}{ll} > \gamma & H1 \\ < \gamma & H0 \end{array} \quad (21)$$

Where D(Y) is the decision variable and γ is the decision threshold, N is the number of samples. If the noise variance is completely known, then from the central limit theorem the following approximations can be made [24]

$$D(Y|H0) \sim N(\sigma_n^2, 2\sigma_n^4/N)$$

$$D(Y|H1) \sim N(P + \sigma_n^2, 2(P+\sigma_n^2)^2/N) \quad (22)$$

The probability expressions are

$$P_{FA} = P_r(D(Y/H0) > \gamma = Q(\frac{\gamma-\sigma_n^2}{\sqrt{2\sigma_n^4/N}}) \tag{23}$$

$$P_D = Q(\frac{\gamma-(P+\sigma_n^2)}{\sqrt{2(P+\sigma_n^2)^2/N)}}) \tag{24}$$

Where Q(.) is the standard gaussian complementary cumulative distribution function and $Q^{-1}(.)$ is the inverse standard gaussian complementary CDF.

From (23) and (24) eliminating threshold γ

From (23)

$$Q^{-1}(P_{FA}) = \frac{\gamma-\sigma_n^2}{\sqrt{2\sigma_n^4/N}} \tag{25}$$

From (24)

$$Q^{-1}(P_D) = \frac{\gamma-(P+\sigma_n^2)}{\sqrt{2(P+\sigma_n^2)^2/N)}} \tag{26}$$

Substituting (25) in(26) we get

$$\sqrt{\frac{2}{N}}\ (P+\sigma_n^2)\ * Q^{-1}(P_D) = \left(\sqrt{\frac{2}{N}}\sigma_n^2\ * Q^{-1}(P_{FA})\right) -\ p$$

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

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

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

With this we get the relationship for N, SNR, $\mathrm{P_{FA}}$ and $\mathrm{P_D}$

$$\mathrm{N} = 2[\,Q^{-1}(\mathrm{P_{FA}}) - Q^{-1}(\mathrm{P_D})]^2\,(\mathrm{SNR})^{-2} \tag{27}$$

Figure 4.5 shows the numerical results of (27) for given $\mathrm{P_{FA}}(0,0.9)$, sample number N=500, with different SNR values with that the performance is improved by increasing SNR value

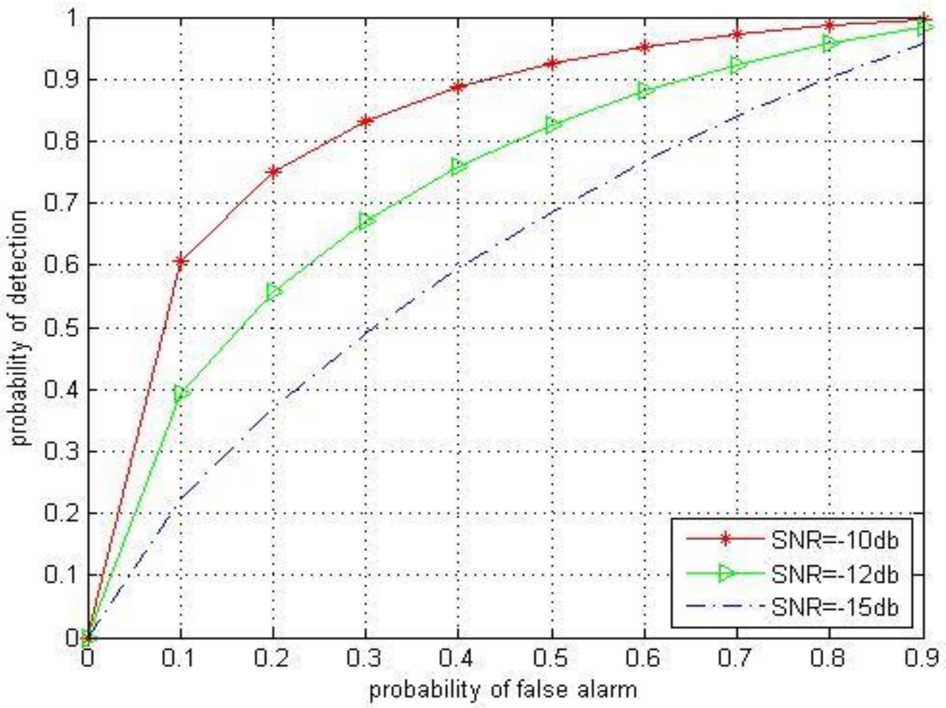

Figure 4.5 ROC curves of energy detection scheme with different SNR

Figure 4.6 is the numerical results of (27) for given$\mathrm{P_{FA}} \in (0,0.9)$, SNR=-15dB. It shows that the performance is improved by increasing N, and probability of detection can be improved by increasing N value even if the SNR is much lower, as long as N is large enough without noise uncertainty.

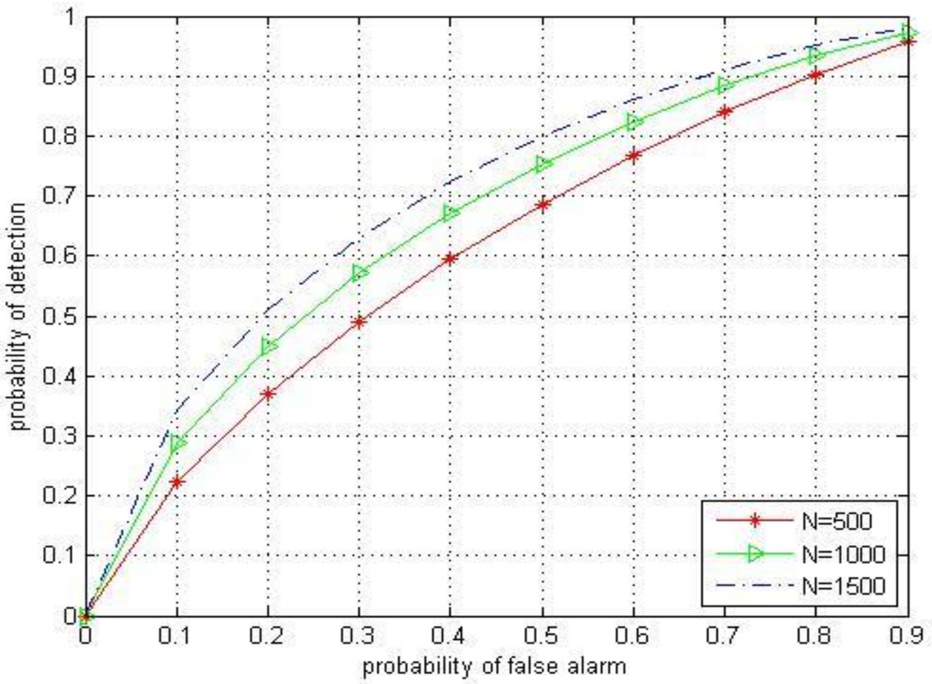

Figure 4.6 ROC curves of energy detection scheme with different N

4.5 Energy Detection Based On Dynamic Threshold

4.5.1Noise uncertainty

We have discussed and analyzed the case of no noise uncertainty. Now, considering the case with uncertainty in the noise model [20], the distributional uncertainty of noise can be represented as

$$\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]$$

ρ is the noise uncertainty coefficient and $\rho > 1$

Now (23) and (24) are modified as

$$P_{FA} = Q\left(\frac{\gamma - \rho\sigma_n^2}{\sigma_n^2\rho\sqrt{2/N}}\right) \tag{28}$$

$$P_D = Q\left(\frac{\gamma - (P + \sigma_n^2/\rho)}{(P + \sigma_n^2/\rho)\sqrt{2/N}}\right) \tag{29}$$

From (28) and (29)

From (28) we get

$$Q^{-1}(P_{FA}) = \frac{\gamma - \rho\sigma_n^2}{\sqrt{2/N}\,\sigma_n^2\rho} \tag{30}$$

From (29) we get

$$Q^{-1}(P_D) = \frac{\gamma - (P + \sigma_n^2/\rho)}{\sqrt{2/N}(P + \sigma_n^2/\rho)} \tag{31}$$

$$Q^{-1}(P_D) = \frac{\gamma}{\sqrt{2/N}(P + \sigma_n^2/\rho)} - \frac{1}{\sqrt{2/N}} \tag{32}$$

$$Q^{-1}(P_{FA}) = \frac{\gamma}{\sqrt{2/N}\,\sigma_n^2\rho} - \frac{1}{\sqrt{2/N}} \tag{33}$$

Substituting (32) in (33) we get

$$(\frac{1}{\rho} + \mathrm{SNR})\times\left(\sqrt{\frac{N}{2}} + Q^{-1}(P_D)\right) = \frac{\gamma}{\sqrt{2/N}\,\sigma_n^2}$$

$$\rho \times \left(\sqrt{\frac{N}{2}} + Q^{-1}(P_{FA})\right) = \frac{\gamma}{\sqrt{2/N}\,\sigma_n^2}$$

$$(\frac{1}{\rho} + \mathrm{SNR})\times\left(\sqrt{\frac{N}{2}} + Q^{-1}(P_D)\right) = \rho \times \left(\sqrt{\frac{N}{2}} + Q^{-1}(P_{FA})\right)$$

$$\sqrt{\frac{N}{2}}\left(\mathrm{SNR} - \left(\rho - \frac{1}{\rho}\right)\right) = \rho(Q^{-1}(P_{FA}) - (\frac{1}{\rho} + \mathrm{SNR})\,Q^{-1}(P_D)$$

With this we get

$$N = 2[\rho Q^{-1}(P_{FA}) - (1/\rho + \mathrm{SNR})Q^{-1}(P_D)]^2 \times (\,\mathrm{SNR} - (\rho - 1/\rho))^{-2} \tag{34}$$

Figure 4.7 represents the numerical results of (34) for a given SNR=-15dB, $P_{FA} \in (0,0.9)$ and N=1500.

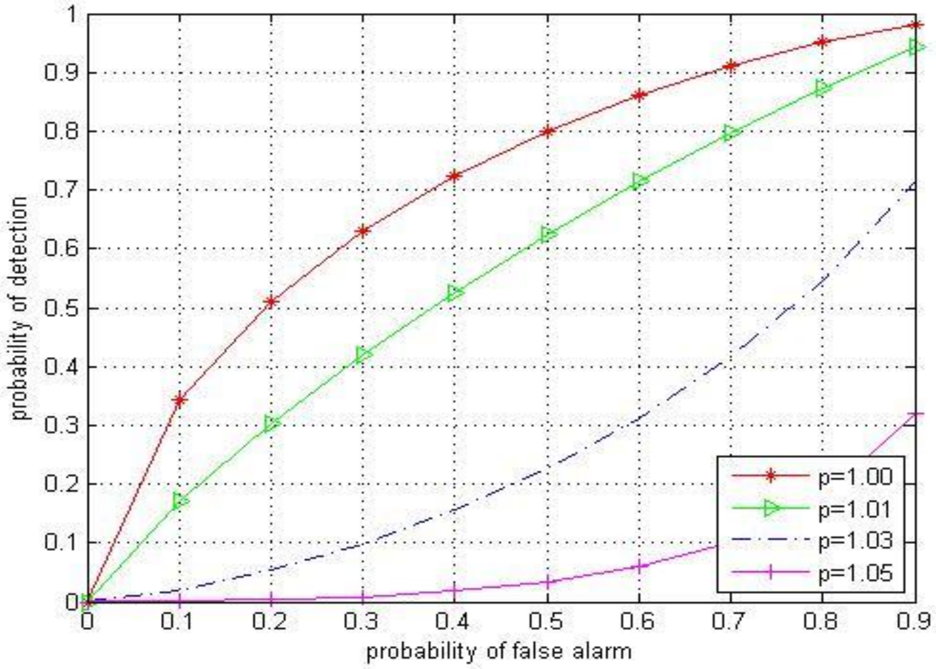

Figure 4.7 ROC curves of energy detection scheme with different noise uncertainty

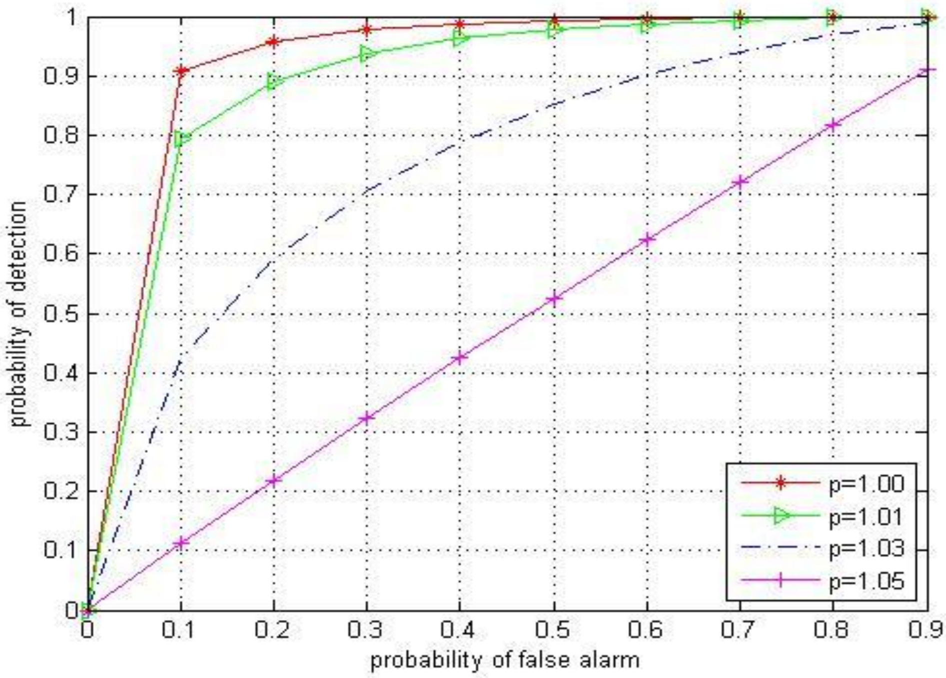

Figure 4.8 ROC Curves of Energy detection scheme with different noise uncertainty at SNR=-10dB

Figure 4.8 shows the numerical results of (34) probability of false alarm on X-axis and probability of detection on Y-axis for a given SNR=-10dB, $P_{FA} \in (0,0.9)$ and N=1500.

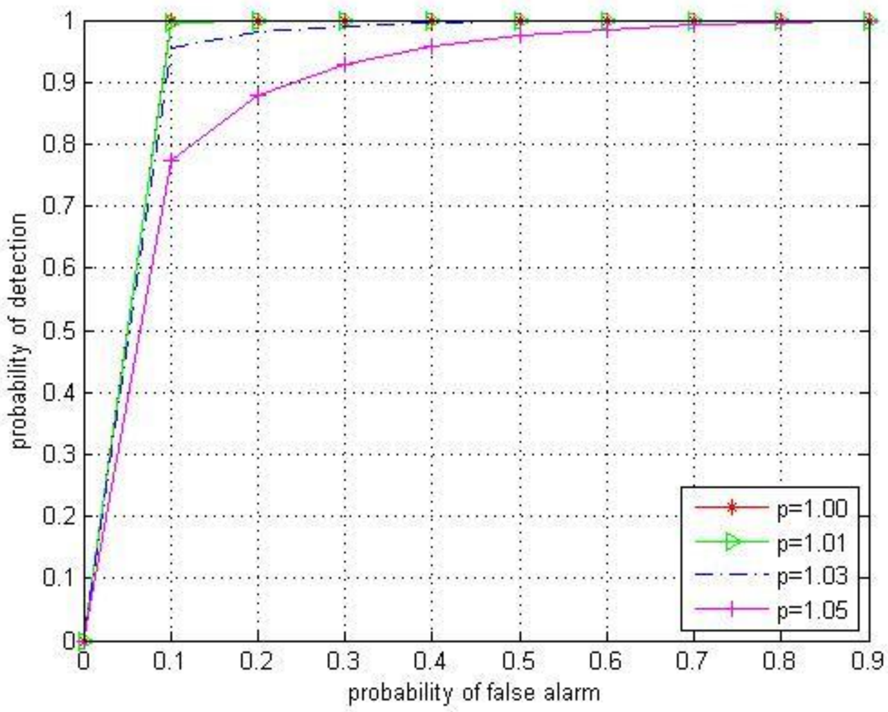

Figure 4.9 ROC Curves of Energy detection scheme with different noise uncertainty at SNR=-7.5dB

Figure 4.9 shows the numerical results of (34) probability of false alarm on X-axis and probability of detection on Y-axis for a given SNR=-7.5dB, $P_{FA} \in (0,0.9)$ and N=1500. It is observed that the performance is decreases by increasing the noise factor.

The following Figure 4.10 shows the numerical result of (34) probability of false alarm on X-axis and probability of detection on Y-axis for an SNR=-15dB, $P_{FA} \in (0,0.9)$. Here we are decreasing the number of samples (N=1000) and varying the noise uncertainty value.

Figure 4.11 shows the numerical result of (34) probability of false alarm on X-axis and probability of detection on Y-axis for an SNR=-15dB, $P_{FA} \in (0,0.9)$, N=500 and varying the noise uncertainty value.

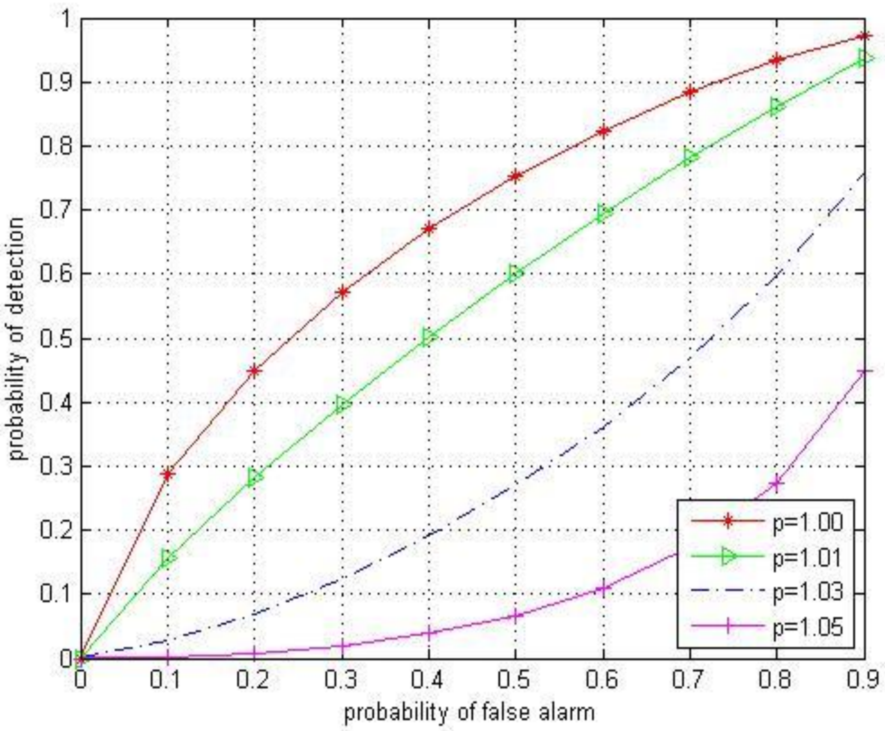

Figure 4.10 ROC Curves of Energy detection scheme with different noise uncertainty at N=1000

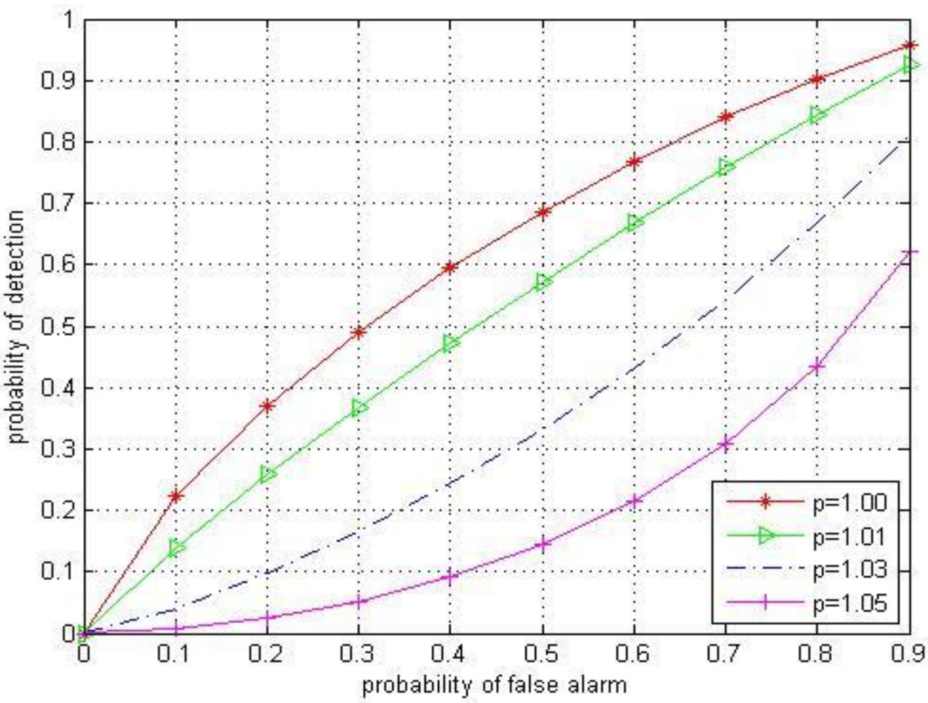

Figure 4.11 ROC Curves of Energy detection scheme with different noise uncertainty at N=500

From the above Figures it is seen that the performance gradually drops as the noise factor increasing .This indicates that Energy detector is very sensitive to noise uncertainty. It means that cognitive users predict the spectrum to be idle no matter whether there are primary users present or absent. Consequently, cognitive users are harmful to licensed users when primary users are present. This situation often occurs in cognitive radio systems, particularly in lower signal-to-noise ratio environments. In order to guarantee a good performance, choosing a suitable threshold is very important. Traditional energy detection algorithms are based on fixed threshold and we have verified that performance decreased under noise uncertainty environments. This indicates that the choice of a fixed threshold is no longer valid under noise uncertainty and threshold should be chosen flexible based on the necessities.

4.5.2Dynamic threshold

Performance of cognitive radio declined sharply due to noise uncertainty and cognitive users' accessing will be serious interference to licensed users. This should be avoided in dynamic spectrum access technology. For this reason, a new algorithm combating the noise uncertainty is presented [21][20].

Assume that the dynamic threshold factor ρ' and $\rho' > 1$ the distributional of dynamic threshold in the interval $\gamma\,' \in [\,\gamma/\rho', \rho'\,\gamma]$

Then the probability relationships are represented as

$$P_{FA} = \quad Q\left(\frac{\rho'\gamma - \sigma_n^2}{\sigma_n^2\sqrt{2/N}}\right) \tag{35}$$

$$P_D \quad = \quad Q\left(\frac{\gamma-(P+\sigma_n^2)}{(P+\sigma_n^2)\sqrt{\frac{2}{N}}}\right) \tag{36}$$

After simplifying (29) and (30) we get the relationship for SNR, N, ρ', P_{FA} and P_D

$$N = 2[Q^{-1}(P_{FA}) - \rho'^2(1 + SNR)Q^{-1}(P_D)]^2 \times \ (\,\rho'^2 SNR + (\rho'^2 - 1))^{-2} \tag{37}$$

Figure 4.12 shows the performance of energy detection scheme, probability of false alarm on X-axis and probability of detection on Y-axis. Here we have taken a SNR=-15dB, $P_{FA} \in$ (0,0.9), N=1500, noise uncertainty1.02 and dynamic threshold1.001.It is observed that the performance is improved by using a dynamic threshold

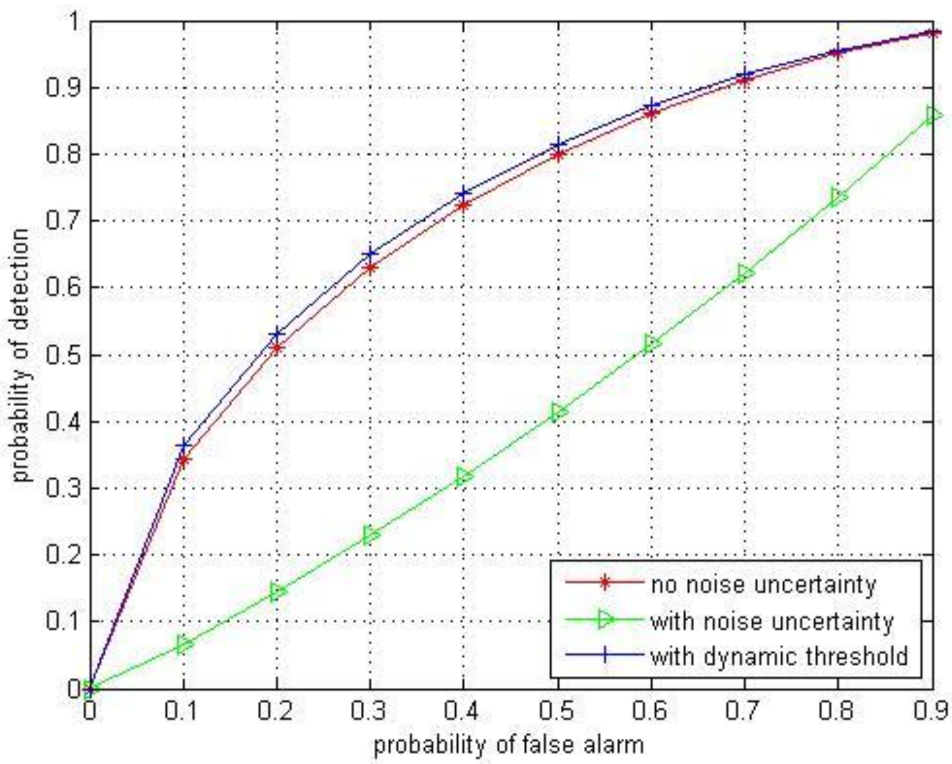

Figure 4.12 ROC curves of energy detection scheme with no noise uncertainty, with noise uncertainty, and with dynamic threshold

4.5.3Noise uncertainty and dynamic threshold

We have discussed two cases that existing noise uncertainty and dynamic threshold respectively, this section will give the expressions that considering noise uncertainty and dynamic threshold together, we got expressions of false alarm probability and detection probability

The noise variance in the interval

$$\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]$$

The threshold value in the interval

$$\gamma' \in [\gamma/\rho', \rho'\gamma]$$

Now the probability relations are represented as

$$P_{FA} = Q\left(\frac{\rho'\gamma - \rho\sigma_n^2}{\rho\sigma_n^2\sqrt{2/N}}\right) \tag{32}$$

$$P_D = Q\left(\frac{\frac{\gamma}{\rho'} - \left(P + \frac{\sigma_n^2}{\rho}\right)}{(P + \sigma_n^2/\rho\sqrt{\frac{2}{N}}}\right) \tag{33}$$

From (32) and (33) Eliminating threshold γ

From (32) we get

$$Q^{-1}(P_{FA}) = \frac{\rho'\gamma - \rho\sigma_n^2}{\sqrt{2/N}\,\sigma_n^2\rho} \qquad (34)$$

From (33) we get

$$Q^{-1}(P_D) = \frac{\frac{\gamma}{\rho'} - (P + \sigma_n^2/\rho)}{\sqrt{2/N}(P + \sigma_n^2/\rho)} \qquad (35)$$

$$Q^{-1}(P_D) = \frac{\gamma}{\sqrt{2/N}\ \sigma_n^2\rho'(SNR + 1/\rho)} - \frac{1}{\sqrt{2/N}} \qquad (36)$$

Substituting (34) in (36) we get

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

$$\left(\sqrt{\frac{N}{2}} + Q^{-1}(P_D)\right) \times \left(\frac{1}{\rho} + SNR\right) \times \rho' = \frac{\gamma}{\sqrt{2/N}\,\sigma_n^2}$$

$$\left(\sqrt{\frac{N}{2}} + Q^{-1}(P_{FA})\right) \times \frac{\rho}{\rho'} = \frac{\gamma}{\sqrt{2/N}\,\sigma_n^2}$$

$$\sqrt{\frac{N}{2}}\left(\rho' SNR + \frac{\rho'}{\rho} - \frac{\rho}{\rho'}\right) = \left[\frac{\rho}{\rho'}\left(Q^{-1}(P_{FA}) - \rho'\left(\frac{1}{\rho} + SNR\right) Q^{-1}(P_D)\right)\right] \qquad (37)$$

With this we get the inter relationship of SNR, N, ρ, ρ' , P_{FA} and P_D

$$N = 2\left[(\rho/\rho')(Q^{-1}(P_{FA}) - \rho'(1/\rho + SNR)Q^{-1}(P_D)\right]^2 \times (\rho' SNR + \rho'/\rho - \rho/\rho'))^{-2} \qquad (38)$$

Figure 4.13 shows the numerical result of (38) probability of false alarm on X-axis and probability of detection on Y-axis for an SNR=-15dB, $P_{FA} \in (0, 0.9)$, N=1500 and varying the dynamic threshold value.

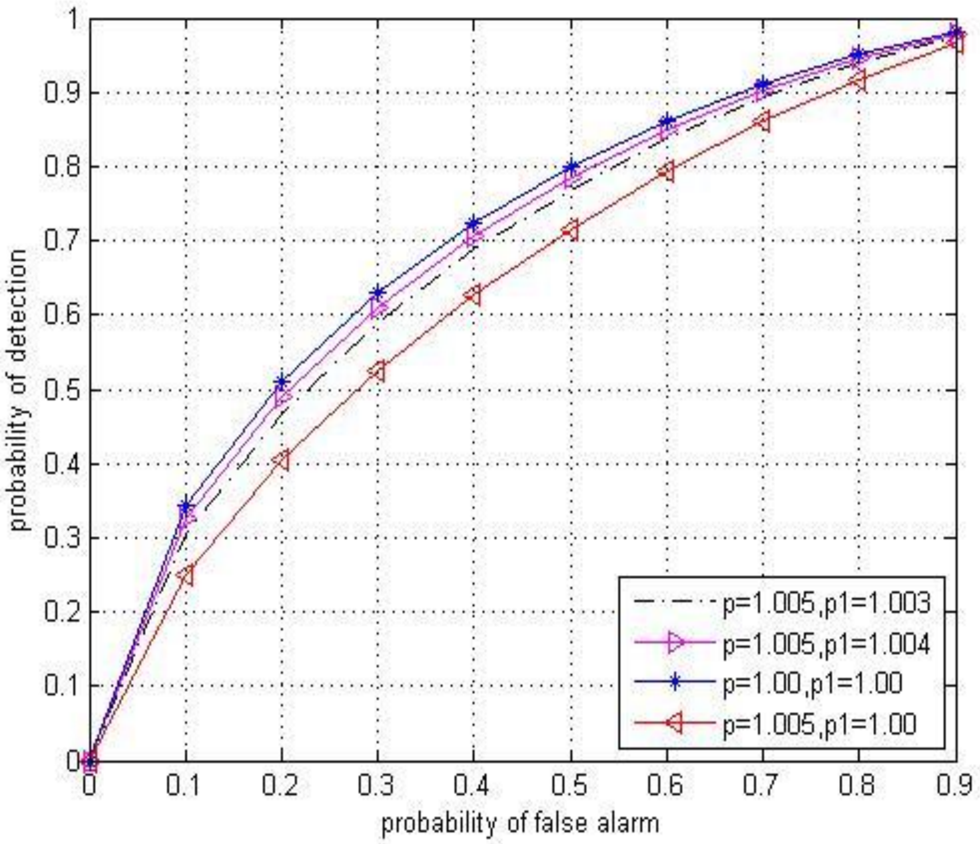

Figure 4.13 ROC curves of energy detection scheme with different noise uncertainty and dynamic threshold

In the Figure 4.14, where ρ = 1.00 denotes that the average noise power keeps constant (without noise uncertainty); ρ'= 1.00 denotes that the algorithm did not use dynamic threshold (the threshold is fixed); otherwise, it represents cases with noise uncertainty and dynamic threshold. Here we have taken SNR=-15dB, N=1500, P_{FA} is varied from 0 to 1.From Figure 4.14, it indicates that a tiny fluctuation of average noise power causes a sharp decline in detection performance. The dynamic threshold improves the performance improve significantly as the dynamic threshold factor increasing. If a suitable dynamic threshold factor is selected, the falling proportion of performance caused by noise uncertainty can be omitted and the performance may be more accurate.

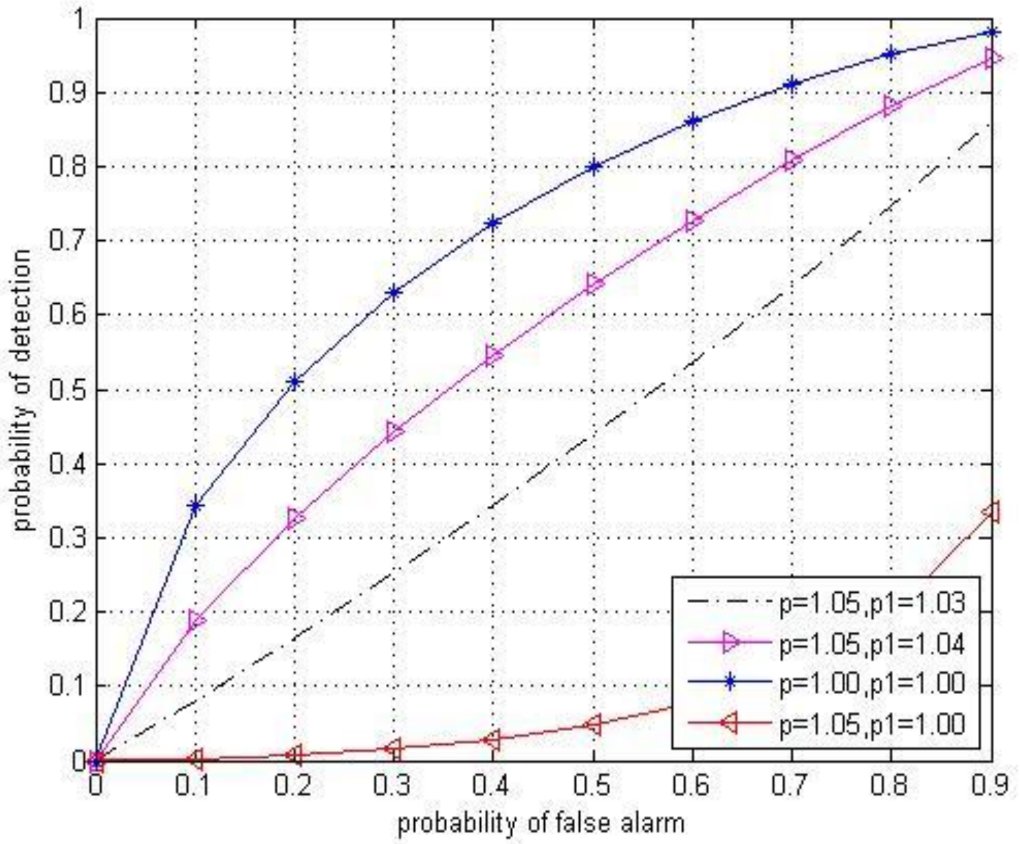

Figure 4.14 ROC curves of energy detection scheme with different noise uncertainty and dynamic threshold

Figure 4.15 shows the numerical result of (38) probability of false alarm on X-axis and probability of detection on Y-axis for an SNR=-15dB, $P_{FA} \in (0,0.9)$, N=1000 and varying the dynamic threshold value.

Consequently, detection duration *N* has been shortened largely to N= 500 with the same probability parameters PD and PFA as shown in Figure 4.16. It can be concluded that as long as the dynamic threshold factor is suitable, even if there is noise uncertainty, we can get a better spectrum performance. To attaining the same performance, the detection time of dynamic threshold energy detection Algorithm is less than the traditional version.

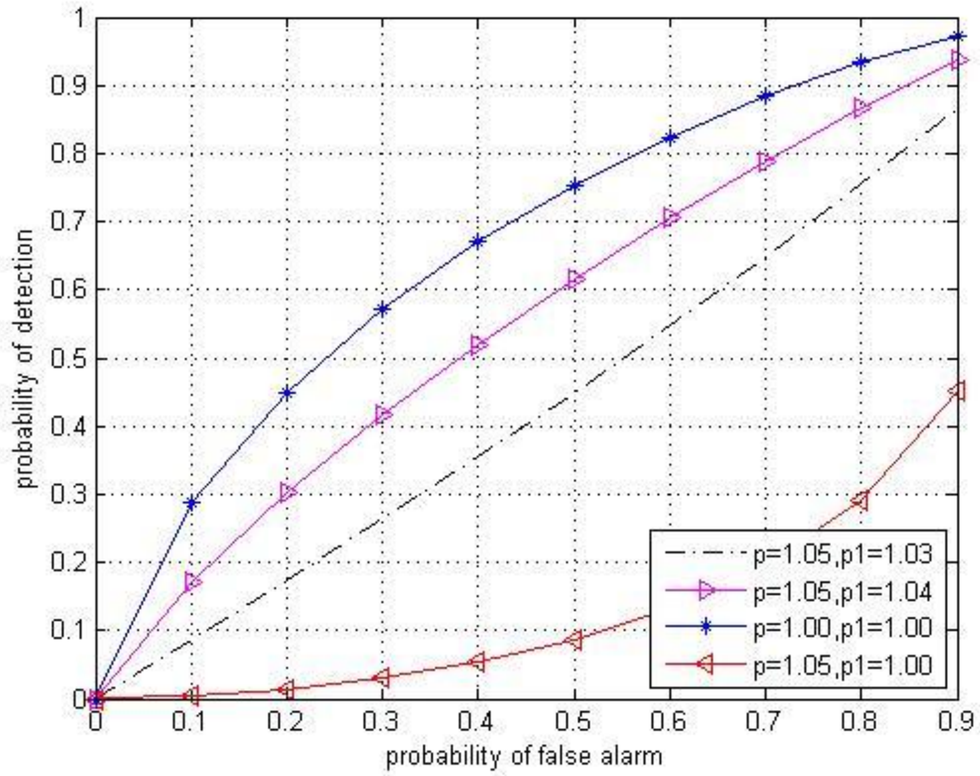

Figure 4.15 ROC curves of energy detection scheme with N=1000, different noise uncertainty and dynamic threshold

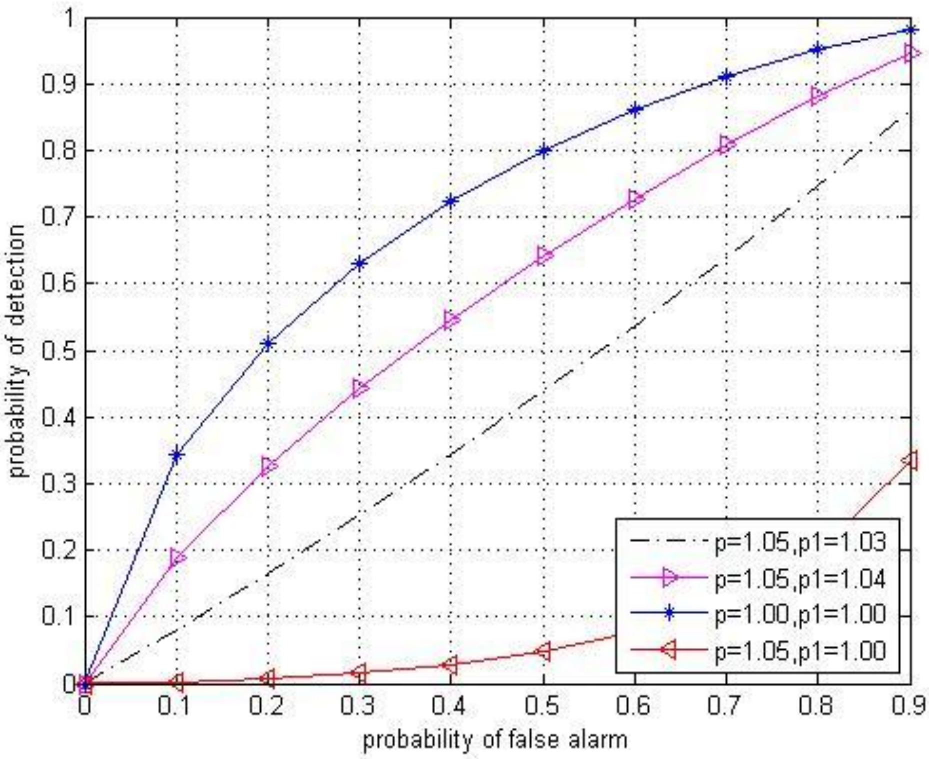

Figure 4.16 ROC curves of energy detection scheme with N=500, different noise uncertainty and dynamic threshold

CHAPTER 5

Conclusion

5.1 Introduction

Thesis studies the performance of energy detector spectrum sensing algorithm and the effect of dynamic threshold on the performance of detection techniques. Thesis explores various types of spectrum sensing techniques and discusses the effect of noise uncertainty, noise uncertainty and dynamic threshold on energy detection algorithm. This chapter discusses the contribution of thesis and scope for future work.

5.2 Contribution of the Thesis

The main purpose of the thesis was to study the performance of energy detection algorithm for spectrum sensing in cognitive radio by drawing the curves between probability of false alarm vs. probability of detection, SNR vs. probability of detection and the performance of dynamic threshold on spectrum detection techniques(Matched filter detection, Energy detection) in cognitive radio systems. As discussed in chapter2 the future of wireless communications will be characterized by highly varying environments with multiple available radio access technologies exhibiting diverse features. So cognitive radio is a paradigm for new wireless communications to meet their standards. Chapter3 discussed that the energy detector performance can be improved by increasing the SNR values and by increasing the number of sample points the detection performance is much better even at lower SNR values. From the graphs it is observed that the simulation results nearly matches with the theoretical values.Chapter4 discussed that the detection performance can be improved by using dynamic threshold based spectrum detection algorithm in cognitive radio systems. Energy detection based on fixed threshold are sensitive to noise uncertainty, a fractional change of average noise power causes decreasing the performance quickly. Matched filter which not sensitive to noise uncertainty, by using dynamic threshold the performance can be improved as compared with the fixed threshold.

5.3 Scope for Future work

The computer simulations of the dynamic threshold based energy detection algorithm in cognitive radio improve the detection performance but in practical how acquire the detection threshold and how to improve the detection performance by other sensing methods.

5.4 limitations

This Thesis is prepared as an extraction of one year research work, which is a part of Master Degree curriculum.

All the simulation results are computer based simulations, which are simulated in MatlabR2009a and are not verified in real environment. For simulation purpose it has been assumed that input is random bit stream, which will be converted into a BPSK signal which is modulated with a 1 MHz sinusoidal signal, not considering any real time captured signals.

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