SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

By

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ABSTRACT

Recent research shows that more than 70% of the available spectrum is not utilized efficiently. The bandwidth becomes expensive due to a shortage of frequencies. Therefore for efficient utilization of spectrum, we need to sniff the spectrum to determine whether it is being used by primary user or not.

The term cognitive radio refers to the adoption of radio parameters using the sensed information of the spectrum. There are various spectrum sensing techniques proposed in the literature but still there is room for researchers in this field to explore more sophisticated approaches. There are three major categories of spectrum sensing techniques; transmitter detection, receiver detection and interference temperature detection. This thesis presents a survey of techniques suggested in the literature for spectrum sensing with a performance analysis of transmitter-based detection techniques.

An algorithm for minimizing sensing time has been proposed in which under high SNR values we can minimize sensing time. Its results are also reliable in comparison with other transmitter detection techniques.

A Fuzzy based technique for primary user detection has also been proposed. In comparison with transmitter detection techniques Fuzzy based detection provides good results under low SNR values at the cost of increased in computation time.

All simulations are done in MATLAB.

DEDICATION

I would like to dedicate this thesis to my family, teachers and friends.

ACKNOWLEDGMENTS

First of all, I am thankful to almighty Allah who has given me the strength and courage to work on the thesis. My special thanks to my supervisor Dr. Shoab Ahmed Khan for his guidance and technical support in the development of the project. It has been a pleasure to work with and learn from him.

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Waleed Ejaz
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INTRODUCTION

1.1 Introduction

The Federal Communications Commission (FCC) is responsible for regulation of interstate telecommunication, management and licensing of electromagnetic spectrum within the United States and it enforces requirements on inter station interference in all radio frequency bands. They license segments to particular user's in particular geographic areas. A few, small, unlicensed bands were left open for anyone to use as long as they followed certain power regulations. With the recent boom in personal wireless technologies, these unlicensed bands have become crowded with everything from wireless networks to digital cordless phones.

To combat the overcrowding, the FCC has been investigating new ways to manage RF resources. The basic idea is to let people use licensed frequencies, provided they can guarantee interference perceived by the primary license holders will be minimal. With advances in software and cognitive radio, practical ways of doing this are on the horizon.

Cognitive Radio can smartly senses and adapts with the changing environment by altering its transmitting parameters, such as modulation, frequency, frame format etc.

In the early days of communication there were fixed radios in which the transmitter parameters were fixed and set up by their operators. The new era of communication includes Software Defined Radio (SDR). A SDR is a radio that includes a transmitter in which the operating parameters including the frequency range, modulation type or maximum radiated or conducted output power can be altered by making a change in software without making any hardware changes [1]. SDR is used to minimize hardware requirements; it gives user a cheaper and reliable solution. But it will not take into account spectrum availability. Cognitive Radio (CR) is newer version of SDR in which all the transmitter parameters change like SDR but it will also change the parameters according to the spectrum availability.

In [4] the authors measure the power spectral density (PSD) of the received 6 GHz wide signal. Figure 1.1 shows very low utilization of spectrum from 3-6 GHz. In order to improve spectrum efficiency dynamic spectrum access technique is imperative.

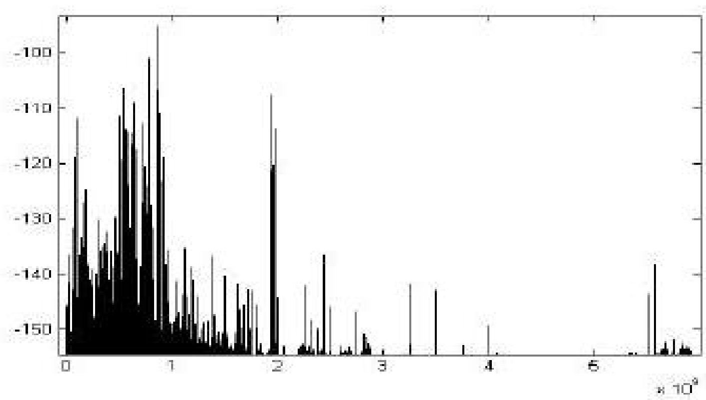


Figure 1.1 Measurement of 0-6 GHz spectrum utilization at BWRC [4]

Dynamic spectrum access techniques allow the cognitive radio to operate in the best available channel. More specifically the cognitive radio technology will enable the user to determine which portion of the spectrum is available, detect the presence of primary user (spectrum sensing), select the best available channel (spectrum management), coordinates the access to the channel with other users (spectrum sharing) and migrate to some other channel whenever the primary user is detected (spectrum mobility)[2].

1.2 Characteristics of Cognitive Radios

Cognitive radio dynamically selects the frequency of operation and also dynamically adjusts its transmitter parameters. The main characteristics of cognitive radios are **Cognitive Capabilities** and **Reconfigurability**.

1.2.1 Cognitive Capability

Cognitive capability refers to the ability of radio to sniff or sense information from its environment and perform real time interaction with it. The cognitive capability can be explained with the help of three characteristics; Spectrum Sensing, Spectrum Analysis and Spectrum Decision. The spectrum sensing performs the task of monitoring and detection of spectrum holes. The spectrum analysis will estimate the characteristic of detected spectrum hole. In the spectrum decision, the appropriate spectrum is selected by determine the parameters like data rate, transmission mode etc.

1.2.2 Reconfigurability

Reconfigurability refers to the ability of radio that allows the cognitive radio to adjust its parameters like link, operating frequency, modulation and transmission power at run time without any modifications in the hardware components. In other words Reconfigurability of CR is SDR. Doing so we dynamically change all the layers of communication as shown in Figure 1.2. We can use different technologies depending on their spectrum availability with the same hardware.

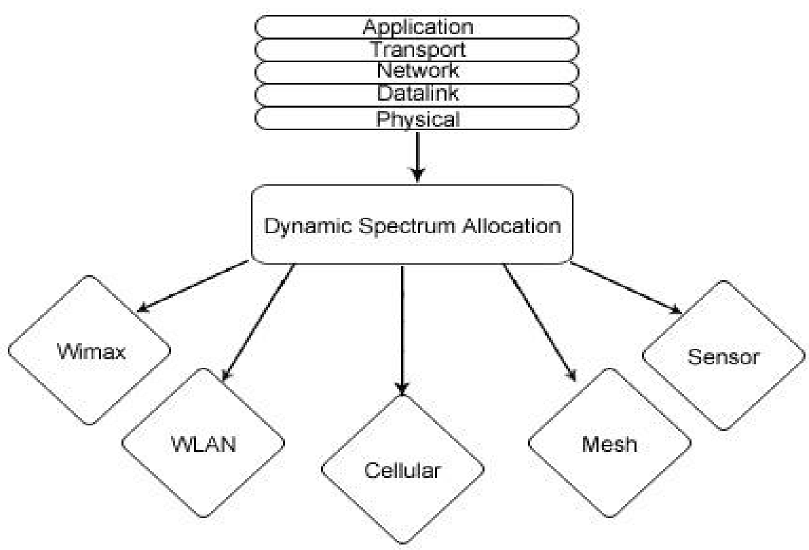


Figure 1.2 Dynamic changes in all Layers

1.3 Spectrum Sensing

The ultimate objective of the cognitive radio is to obtain the best available spectrum through Cognitive Capability and Reconfigurability as described above. Since there is already a shortage of spectrum, the most important challenge is to share the licensed spectrum without interfering with the transmission of other licensed users as illustrated in Figure 1.3. The cognitive radio enables the usage of temporally unused spectrum, which is referred to as spectrum hole or white space [16]. If this band is further used by a licensed user, the cognitive radio moves to another spectrum hole or stays in the same band, altering its transmission power level or modulation scheme to avoid interference.

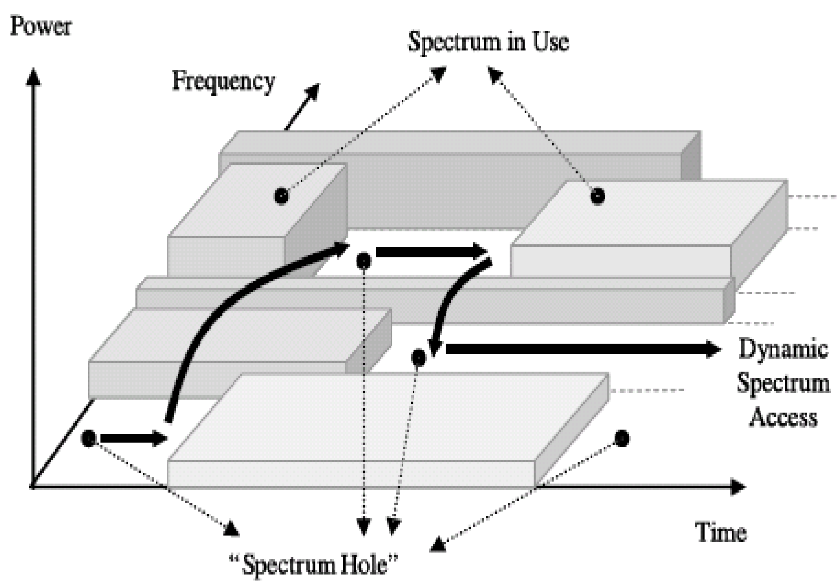


Figure 1.3 Spectrum hole concept

The cognitive capability of a cognitive radio enables real time interaction with its environment to determine appropriate communication parameters and adapt to the dynamic radio environment.

The tasks required for adaptive operation in open spectrum are shown in Figure 1.4 [16], which is referred to as the cognitive cycle. The three main steps of the cognitive cycle, shown in Figure 1.4, are as follows:

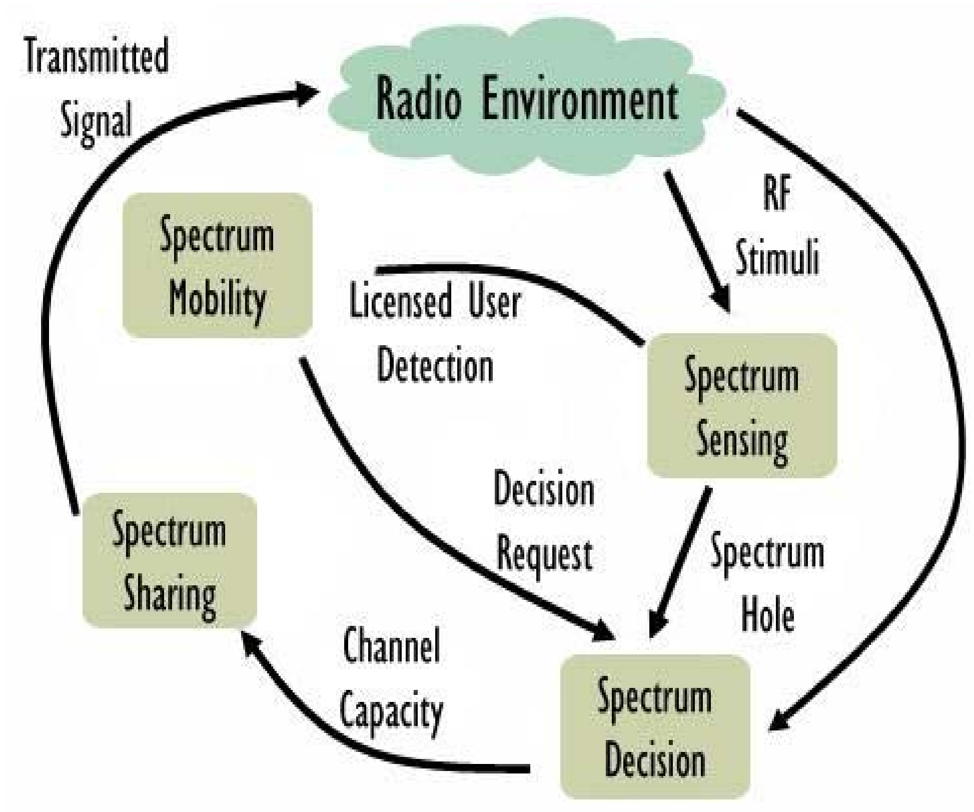


Figure 1.4 Cognitive Cycle

1.3.1 Spectrum sensing

A cognitive radio senses the radio environment. Finds available spectrum band, the information related to its parameters and detects spectrum holes.

1.3.2 Spectrum analysis

The analyses of the spectrum holes that are detected through spectrum sensing and their characteristics are estimated.

1.3.3 Spectrum decision

Cognitive radio first determines its own capabilities e.g. the data rate, the transmission mode, and the bandwidth of the transmission. Then, the appropriate spectrum band selection is made from the spectrum holes determined in spectrum sensing. Once the operating spectrum band is determined, the communication can be performed over this spectrum band. However, since the radio environment changes from time to time, the cognitive radio should be aware of the changes of the radio environment.

If some primary user wants to communicate on the spectrum band, which is in the use of cognitive radio then the spectrum mobility function is invoked to provide a seamless transmission. Any environmental change during the transmission such as primary user appearance, user mobility, or traffic variation can activate this adjustment.

1.4 The Cognitive Radio Architecture

Existing wireless network architectures employ heterogeneity in terms of both spectrum policies and communication technologies [17]. Moreover, some portion of the radio spectrum is licensed for different technologies and some bands remain unlicensed (called Industrial Scientific Medical (ISM) band). A clear description of Cognitive Radio Network architecture is essential for the development of communication protocols.

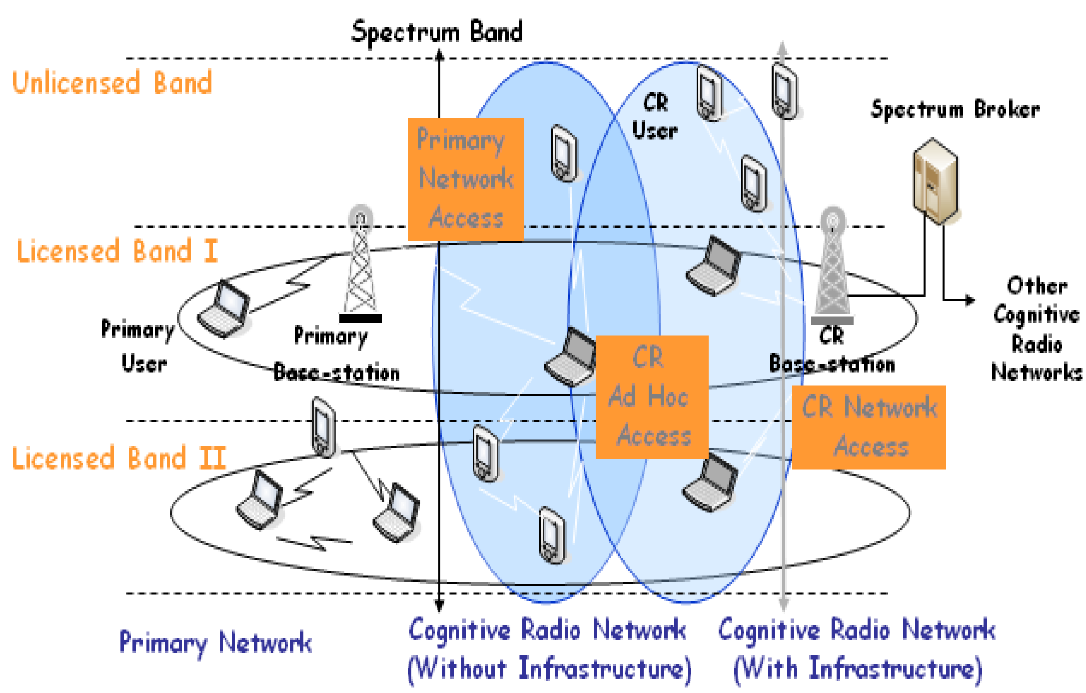


Figure 1.5 Cognitive Radio Network Architecture [2]

The components of the Cognitive Radio network architecture, as shown in Figure 1.5, can be classified in two groups such as the primary network and the CR network. The basic elements of the primary and the CR network are defined as follows:

1.4.1 Primary network

A network with rights for a specific radio spectrum band is called primary network. Examples include the common cellular network, WiMAX, CDMA and TV broadcast networks. The components of the primary network are as follows.

1.4.1.1 Primary user

A user of primary network which has a license to operate in a certain spectrum band. Primary user has access to the network via base-station. All of its services and operations are controlled by base-station. Hence, it should not be affected by any unlicensed user or user of any other network. Therefore, primary users do not need any change for coexistence with Cognitive Radio base-stations and Cognitive Radio users.

1.4.1.2 Primary base-station

A fixed infrastructure network component for a specific technology with licensed band is called Primary base-station. Examples are base-station transceiver system (BTS) in a cellular system and BTS in WiMAX etc. Primary base-station does not have capability for coexisting with Cognitive Radio Network, hence, the primary base-station require some modifications such as the need to have both licensed and Cognitive Radio protocols present for the primary network access of CR users.

1.4.2 Cognitive Radio network

A network where the spectrum access is allowed only in opportunistic manner and does not have license to operate in a desired band is called Cognitive Radio Network. It can be deployed both as an infrastructure network and an ad hoc network as shown in Figure 1.5. The components of a CR network are as follows.

1.4.2.1 Cognitive Radio user

Cognitive Radio user or secondary user has no spectrum license for its operation so some additional functionality is required to share the licensed spectrum band.

1.4.2.2 Cognitive Radio base-station

Cognitive radio base-station or secondary base-station is a fixed infrastructure component that provides single hop connection to Cognitive Radio users without any license of radio spectrum. Cognitive Radio user can access the other networks with the help of this connection.

1.4.2.3 Spectrum broker

Spectrum broker is a central network entity that provides the sharing of spectrum resources among different CR networks. Hence, spectrum broker can be connected to each network like star topology in Networks and can act as centralized server having all information about spectrum resources to enable coexistence of multiple CR networks.

1.5 Applications of Cognitive Radios

Cognitive Radio Networks can be applied to the following cases:

1.5.1 Leased network

In [18] authors proposes that primary network may provide a leased network by allowing cognitive radio user to access its licensed spectrum in an opportunistic manner without harming the communication of the primary user.

1.5.2 Cognitive mesh network

For providing broadband connectivity wireless mesh networks are emerging as a cost-effective technology [19]. However mesh networks require higher capacity to meet the requirements of the applications that demand higher throughput. Since the cognitive radio technology enables the access to larger amount of spectrum, therefore cognitive radio networks will be a good choice to meet the requirements of mesh networks.

1.5.3 Emergency network

Cognitive Radio Networks can be implemented for Public safety and emergency networks [22]. In the case of natural disasters, when primary networks are temporarily disable their spectrum band can be used by CR users. CR networks can communicate on available spectrum band in ad hoc mode without the need for an infrastructure and by maintaining communication priority and response time.

1.5.4 Military network

In [23] authors proposed that the CR networks can be used in military radio environment. CR networks can enable the military radios to choose arbitrary intermediate frequency (IF) bandwidth, modulation schemes, and coding schemes, adapting to the variable radio environment of battlefield.

1.6 Problem Statement

The purpose of the research is to detect and classify the spectrum sensing techniques for cognitive radio networks by using signal processing techniques. The sensing has been analyzed for a few identified situations and then these behaviors have been reported to the operator for further action.

1.7 Objectives

The primary objective of this thesis is to conduct a comprehensive appraisal of the contemporary techniques used for spectrum sensing in cognitive radio networks and to provide implementation of suitable techniques. The secondary objective includes identification of the areas for improvement of the results and the resolution of the identified deficiencies.

1.8 Thesis Organization

The rest of the research is organized as follows. Chapter 2 gives a review of the techniques that have been used for spectrum sensing. Chapter 3 gives the formal definition and provides a framework for the solution of the problem in hand. It also lists the assumptions and conditions that define the scope of the work. Chapter 4 illustrates the detailed design of different spectrum sensing techniques. It also further explains how these modules are finally integrated to form a complete test program. Chapter 5 gives an in depth analysis of the results obtained during the experimentation and comparison of Transmitter detection based spectrum sensing techniques. Lastly, chapter 6 concludes the research and highlights the future work, which can be done to carry forward this effort.

1.9 Summary

This Chapter covers the broader aspects of the research topic. It presents the motivation behind the selection of this subject as final thesis. It has highlighted the basic aspects of Cognitive Radio Networks. The problem statement is given to clarify the scope of the project. At the end an organization of the rest of the document is provided.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

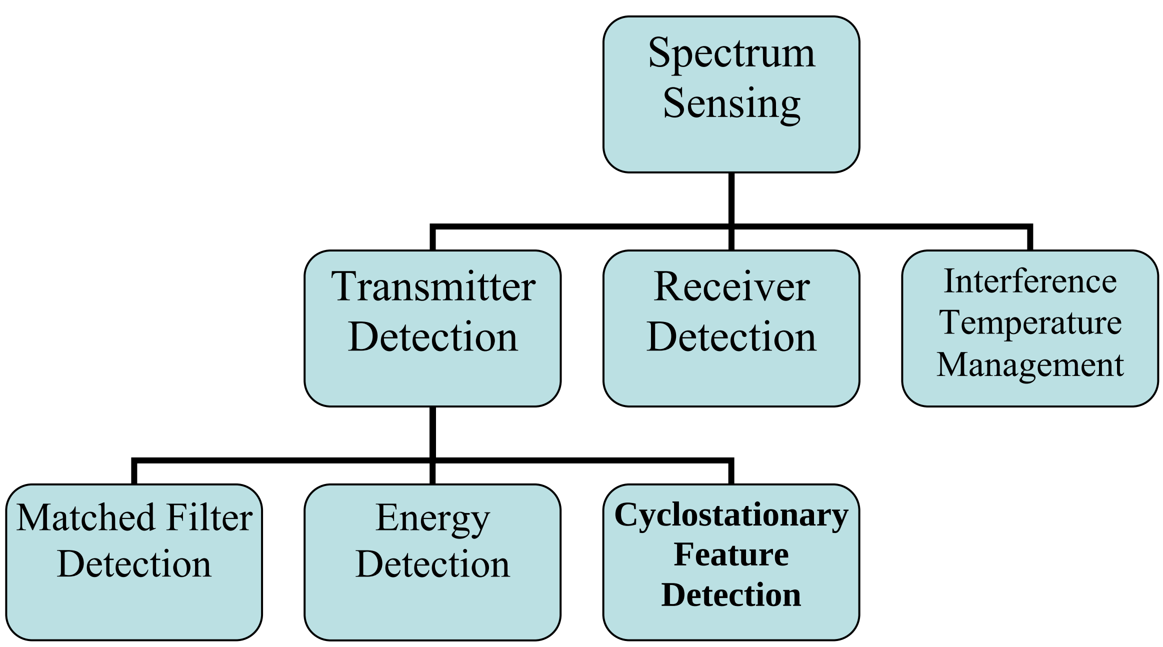
This chapter includes the summary of various approaches used to address the problem of Spectrum Sensing. The chapter encompasses the background work on spectrum sensing techniques.

2.2 Classification of Techniques

The main challenge to the Cognitive radios is the spectrum sensing. In spectrum sensing there is a need to find spectrum holes in the radio environment for CR users. However it is difficult for CR to have a direct measurement of channel between primary transmitter and receiver [2].

A CR can not transmit and detect the radio environment simultaneously, thus, we need such spectrum sensing techniques that take less time for sensing the radio environment.

In literature the spectrum sensing techniques have been classified in the following three categories [2].



2.2.1 Transmitter Detection

In transmitter detection we have to find the primary transmitters that are transmitting at any given time.

Hypothesis model for transmitter detection is defined in [7] that is, the signal received (detected) by the CR (secondary) user is

$$x(t) = \{n(t) H_0 \qquad (2.1)$$

$$x(t) = \{hs(t) + n(t) H_1$$

Where x (t) is the signal received by CR, s (t) is the transmitted signal of primary user, n (t) is the Additive white Gaussian noise (AWGN) and h is the amplitude gain of the channel. On the basis of this hypothesis model we generally use three transmitter detection techniques [4]: Matched Filter Detection, Energy Detection and Cyclostationary Feature Detection.

Now in the following section we will discuss each of the transmitter detection technique their pros and their cons.

2.2.1.1 Matched Filter Detection

A matched filter is a linear filter designed to provide the maximum signal-to noise ratio at its output for a given transmitted waveform [3]. Figure 2.1 depicts the block diagram of matched filter. The signal received by CR is input to matched filter which is r (t) = s (t) + n (t). The matched filter convolves the r (t) with h (t) where h (t) = s (T-t + τ). Finally the output of matched filter is compared with a threshold λ to decide whether the primary user is present or not.

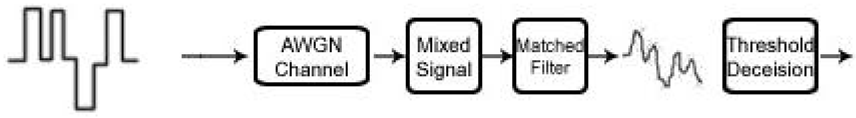


Figure 2.1 Block Diagram of Matched Filter

A Matched filter is an optimal detector in an AWGN channel if the waveform of primary user is previously known by CR. It means that CR should have knowledge about the waveform of primary user such as modulation type and order, the pulse shape and the packet format. So if CR doesn't have this type of prior information then it's difficult to detect the primary user. We can still use Matched Filter Detection because in most of the communication networks we can achieve this coherency by introducing pilots, preambles, synchronization word or spreading codes in the waveform of primary users. Still there are limitations in matched filter because each CR should have the information of all the primary users present in the radio environment. Advantage of matched filter is that it takes less time for high processing gain. However major drawback of Matched Filter is that a CR would need a dedicated receiver for every primary user class [4].

2.2.1.2 Energy Detection

If CR can't have sufficient information about primary user's waveform, then the matched filter is not the optimal choice. However if it is aware of the power of the random Gaussian noise, then energy detector is optimal [2].

In [7] the authors proposed the energy detector as shown in Figure 2.2. The input band pass filter selects the center frequency fs and bandwidth of interest W. The filter is followed by a squaring device to measure the received energy then the integrator determines the observation interval, T. Finally the output of the integrator, Y is compared with a threshold, λ to decide whether primary user is present or not.

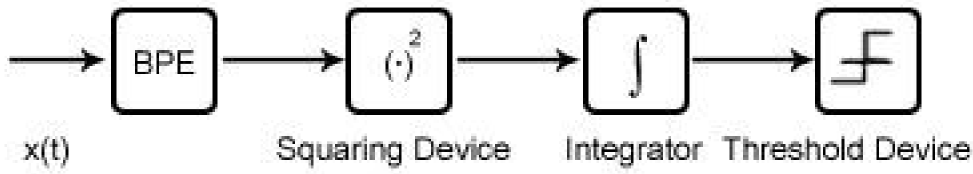


Figure 2.2 Block Diagram of Energy Detector

In a non fading environment where h is amplitude gain of the channel, probability of detection Pd and probability of false alarm Pf are given by following formulas [8]:

$$Pd = P(Y > \lambda / H1) = Qm(\sqrt{2\gamma}, \sqrt{\lambda}) \qquad (2.2)$$

$$Pf = P(Y > \lambda / H0) = \Gamma(m, \lambda / 2) / \Gamma(m) \qquad (2.3)$$

Where Y is the SNR, m = TW is the (observation/sensing) time bandwidth product Γ (.) and Γ (.,.) are complete and incomplete gamma functions, Qm ( ) is the generalized Marcum Q-function.

In a fading environment h is the amplitude gain of the channel that varies due to the shadowing or fading effect which makes the SNR variable. Pf is the same as that of non fading case because Pf is independent of SNR. Pd gives the probability of detection conditioned on instantaneous SNR. In this case average probability of detection may be derived by averaging (2.2) over fading statistics:

$$Pd = \int xQm(\sqrt{2\gamma}, \sqrt{\lambda}) f\gamma(x) dx \qquad (2.4)$$

Where f γ (x) is the probability distribution function of SNR under fading.

A low value of Pd indicates an absence of primary user with high probability; it means that the CR user can use that spectrum. A high value of Pf indicates minimal use of spectrum.

In [7] the authors suggest that in fading environment, where different CR users need to cooperate in order to detect the presence of the primary user. In such a scenario a comprehensive model relating different parameters such as detection probability, number and spatial distribution of spectrum sensors and more importantly propagation characteristics are yet to be found.

One of the main problems of energy detection is that performance is susceptible to uncertainty in noise power. It cannot differentiate between signal power and noise power rather it just tells us about absence or presence of the primary user.

2.2.1.3 Cyclostationary Feature Detection

Modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading, hopping sequences, or cyclic prefixes, which result in built-in periodicity [4]. Even though the data is stationary random process, these modulated signals are characterized as Cyclostationary, since their statistics, mean and autocorrelation, exhibits periodicity. These features are detected by analyzing a spectral correlation function. The periodicity is provided for signal format so that receiver can use it for parameter estimation like pulse timing, carrier phase etc. This periodicity can be used in the detection of random signals with a particular type of modulation with the noise and other modulated signals.

Recent research efforts exploit the Cyclostationary feature of signal as method for classification, which has been found to be superior to simple energy detection and match filtering. As discussed, a matched filter as a coherent detector requires prior knowledge about primary user's wave while as in energy detector as a non coherent detection does not require any sort of prior knowledge about primary user's waveform. Although energy detector is easy to implement, it is highly susceptible to in band interference and changing noise levels [9] and cannot differentiate between signal power and noise power.

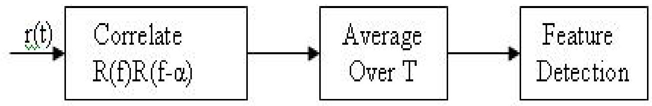


Figure 2.3 Block Diagram of Cyclostationary Feature Detector

Implementation of spectrum correlation function for Cyclostationary feature detection is depicted in Figure 2.3. Detected features are the number of signals, their modulation types, symbol rates and presence of interferers. If the correlation factor is greater than the threshold then it means that there is a primary user in radio environment. Although it performs better than energy detector because it can differentiate between signal power and noise power, it is computationally very complex that requires long processing time, which generally degrades the performance of Cognitive radio.

Signal processing techniques motivate the need to study other feature detection techniques that can improve sensing detection and recognize modulation, number and type of signals in low SNR regimes.

2.2.1.4 Limitations of Transmitter Detection

There are two limitations of transmitter detection, Receiver uncertainty problem and shadowing problem [2]. First, in transmitter detection cognitive radio users have information only about primary transmitter and it has no information about primary receiver. So cognitive radio can identify receiver through weak transmitted signals. This sort of problem is called receiver uncertainty problem. Moreover transmitter detection faces the hidden node problem that limits its usability. Secondly, shadowing causes cognitive radio transmitter unable to detect the transmitter of primary user.

2.2.1.5 Cooperative Vs Non Cooperative

The detection behavior can be categorized into two main branches, Non cooperative and cooperative. In non cooperative detection behavior cognitive radio user can detect the signal of primary transmitter by its own observation and analysis independent of the other cognitive radio users. While in Cooperative detection behavior the information from many cognitive radio users are combined to detect the primary user.

Moreover, Cooperative behavior helps to overcome the multi path fading and shadowing effect that will increase its usability. There are two ways for the implementation of cooperative detection, centralized and distributed. In

Centralized Cooperative detection mechanism the base station is responsible for gathering all information from other cognitive radio users to detect the primary user. While in distributed mechanism cognitive radio exchange messages among each other to get the desired objective. With comparison to non cooperative mechanism cooperative detection provides more accurate performance at the expense of additional operations and overheads but it still lacks about location of the primary receive

2.2.2 Receiver Detection

Now we need such spectrum sensing techniques which are able to remove the problems in transmitter detection. To remove receiver's uncertainty, we have to design techniques which we have some information about primary receiver. The makers of transmitter detection techniques state that we have available the information of primary receiver. The detection of weak signals from primary transmitter where it was shown [13] that the problems becomes very difficult when there is uncertainty in the receiver noise variance. Then new spectrum sensing techniques are introduced in which we will get information about receiver from its own architecture.

2.2.2.1 Local Oscillator Leakage

Modern day radio receivers are based on super heterodyne receiver architecture invented by Edwin Armstrong in 1918. This architecture is shown in Fig 2.4.

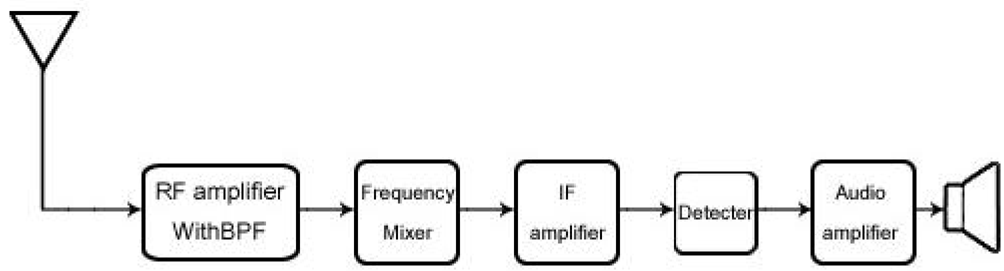


Figure 2.4 Architecture of Super heterodyne Receiver

This type of receiver architecture converts Radio frequency (RF) into fixed low intermediate frequency (IF). In order to convert RF to IF, frequency mixer is used which consists of local oscillator (LO). Local oscillator is tuned on a frequency such that when mixed with incoming RF signal, it converts it into fixed low IF band. In all of these receivers, there is inevitable reverse leakage, and therefore some of the local oscillator power actually couples back through the input port and radiates out of the antenna [14]. If we are able to measure this LO leakage then problem of receiver uncertainty is solved.

But things are never this simple. In the past decade, some improvements have been made to the receiver's architecture, resulting in reduced LO leakage power. Fig 2.5 tells the leakage of television receiver versus years.

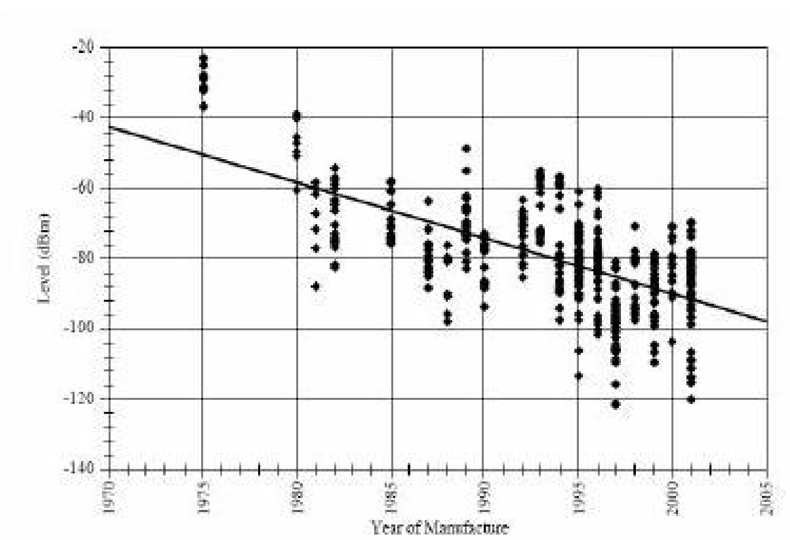


Figure 2.5 TV Local Oscillator leakage versus model year [14]

Detecting this leakage power directly with a CR would be impractical for two reasons [12]. First, it would be difficult for the receive circuitry of the CR to detect the LO leakage over larger distances. In [12] they calculate and prove that at a distance of 20m, it would take on order of seconds to detect the LO leakage with a high probability. In section 1 we see that we need sensing time in milliseconds in worst cases. The second reason that it would be impractical to detect the LO leakage directly is that LO leakage power is very variable and depends on the receiver model and year. Currently this method is only feasible in the detection of the TV receivers.

2.2.2.2 Sensor Nodes for Receiver Detection

In [12] the authors proposed to build tiny, low cost sensor nodes that would be mounted close to the primary receivers. The node would first detect the LO leakage to determine to which channel the receiver was tuned. It would then relay this information to the CR through a separate control channel using a fixed power level. Working of this is shown in Figure 2.6.

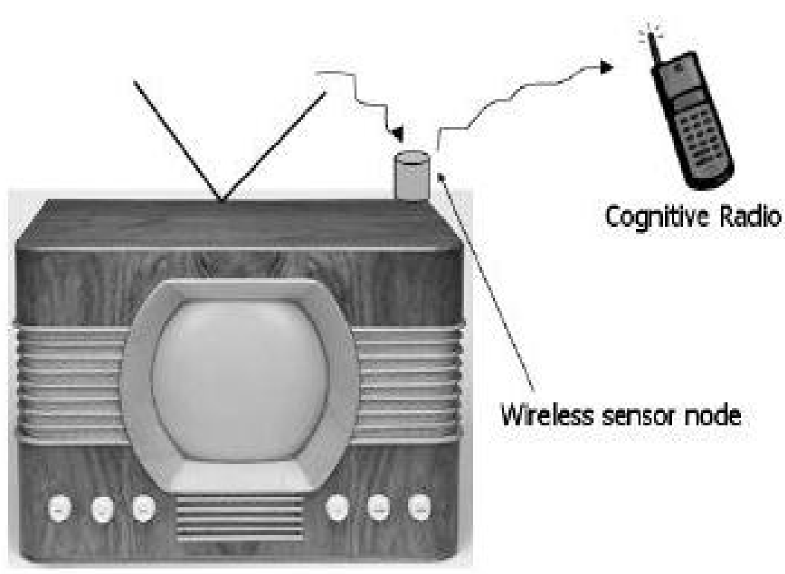


Figure 2.6 Sensor Nodes Notifying Cognitive Radio [12]

2.2.3 Interference Temperature Management

Interference is typically regulated in a transmitter centric way. Interference can be controlled at the transmitter through radiated power, out-of-band emissions, location of individual transmitters and frequencies used by specific type of radio operations. There interference management techniques served well in the past but do not take into account the interference from the receiver point of view, as most of interferences occur at the receiver. Moreover, the dramatic increase in the overall demand for spectrum based services, rapid technical advancements in radio systems; in particular the introduction of new robust modulation techniques demands a new technique that focuses on actual RF environment and interaction between transmitter and receiver.

This demand moves us towards new interference management technique known as Interference Temperature Management. We can define interference temperature as measure of the RF power generated by undesired (CR) emitters plus noise that is present in the receiver system per unit of bandwidth. The emissions from undesired (CR) transmitters could include out of band emission from transmitters operating on adjacent frequencies as well as from transmitters operating on the same frequency as a desired transmitter. In principle, the interference temperature measurements would be taken at various receiver locations and these measurements would be combined to estimate real time condition of RF environment. The interface temperature model shown below explains the signal of a radio designed to operate in a range at which the received power approaches the level of the noise floor. As additional interfering signals appear, the noise floor increases at various points within the service area, as indicated by the peaks above the original noise floor. This model manages the interference at the receiver through the interference temperature limit, which is represented by the amount of new interference that the receiver can tolerate.

2.3 Summary

This Chapter reviews the techniques and algorithms developed and implemented for the spectrum sensing for cognitive radios. Since the purpose of this work is to analyze the transmitter detection techniques therefore the focus has been kept on the transmitter detection techniques.

C h a p t e r 3

MODELING PHILOSOPHY

3.1 Introduction

This project is another step towards developing an efficient spectrum sensing scheme in the cognitive radio environment. Extensive research has been carried out to arrive at the final results which shall be presented later in this thesis report.

3.2 Scope

In a system for spectrum sensing for Cognitive Radio Networks, the input data is in of the form of signals coming from primary users or licensed users. This signal contains the information that is exchanged between primary users on licensed band. In order to classify the primary users signal we first have to sense the radio environment to determine whether the band is available for CR user/ secondary user or not and if the primary user is present then classify its features like modulation scheme and operating frequency of primary user.

3.3 Primary Users Transmitter

Block diagram of Primary Users Transmitter is shown in 3.1. The input is any piece of information (a text file, a sampled speech signal, a coded image …) that is converted to sequence of bits. Information bits, b[n] are coded by adding some redundant bits to protect information against channel noise and interference from other users. Data symbols, s[n] are obtained by grouping the bits into symbol. After that, data symbols are passed through pulse shaping filter p_T (t) and modulate the resulting signal to generate an RF (radio frequency) signal for transmission through channel.

The channel affects the signal by adding noise and distortion into it. There may be interference from other users also present.

At the receiver, all the steps which are mentioned in transmitter are operated with their reverse functionalities to obtain the original input signal.

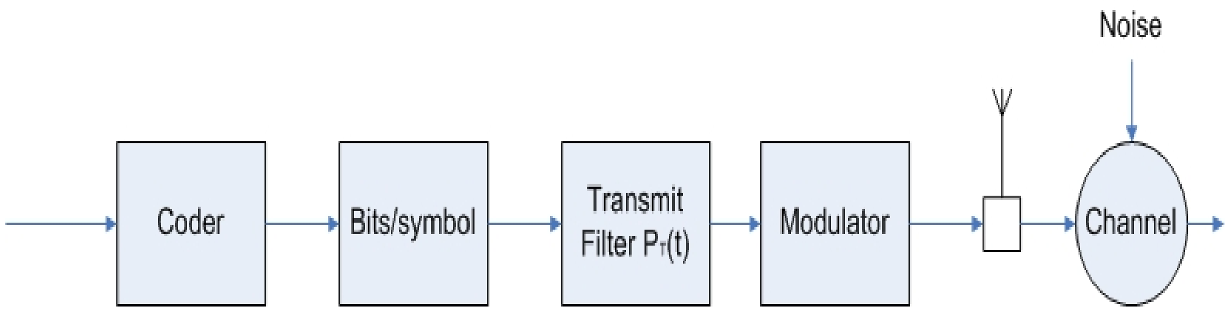


Figure 3.1 Block Diagram of Digital Communication Transmitter

3.4 Problem Decomposition into Modules

The system is decomposed in to five modules. The modules are formed in a way so that the output of every module becomes the input for the next module. However the primary input of the system is the primary user's waveform from primary user. The modules forming the entire system include; *Primary Users Waveform, Processing on Waveform, Detection of Waveform, Feature Extraction* and *Classification*. The flow of data and information between various modules is shown in Figure 3.2.

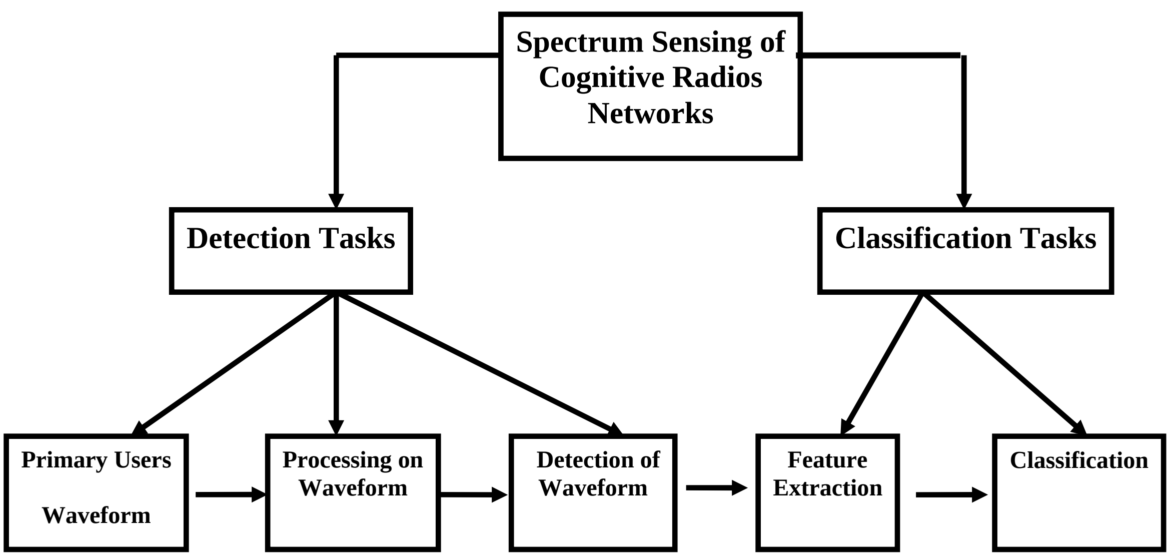


Figure 3.2 System Process Diagram

3.4.1 Primary Users Waveform

The first step is to check the radio environment whether there is any waveform present or not. For experimentation purposes, various types of primary user's waveforms have been developed. Radio environment is searched by cognitive radio and from radio environment primary users wave form is extracted.

3.4.2 Processing on Waveform

After getting primary users waveform, this waveform is processed using spectrum sensing techniques discussed in Chapter 2. As from the theoretical background, first it is important for cognitive radio user to know whether there is primary user is present or not. If yes then starts communication on that band. If no then try to get some parameters about primary user's waveform e.g. operating frequency, modulation scheme etc. This can be done quite effectively using cyclostationary feature detection technique. There are also other techniques present in which we can detect whether primary user is present at some particular frequency or not. These techniques include energy detection and matched filter. One obvious drawback for the matched filter detection is that it needs priory knowledge about primary user's waveform. However this technique is simple and reduces considerable computation.

3.4.3 Detection of Waveform

In a radio environment there are many primary users present at some particular time. Moreover, at any one instant, different primary user from different technologies can also be there. However, technology is usually more concerned with particular features such as modulation type and operating frequency. There are many techniques which can be used for the detection of waveform. For detection of primary user matched filter detection [3] can be used but it requires prior knowledge about primary user's waveform. Energy Detection [7] can also be used to detect waveform but it will have its own limitations discussed in Chapter 2. Both the above mentioned techniques not give much about the features of the waveforms. Cyclostationary feature detection [4] can be a good solution for it. It will not only detect waveform but also helps to extract features. But last mentioned technique is computationally complex as compared to energy detection and matched filter.

3.4.4 Feature Extraction

Once cyclostationary feature detection is applied, certain features are extracted from the primary user's waveform for the purpose of classification of waveform. The two obvious features are operating frequency and modulation type of each waveform. In addition to operating frequency and modulation type, data rate of each waveform can also be determined.

3.4.5 Classification

The purpose of this module is to classify the primary user's waveform using features extracted from the previous module. The classifier should know about the features of well known wireless technologies e.g. Wireless LAN, Bluetooth etc. Once it takes features from previous module it can classify the technology used by primary user using previously stored information about technology.

3.5 Minimizing Sensing Time for Detection

In order to minimize the sensing time an algorithm has been proposed, whose flow chart is shown in Figure 3.3. According to this algorithm there are three possible states for the output of each detection technique i.e. Low 'L', Medium 'M' and High 'H'. If its output is 'H'; it indicates the presence of primary user, if its output is 'L'; it means that primary user is not present. If the output is 'M' then detection technique is not sure about the presence or absence of primary user.

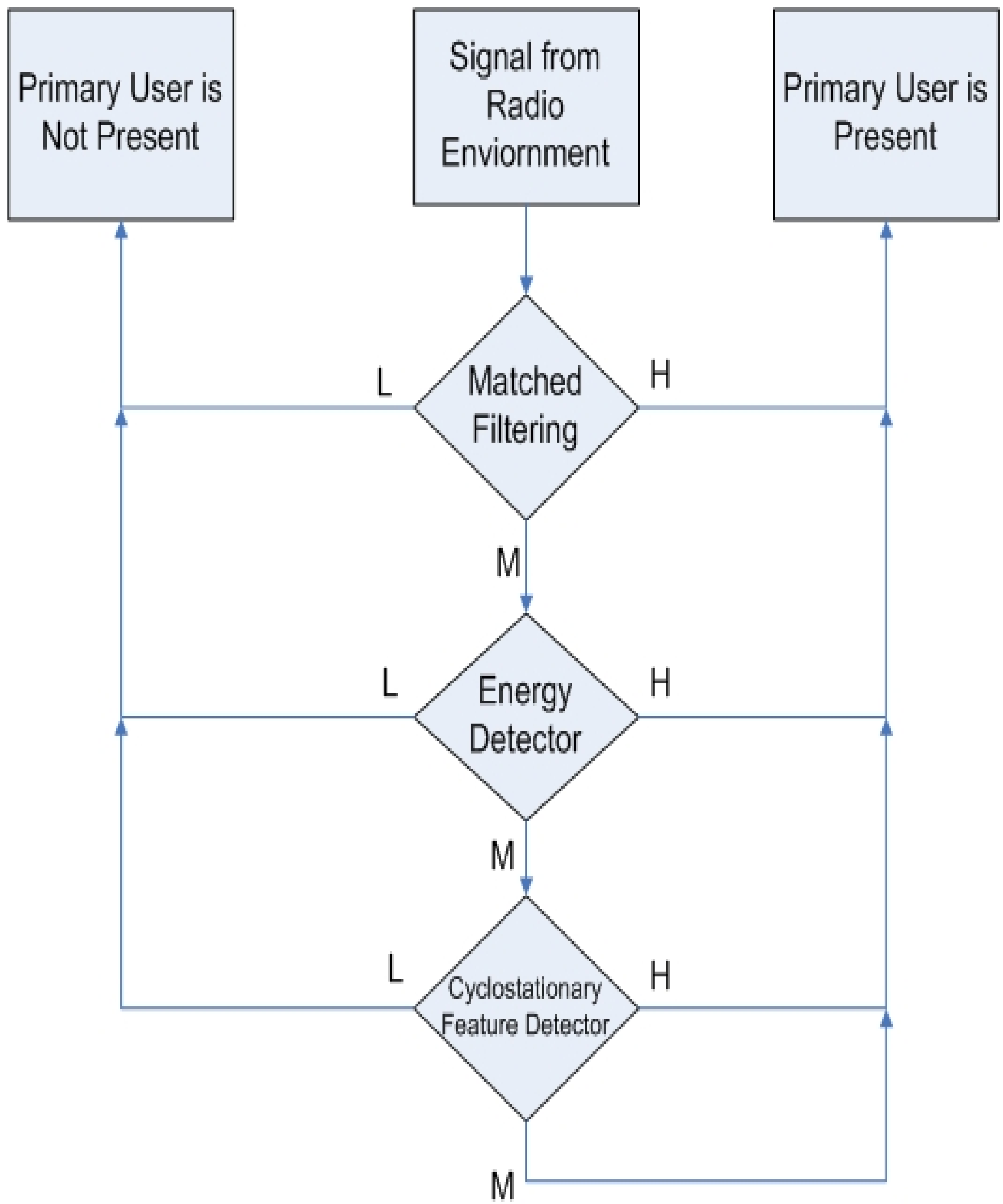


Figure 3.3 Algorithm for minimizing sensing time for detection

The received signal is first passed through Matched Filter, as it takes least time for sensing among all three mentioned techniques. If output is ‘H’ or ‘L’ then it’s fine that we concluded about presence or absence of primary user. If output is ‘M’ then we have to go for some other technique. As Energy detection technique takes less sensing time compared to Cyclostationary feature detection. Then signal is passed through energy detection filter and if its output is ‘L’ or ‘H’ then again there is no need to go for another detection technique. Finally if energy detectors output is ‘M’ then go for Cyclostationary feature detection. If its output is ‘H’ or ‘M’ then we said that primary user is present, otherwise primary user is not present.

3.6 Fuzzy Logic Based Decision

Fuzzy Logic based decision uses ‘soft’ linguistics (e.g. High, Medium, Low) system variables and can have more values in interval of [0,1], instead of strict binary decision that whether primary user is present or not. Formally, fuzzy logic is a structured, model-free estimator that approximates a function through linguistic input/output associations [21]. The block diagram of the system is shown in Figure 3.4.

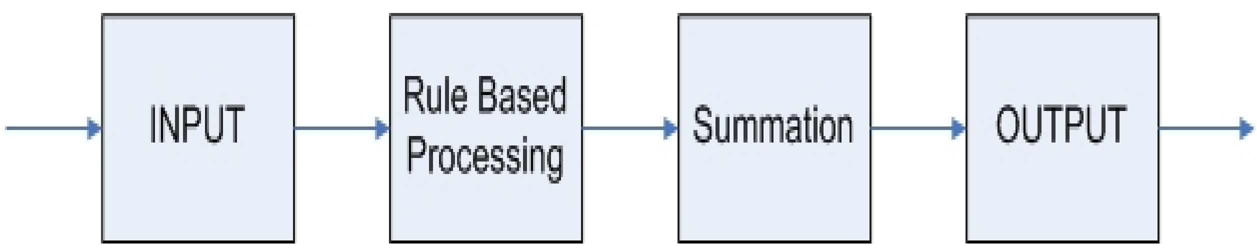


Figure 3.4 Block Diagram for Fuzzy based Detection System

The following are the steps in building fuzzy logic based spectrum sensing decision.

3.6.1 Determine the input of the system

Examples: The temperature is the input for your home air conditioner control system. In current situation output of the spectrum sensing techniques is the input of the Fuzzy based Detection System (Energy Detector, Matched Filtering and Cyclostationary Feature Detection).

3.6.2 Determine the output of the system

For a home air conditioner, the output is the opening and closing of the switch that turns the fan and compressor on and off. In current situation output of the system is final result whether the primary user is present or not.

3.6.3 Choose Word Description

Choose word descriptions for the status of input and output. The description for the status of the input is

L means primary user is not present.

M means not sure about presence or absence of primary user.

H means primary user is present.

The description for the status of output is

P means primary user is present.

A means primary user is absent.

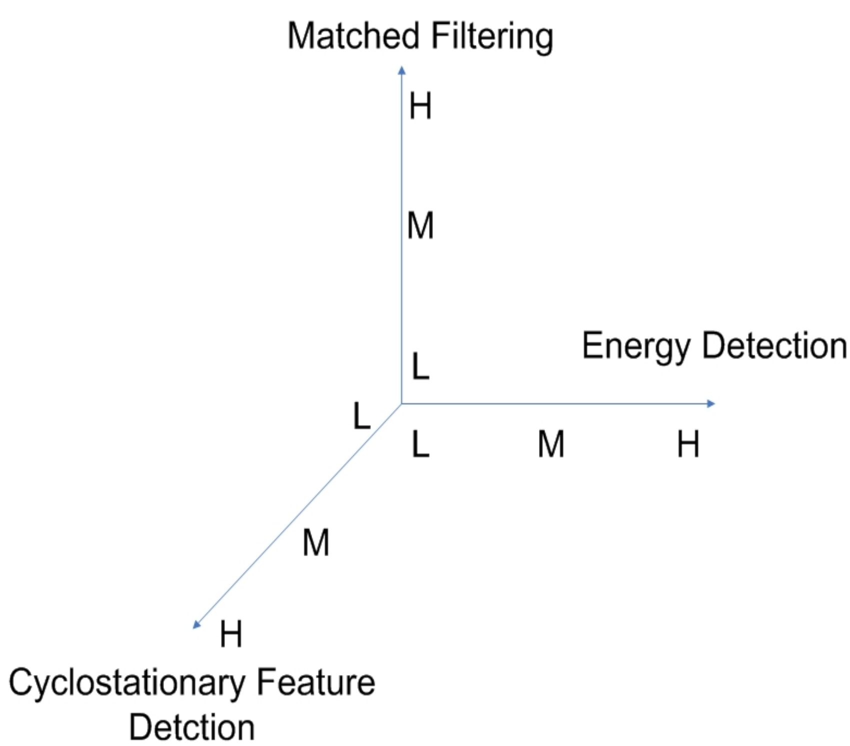


Figure 3.5 Description for the status of Input

3.6.4 Action Taken

Determine action to be taken based on the fuzzy "If-then" rules. Rules are:

Assign input 'H' to 1, 'M' to 0.5 and 'L' to 0. The inputs coming from each technique is mapped to these values and then values from all three techniques are summed up if there summation is greater then 1.5 then we conclude that primary user is present 'P' else primary user is absent 'A'. Table 3.1 leads to a computer program.

Energy Detector	Matched Filtering	Cyclostationary Feature Detection	Decision
L	L	L	A
L	L	M	A
L	L	H	A
L	M	L	A
L	M	M	A
L	M	H	P
L	H	L	A
L	H	M	P
L	H	H	P
M	L	L	A
M	L	M	A
M	L	H	P
M	M	L	A
M	M	M	P
M	M	H	P
M	H	L	P
M	H	M	P
M	H	H	P
H	L	L	A
H	L	M	P
H	L	H	P
H	M	L	P
H	M	M	P
H	M	H	P
H	H	L	P
H	H	M	P
H	H	H	P

Table 3.1 Detection using Fuzzy logic

3.7 Summary

Chapter 3 sets up the basis of this research. It narrows down the vastness of the topic to the conditions and assumptions under which this work has been done. The chapter breaks down the process into modules and briefly explains the functioning of each individual module.

Chapter 4

IMPLEMENTATION

4.1 Introduction

This chapter concentrates on the implementation of spectrum sensing techniques to obtain results for all designed classifiers and subsequent analysis. First, overall program structure has been discussed followed by the algorithms. Lastly, composition of the nine different experiments designed and conducted during the research has been discussed.

4.2 Transmitter of Primary Users

First of all we need primary user waveform on which we can apply different spectrum sensing techniques. Transmitter can have different transmitting parameters like they can have different operating frequency, different modulation scheme. Block diagram of digital transmitter is shown in Chapter 3. Flow chart of implementation of primary transmitter is shown in Figure 4.1.

Step 1: The system parameters are set in this step. The parameters are: (i) the operating frequency, ‘freq’; (ii) the sampling frequency, ‘Fs’; (iii) number of samples per symbol period, ‘L’; (iv) the sampling period, ‘Ts’; (v) roll-off factor for the (square-root) raised cosine filters, ‘alpha’; (vi) N+1 is the length of the square-root raised cosine filter, ‘N’; (vii) signal to noise ratio, ‘snr’; (viii) channel impulse response, ‘h’.

Step 2: This is any piece of information (a text file, a sampled speech signal, a coded image, ……) that is converted to sequence of bits. Here are two options either take input from the user to transmit or use default data sequence.

Step 3: This a square-root raised-cosine filters with roll-off factor α. Here, α is set equal to 0.5. In the real world, the transmit signal is continuous time. Since in computer simulation, we can only have sampled signals, we approximate continuous-time signals by a dense grid of samples. Here, we have L = 100 samples per symbol period. The function 'sr_cos p' generates a square-root raised-cosine pulse, for the transmit filter, pT(t). The output of this step is Y.

Step 4: Modulation is done to generate an RF (radio frequency) signal for transmission through channel. Here two modulation techniques BPSK (Binary Phase Shift Keying) and QPSK (Qaurdrature Phase Shift Keying) are available. It depends on type of primary transmitter that whether to use BPSK or QPSK.

Step 5: This is characterized by an impulse response c(t) and an additive noise. Here, we have chosen c(t) = δ(t) which in the discrete domain becomes c = 1. If the channel is multipath, e.g., with the impulse response c(t) = a0δ(t −t0) + a1δ(t − t1), it has the equivalent discrete domain c = [zeros(N0,1); a0; zeros(N1,1); a1], where N0 and N1 are t0 and t1 in unit of Ts.

Step 6: The channel noise is assumed to be Additive White Gaussian with signal strength 2dB. In MATLAB 'awgn' function is used for this purpose.

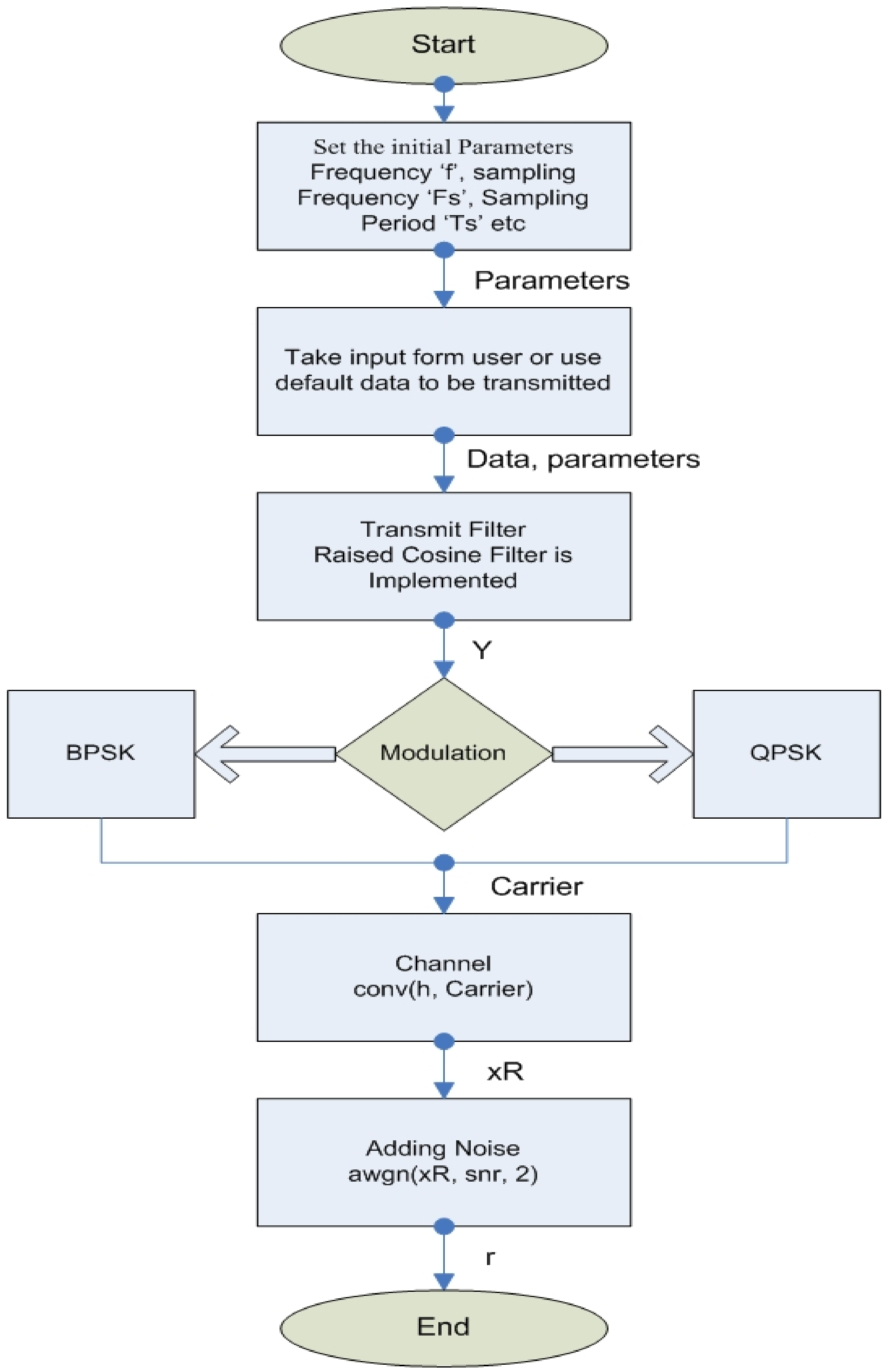


Figure 4.1 Flow chart for Implementation of Primary Transmitter

The MATLAB script ‘transmitter.m’, presented in Annex I, simulates two types of Primary transmitter for Spectrum Sensing in Cognitive Radio Networks, one using BPSK modulation technique and other using QPSK modulation technique. The code is self-explanatory.

4.3 Energy Detection

The simplest detection technique for spectrum sensing is Energy Detection. As discussed in Chapter 2 energy detector measures the energy received from primary user during the observation interval. If energy is less then certain threshold value then it declares it as spectrum hole. Let r(t) is the received signal which we have to pass from energy detector. The procedure of the Energy Detector is as follows.

Step 1: First estimate Power Spectral Density (PSD) by using periodogram function in MATLAB.

Pxx = Periodogram(r)

Step 2: The power spectral density (PSD) is intended for continuous spectra. The integral of the PSD over a given frequency band computes the average power in the signal over that frequency band.

Hpsd=Dspdata.psd(Pxx)

Step 3: Now one frequency component takes almost 20 points in MATLAB. So for each frequency there points are summed and get the result.

Step 4: On experimental basis when results at low and high SNR are compared then threshold λ is set to be 5000.

Step 5: Finally the output of the integrator, Y is compared with a threshold value λ to decide whether primary user is present or not.

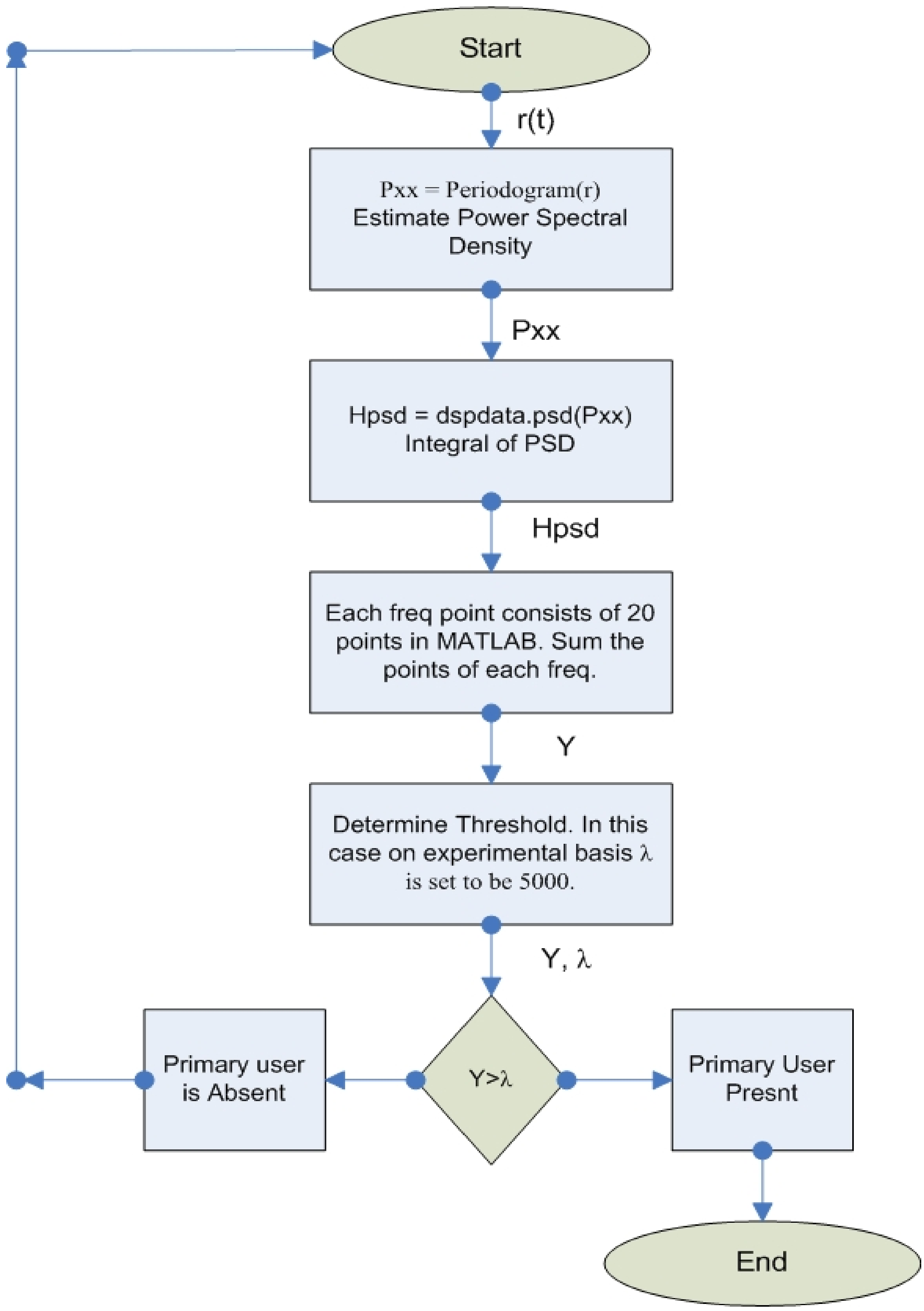


Figure 4.2 Flow chart for Implementation of Energy Detector

Flow chart for the implementation of Energy Detector is shown in Figure 4.2. The MATLAB script 'energydetector.m', presented in Annex I, simulates the Energy Detector for Spectrum Sensing in Cognitive Radio Networks. The code is self explanatory.

Figure 4.3 shows the output of energy detector when there is a primary user at 200 Hz using BPSK is present with very good SNR. It's very clear in the figure that there is peak at exactly 200 Hz. So energy detector compared this peak with threshold value, in this case its greater then threshold. Hence, energy detector said that primary user is present at 200 Hz.

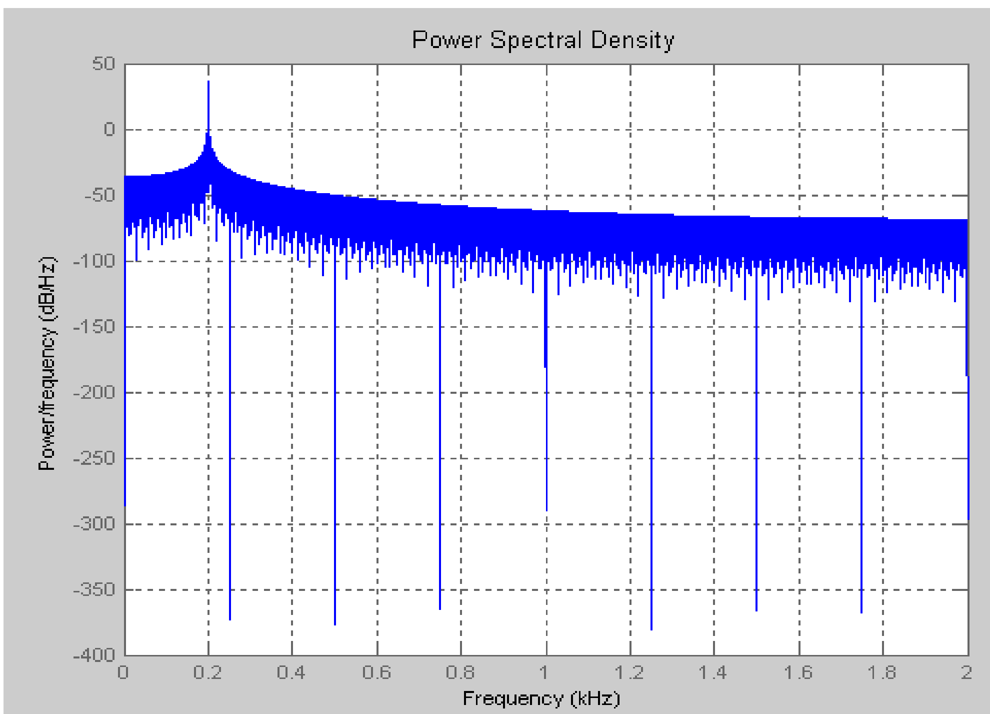


Figure 4.3 Energy Detector Output at SNR 30dB for BPSK when primary user is present at 200Hz

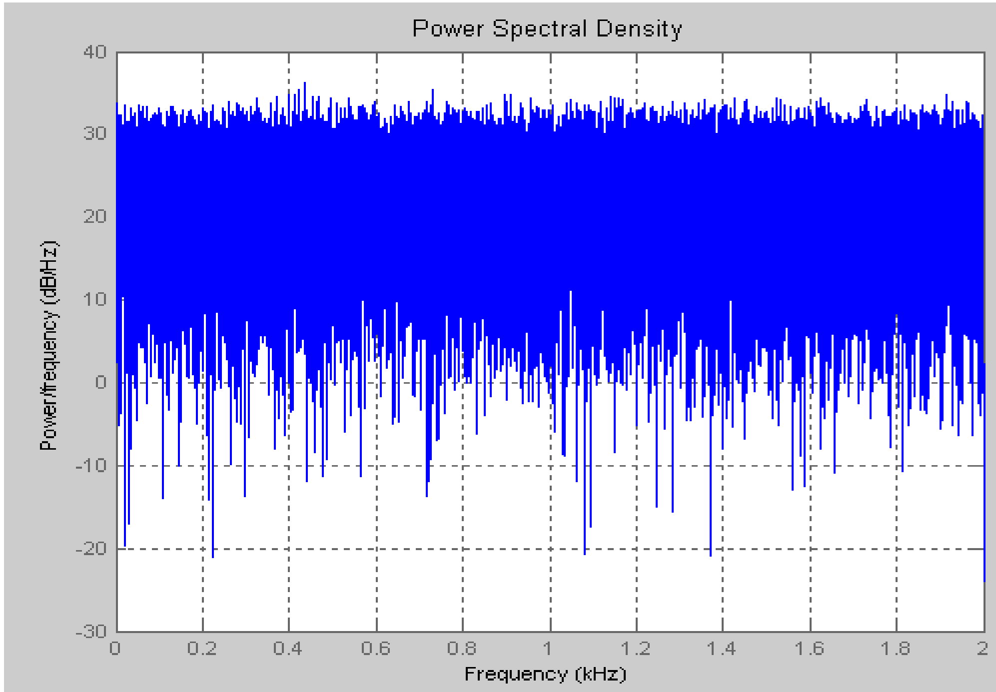


Figure 4.4 Energy Detector Output at SNR -30dB for BPSK when primary user is present at 200Hz

Figure 4.5 Energy Detector Output at SNR 30dB for QPSK when primary user is present at 200Hz

Figure 4.4 shows the output of energy detector when there is a primary user at 200 Hz using BPSK is present with very poor SNR. It's very clear in the figure that there are so many peaks in whole figure. So energy detector compared value of each point with threshold, in this case its greater then threshold at many points. Hence, energy detector said that primary users are present at all along the spectrum.

Figure 4.5 shows the output of energy detector when there is a primary user at 200 Hz using QPSK is present with very good SNR. It's very clear in the figure that there is peak at exactly 200 Hz. So energy detector compared value of each point with threshold, in this case its greater then threshold at 200 Hz. Hence, energy detector said that primary user is present at 200 Hz.

Figure 4.6 shows the output of energy detector when there is a primary user at 200 Hz using QPSK is present with very poor SNR. It's very clear in the figure that there are so many peaks in whole figure. So energy detector compared value of each point with threshold value, in this case its greater then threshold at many points. Hence, energy detector said that primary users are present at all along the spectrum.

When there is no primary user, even then energy detector detects that primary user is present under low SNR conditions. This is the main drawback of energy detection that it can't distinguish between noise and energy of the signal. Under low SNR conditions energy detector told that primary user is present in all around the spectrum if it is white noise.

Figure 4.6 Energy Detector Output at SNR -30dB for QPSK when primary user is present at 200Hz

4.4 Matched Filter

Another technique for spectrum sensing is Matched Filter as discussed in Chapter 2. Matched filter requires prior knowledge about primary user's waveform. Hence, it requires less sensing time for detection. Flow chart of Matched Filter is shown in Figure 4.7. Let r (t) is the received signal which we have to pass from matched filter. The procedure of the matched filter is as follows.

Step 1: For the matched filter prior knowledge of primary user waveform is required. Therefore a local carrier is generated using local oscillator.

Step 2: xcorr estimates the cross-correlation sequence of a random process. Autocorrelation is handled as a special case.

Step 3: On experimental basis when results at low and high SNR are compared then threshold λ is set to be ±35.

Step 4: Finally the output of the integrator, Y is compared with a threshold value λ to decide whether primary user is present or not.

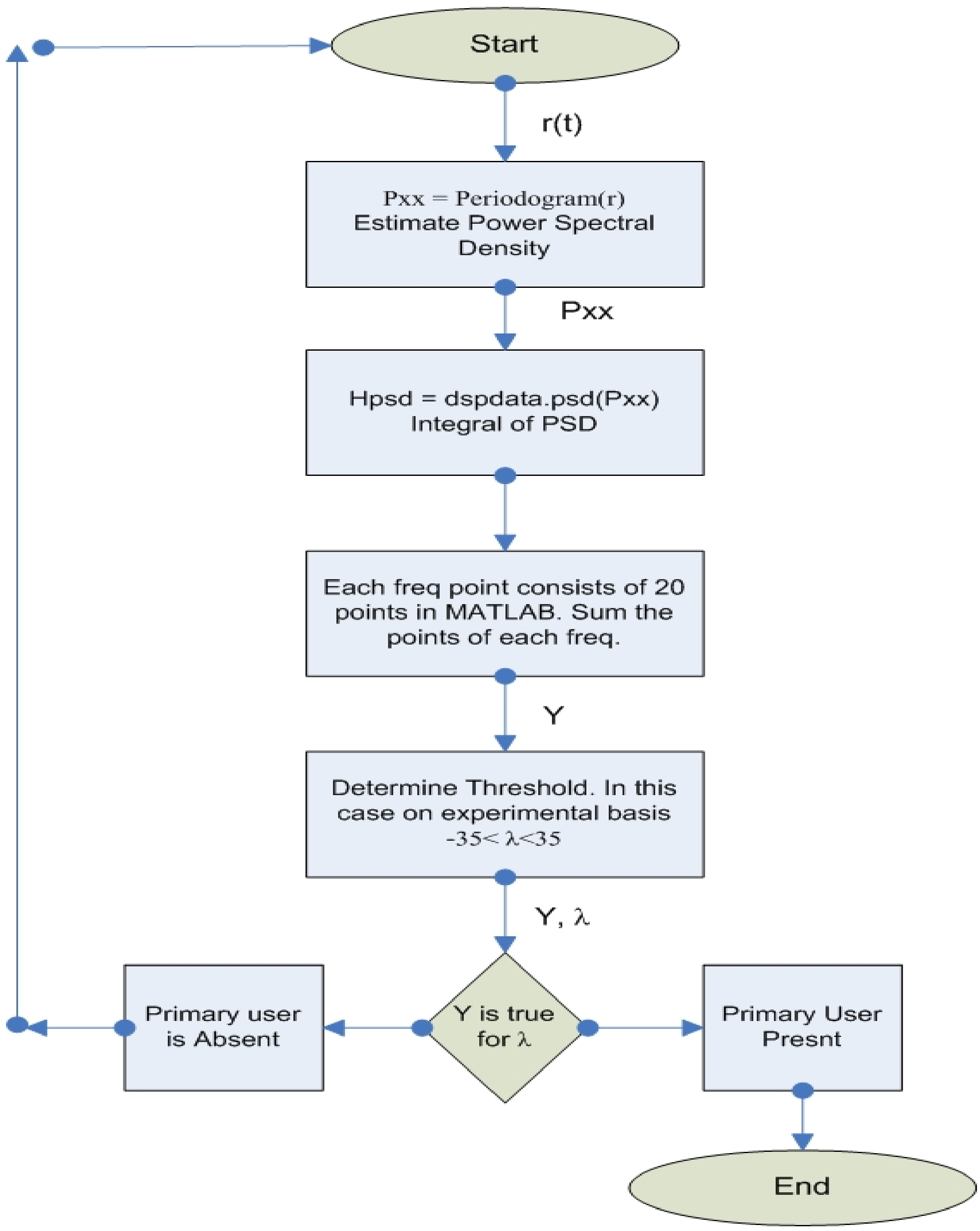


Figure 4.7 Flow chart for Implementation of Matched Filter

The MATLAB script ‘matchedfilter.m’, presented in Annex I, simulates the Matched Filter for Spectrum Sensing in Cognitive Radio Networks. The code is self-explanatory. For the case of BPSK in which the two pulses are p(t) and –p(t). The correlation coefficient c of these pulses is -1. Under good SNR conditions the receiver computes the correlation between p(t) and received pulse. If correlation is 1 we decide p(t) is received as in Figure 4.5, otherwise we will decide that –p(t) is received. When SNR conditions are not good then correlation coefficient is no longer +1 or -1, but has smaller magnitude, thus reducing the distingushability. Figure 4.8 shows the correlation of received signal with signal generated at cognitive radio under good SNR conditions.

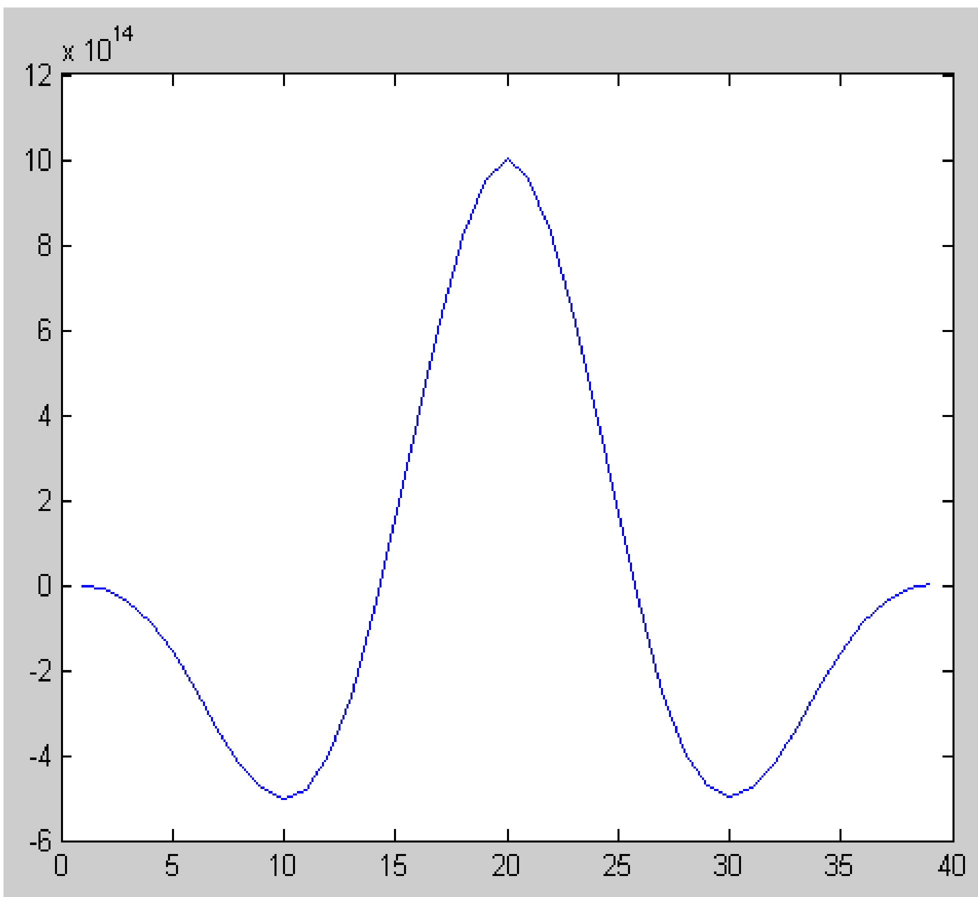


Figure 4.8 Matched Filter Output at SNR 30dB for BPSK

4.5 Cyclostationary Feature Detection

Cyclostationary Feature Detection as discussed in Chapter 2. It uses inbuilt features in the primary user's waveform for detection. Hence, it is computationally complex detector. Flow chart for the implementation of Cyclostationary Feature Detector is shown in Figure 4.9. Let r(t) is the received signal which we have to pass from Cyclostationary feature detector detector. The procedure of the Cyclostationary Feature Detection is as follows.

Step 1: First take fourier of the received signal by using 'fft' function.

R=fft(r)

Step 2: Multiple r with complex exponential. As multiplication with complex exponential in time domain is equivalent to frequency shift in frequency domain.

XT=r.*exp(j*2*pi *shfT);

Step 3: Correlate XT with R

XY=xcorr(XT,R);

Average over time T

pt= fft(XY).*conj(fft(XY))

Step 4: On experimental basis when results at low and high SNR are compared then threshold is set to be $1<\lambda<5$.

Step 5: Finally the output of the integrator, pt is compared with a threshold value λ to decide whether primary user is present or not.

Step 6: Now if the primary user is present then we can find features of the priary signal like operating frequency and modulation technique.

The MATLAB script 'cyclostationary.m', presented in Annex I, simulates the Cyclostationary Feature Detector for Spectrum Sensing in Cognitive Radio Networks. The code is self-explanatory.

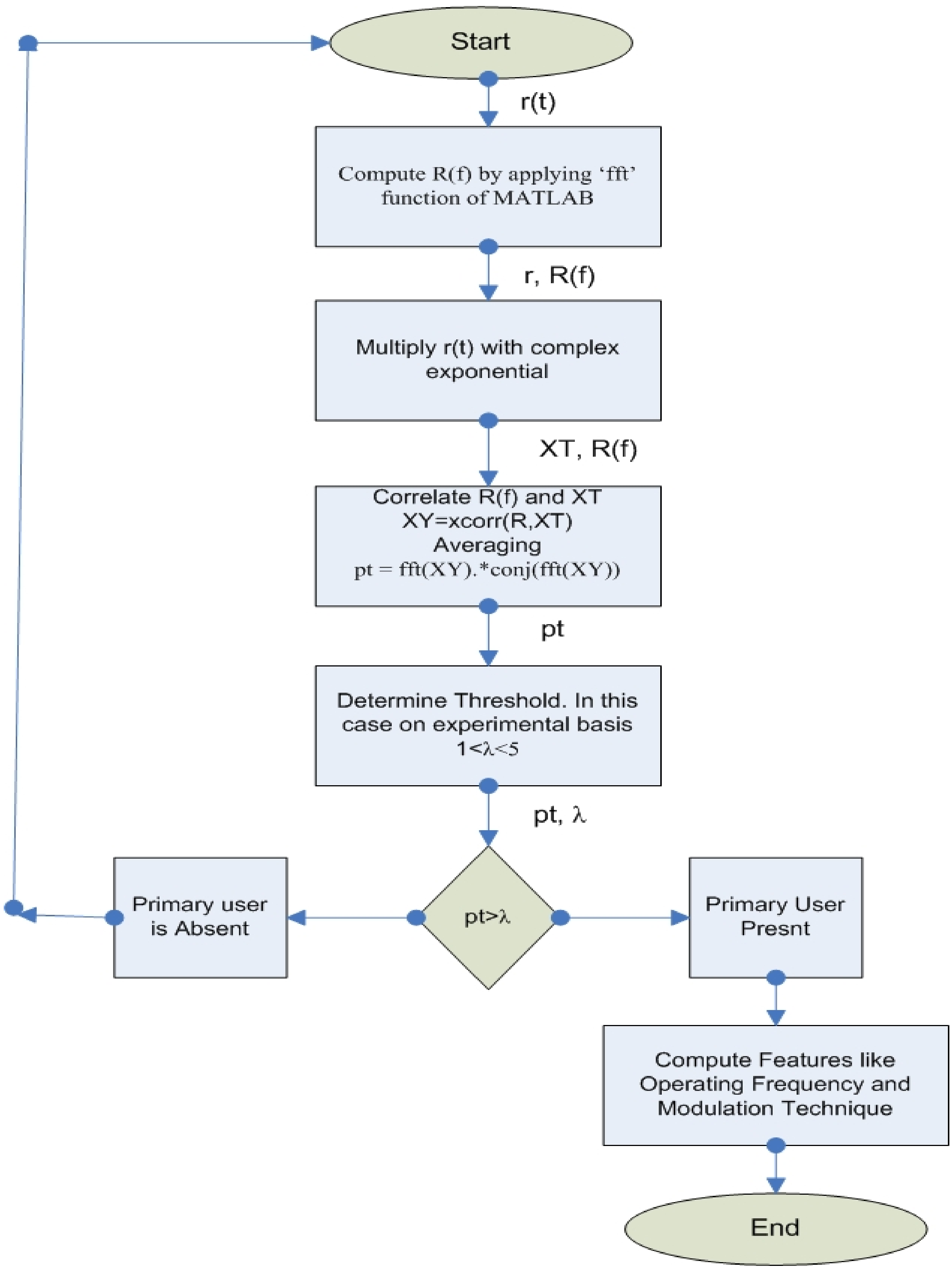


Figure 4.9 Flow chart for the implementation of Cyclostationary Feature Detection

Figure 4.10 shows the output of cyclostationary feature detection when there is a primary user at 200 Hz using BPSK is present with very good SNR. It’s very clear in the figure that there is peak in the center and there is a peak at double of the frequency as well. Now we have to compare second peak with threshold value. So cyclostationary feature detection compared value of each peak with threshold, in this case its greater then threshold at 400. Hence, cyclostationary feature detection said that primary user is present at 200 Hz.

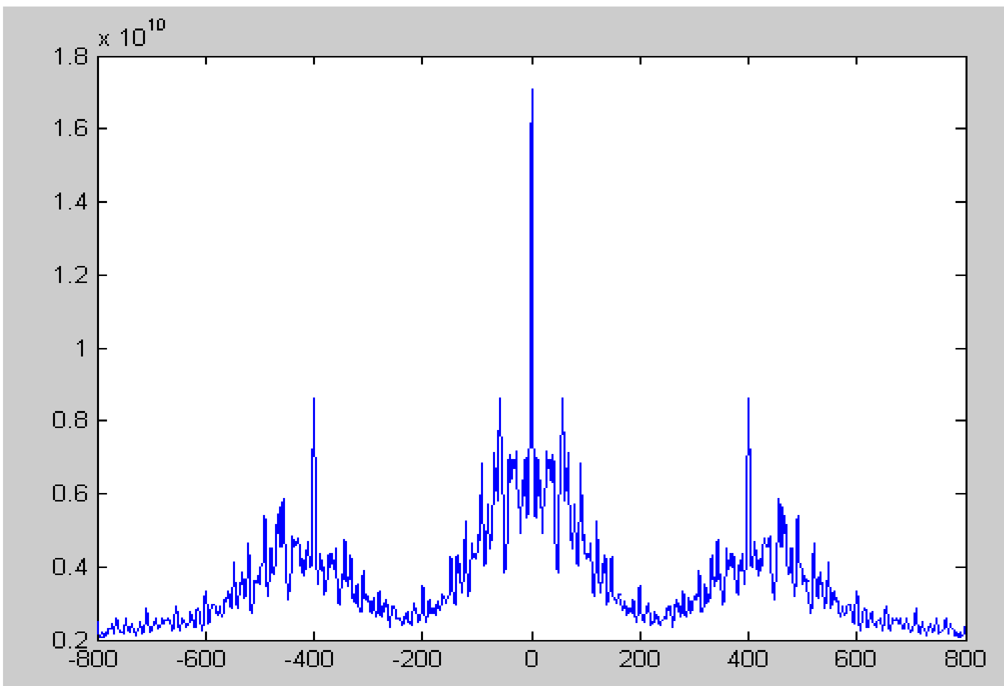


Figure 4.10 Cyclostationary Feature Detector Output at SNR 30dB for BPSK when primary user is present at 200Hz

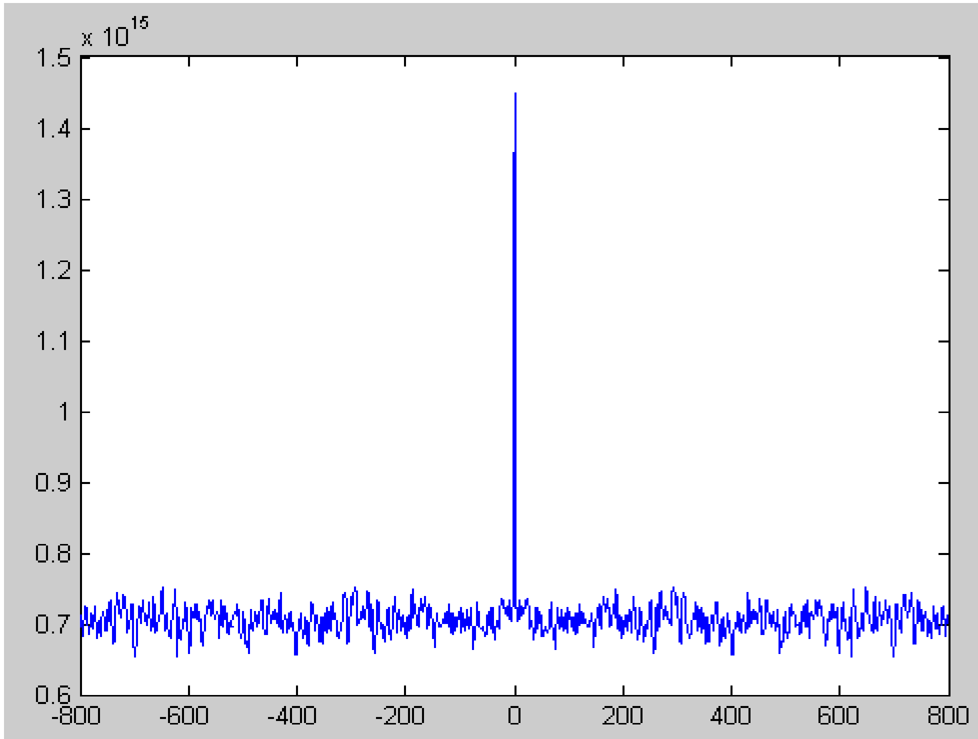


Figure 4.11 Cyclostationary Feature Detector Output at SNR -30dB for BPSK when primary user is present at 200Hz

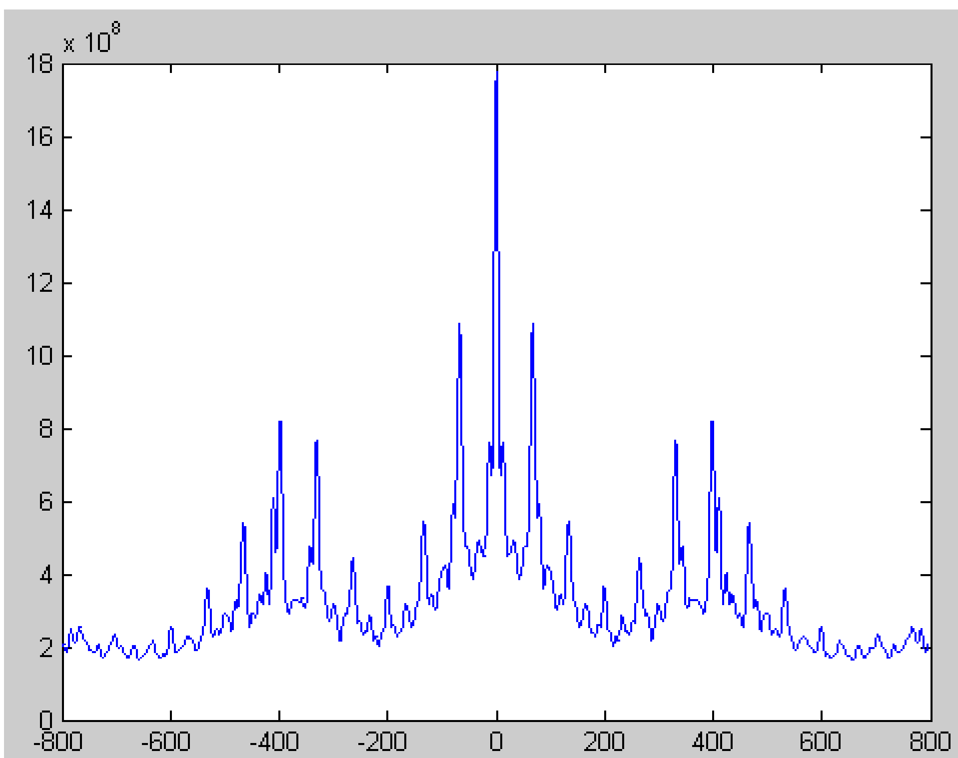


Figure 4.12 Cyclostationary Feature Detector Output at SNR 30dB for QPSK when primary user is present at 200Hz

Figure 4.11 shows the output of cyclostationary feature detection when there is a primary user at 200 Hz using BPSK is present with very poor SNR. It's very clear in the figure that it's very difficult to detect second peak at 400. So we have to compare second peak with threshold value. Hence, cyclostationary feature detection compared value of each peak with threshold, in this case no peak is greater then threshold. Hence, cyclostationary feature detection said that primary user is not present.

Figure 4.12 shows the output of cyclostationary feature detection when there is a primary user at 200 Hz using QPSK is present with very good SNR. It's very clear in the figure that there is peak in the center and there are two peaks at double of the frequency as well. So we have to compare second pair of peaks with threshold value. So cyclostationary feature detection compared value of each peak with threshold, in this case its greater then threshold at 400. Hence, cyclostationary feature detection said that primary user is present at 200 Hz.

Figure 4.13 shows the output of cyclostationary feature detection when there is a primary user at 200 Hz using QPSK is present with very poor SNR. It's very clear in the figure that there is peak in the center and its very difficult to see two peaks at double frequency. So we have to compare second peak with threshold value. So cyclostationary feature detection compared value of each peak with threshold, in this case its less then threshold. Hence, cyclostationary feature detection said that primary user is not present.

The main advantage of cyclostationary feature detection is that it can extract features from the waveform. Comparing Figure 4.6 and Figure 4.8 its very clear that when BPSK is modulation scheme at that time there is only single peak at double frequency and when QPSK is modulation scheme then there are two peaks at double of the frequency. So by counting number of peaks we can estimate modulation technique also.

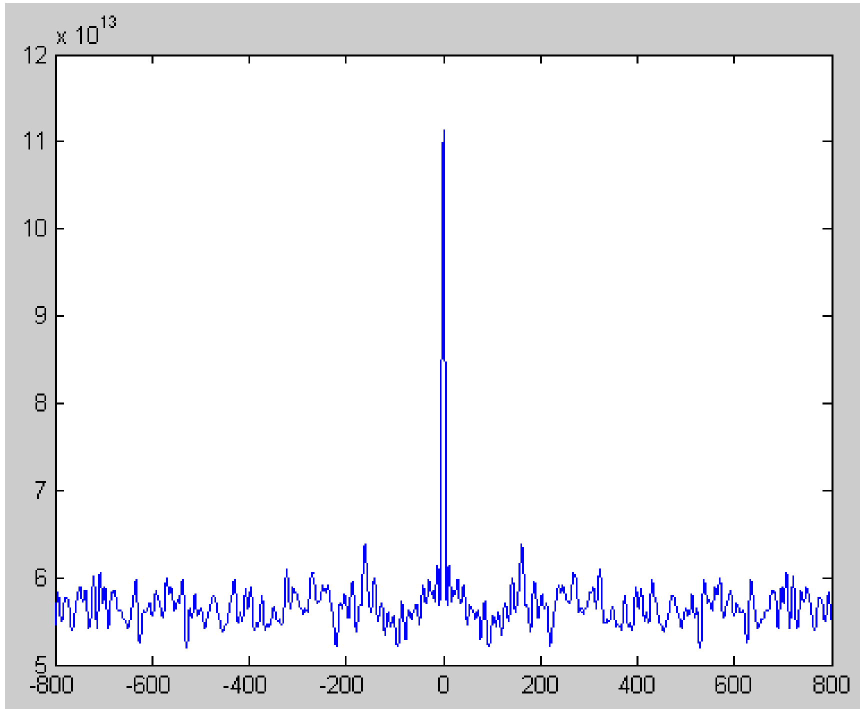


Figure 4.13 Cyclostationary Feature Detector Output at SNR -30dB for QPSK when primary user is present at 200Hz

4.6 Summary

The designed test program is written in MATLAB. The program comprises of three major techniques (i.e. Energy Detector, Matched Filter and Cyclostationary Feature Detection).

Chapter 5

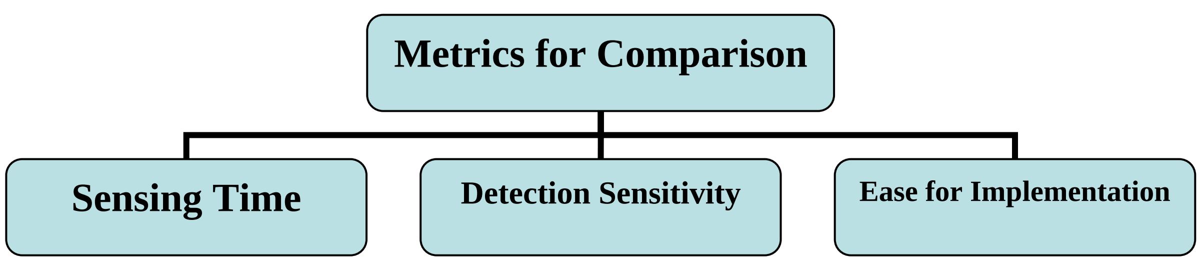
COMPARISON AND ANALYSIS

5.1 Introduction

In this chapter, the results of the algorithms and techniques, given in Chapter 2, have been presented. For experimentation, primary user's waveforms at different SNR have been identified. A comparison of all transmitter detection techniques is presented. In the end the results of two new proposed strategies one for minimizing sensing time and other for reliable detection are compared with individual techniques.

5.2 Comparison of Transmitter Detection Techniques

Now consider some metrics on the basis of which we can compare transmitter detection techniques. There are three metrics on the basis of which we can compare these techniques.



5.2.1 Sensing Time

During communication cognitive radio continuously sense the radio environment for spectrum holes and CR can't transmit and sense at the same time. Therefore we need sensing time as small as possible.

Matched Filtering is a good technique for spectrum sensing in cognitive radio networks if we have prior knowledge about primary users waveform. But in most of cases we have no prior knowledge about primary user's waveform which makes it difficult for the use of spectrum sensing. It requires least sensing time to achieve high processing gain due to coherency. Comparing Energy Detector and Matched Filtering, Energy Detector requires a longer sensing time to achieve good results as shown in Table 5.1.

Cyclostationary Feature Detection is also a non coherent technique which makes it superior to Matched Filtering. Cyclostationary Feature Detection technique is computationally very complex and it takes long observation time for sensing.

Sr. No.	Type of Primary Signal	Energy Detection	Matched Filter	Cyclostationary
1	BPSK	1.20 sec	0.17 sec	9.50 sec
2	QPSK	1.23 sec	0.2 sec	11.21 sec

Table 5.1 Sensing time for Transmitter Detection Techniques

Hence from the experimental results in Table 5.1 shows that matched filter requires least among the all sensing techniques and cyclostationary takes most.

5.2.2 Detection Sensitivity

As matched filter required prior knowledge about primary user's waveform but in comparison with energy detector it is still better under noisy environment. The major drawback of the energy detector is that it is unable to differentiate between sources of received energy i.e. it cannot distinguish between noise and primary user. So this makes it susceptible technique when there are uncertainties in background noise power, especially at low SNR. Cyclostationary Feature Detector is good technique under noisy environment as it is able to distinguish between noise energy and signal energy. Figure 5.1 shows comparison of transmitter detection techniques when there is primary user is present under different SNRs. Results shows that at low SNR when primary user is present cyclostationary and matched filtering are unable to detect primary user but energy detector still detect it. Figure 5.2 shows when there is no primary user present even then energy detector detects primary user at low SNR, which makes energy detector unreliable technique under low SNR values. Hence, when we have no prior knowledge about primary user's waveform then best technique is cyclostationary feature detection.

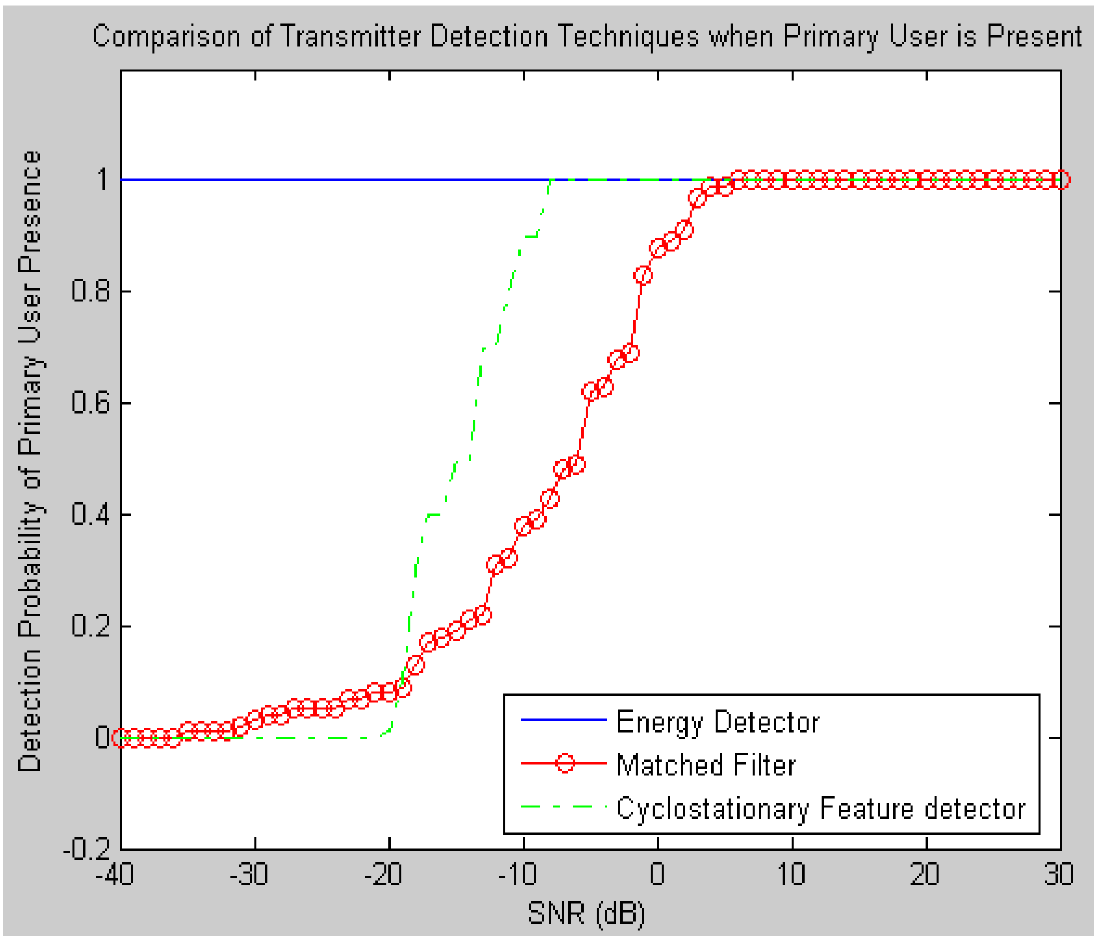


Figure 5.1 Comparison of Transmitter Detection Techniques when Primary User is Present

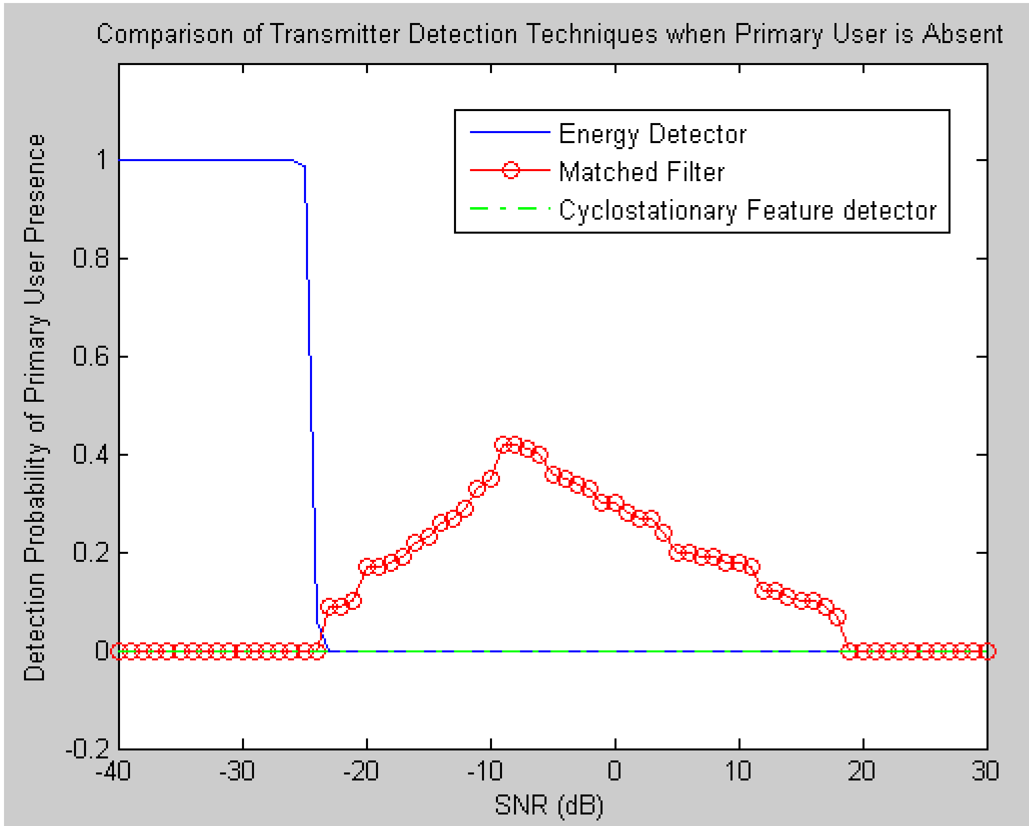


Figure 5.2 Comparison of Transmitter Detection Techniques when Primary User is absent

5.2.3 Ease for Implementation

The advantage of energy detector is its low cost and simple implementation, which makes it a good candidate for spectrum sensing in cognitive radio networks. Matched Filter is not easy to implement because it requires generating carrier at receiver, which increases the cost of cognitive radio. Cyclostationary Feature Detection is also very complex technique which takes high cost and high computational complexity.

Sr. No.	Type	Energy Detection	Matched Filter	Cyclostationary
1	Sensing Time	More	Less	Most
2	Simple to Implement	Yes	No	No
3	Performance under Noise	Poor	Bad	Good
4	Prior Knowledge Required	No	Yes	No

Table 5.2 Summary of comparison of Transmitter Detection Techniques

5.2.4 Comparison with other Related Work

In [24] shows that natural model uncertainties for wireless environments lead to fundamental limits on the sensitivity of cyclostationary feature detectors as well — leading to “SNR Walls” beyond which robust detection is impossible, no matter how long the observations are. These results show that at low enough SNR, all implementable detection schemes will be non-robust to the natural uncertainties in a wireless system. However, the relative locations of the SNR walls for different algorithms are important. They review simple examples to illustrate the above points and to motivate the general class of cyclostationary feature detectors.

In particular, they show that even for feature detection, there exists an SNR threshold below which it is impossible to detect the desired signal robustly. We compare the SNR wall for feature detectors with those for both energy detection and coherent detection.

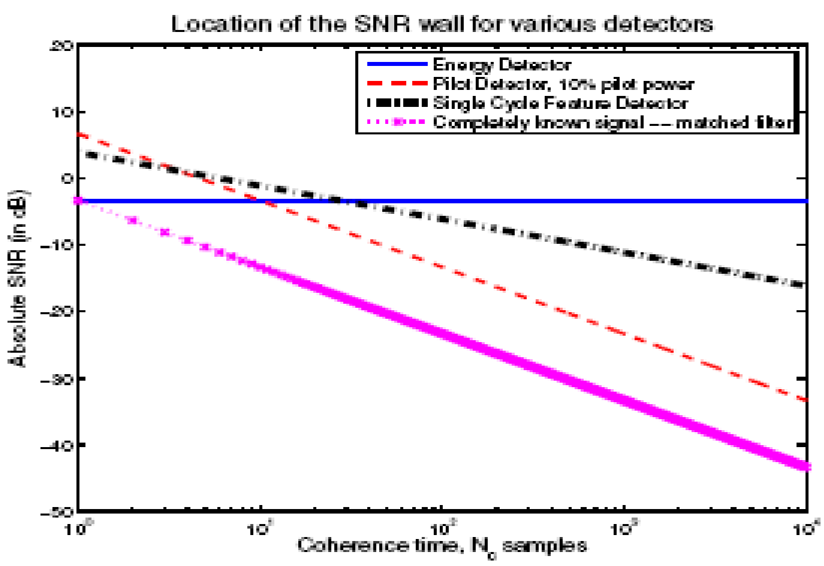


Figure 5.3 Comparison of Transmitter Detection Techniques as a function of channel coherence time

The location of the SNR walls for energy detection, coherent detection and feature detection are plotted as a function of the channel coherence time Nc in Figure 5.3. The solid line corresponds to the energy detection SNR wall, which is independent of the channel coherence time. The dashed curve corresponds to the pilot detector, when the pilot tone has 10% of the total signal energy. The dashed-dotted curved corresponds to the single cycle feature detector trying to detect the strongest feature corresponding to the signal data rate.

Finally, they compare these to the dotted curve which is the best possible case corresponding to the case when the signal is completely known. For all the above plots we assumed that the system has 1dB uncertainty in the noise power.

The main result of the paper is to show that the fundamental SNR wall results hold for feature detection also — there exists an SNR threshold below which feature detection is non-robust. We compared the SNR wall of feature detection with the energy and coherent detection walls. We showed that the feature detection SNR wall is better than the energy detection wall due to noise prediction gains. However, it is strictly worse than coherent detection because there are no coherent processing gains.

In [25] authors investigate the main issues associated with the design of spectrum sensing functionality for cognitive-radio-based dynamic spectrum access. Performance limitations raised by the uncertainties at various levels of operation are discussed, and it is argued that these challenges may be overcome by a proper combination of local signal processing, user-level cooperation among cognitive radios, and system-level coordination among different cognitive radio networks.

Evidently, cooperative sensing enables users to employ less sensitive detectors. A less stringent sensitivity requirement is particularly appealing from the implementation point of view due to the reduced hardware cost and complexity. Figure 5.4 depicted that when single user is present then sensitivity time is 100ms which is comparable with the results achieved with matched filter.

As outlined previously, with increasing the number of cooperating users, target detection sensitivity may be achieved by having less sensitive detectors at the individual users. Given a certain detector, a relaxed sensitivity requirement is translated into a shorter sensing time and hence less local processing. This phenomenon is depicted in Figure 5.5, where the sensing time of local energy detectors, required to achieve an overall detection sensitivity of –20 dB (with 99 percent accuracy), is plotted as a function of the number of cooperating users under independent Rayleigh fading.

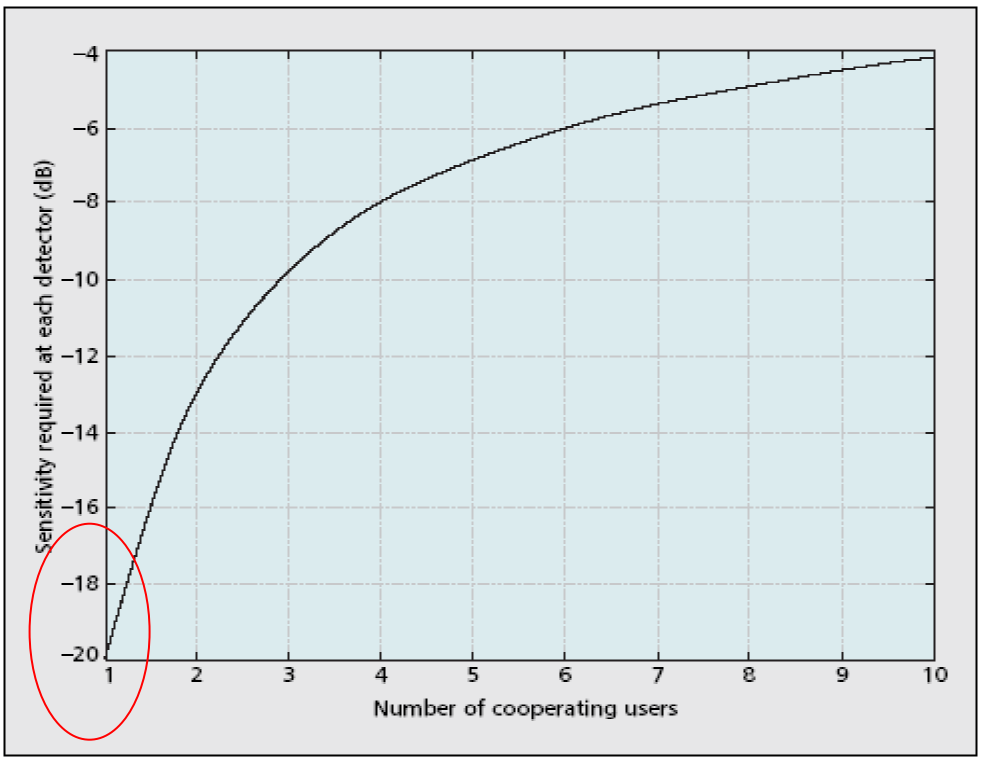


Figure 5.4 Required sensitivity of individual cognitive radios to achieve an overall detection sensitivity of –20 dB under Rayleigh fading vs. the number of cooperating users.

Finally in comparison with the works done by others sensitivity time achieved in this thesis is greater because the sensing time is dependent on the system capabilities on which simulations have been done. SNR Walls discussed in [24] have results comparable with the results achieved in this thesis as shown in Figure 5.3. Detection sensitivity in

[25] is comparable with the results achieved in this thesis as shown in Figure 5.4 for one user.

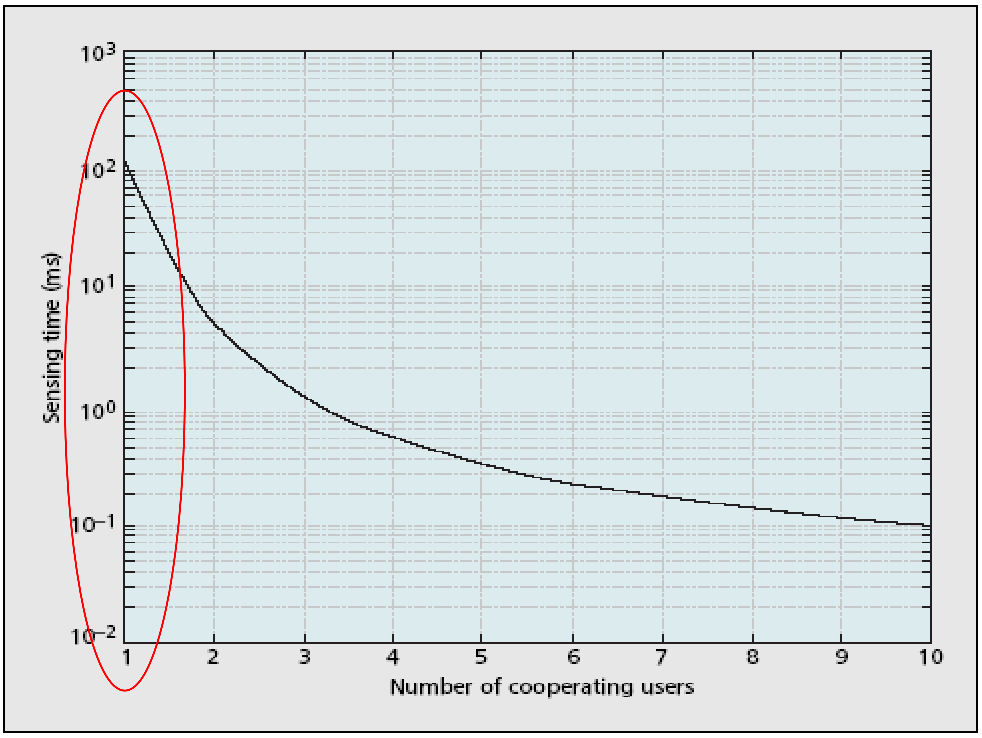


Figure 5.5 Cooperation-processing trade-off under Rayleigh fading.

5.3 Minimized Sensing time for Detection

To minimize sensing time and still have some reliability, an algorithm in section 3.3 has been proposed. If prior knowledge about primary user's waveform is known at the receiver end then under good SNR we can sense spectrum accurately by using matched filter. But if prior knowledge of primary user is not known then we should consult with energy detector for the detection of primary user. In this case we the computation time is increased to achieve reliability. Further if energy detector doesn't give accurate result then cyclostationary feature detection comes into play. In this case it takes too much computation time to achieve reliability. This is the worst case of this algorithm. The best case for this algorithm is that if matched filter provides indication about the presence or absence of primary user.

Figure 5.6 compares the results of algorithm based detection with transmitter detection techniques when there is no primary user. It gives 100 % accurate results in this case when we know prior knowledge of primary user's waveform.

Figure 5.7 compares the results of algorithm based detection with transmitter detection techniques when primary user is present. It still gives good results but under low SNR conditions matched filter gives wrong results therefore algorithm gives some false detection also.

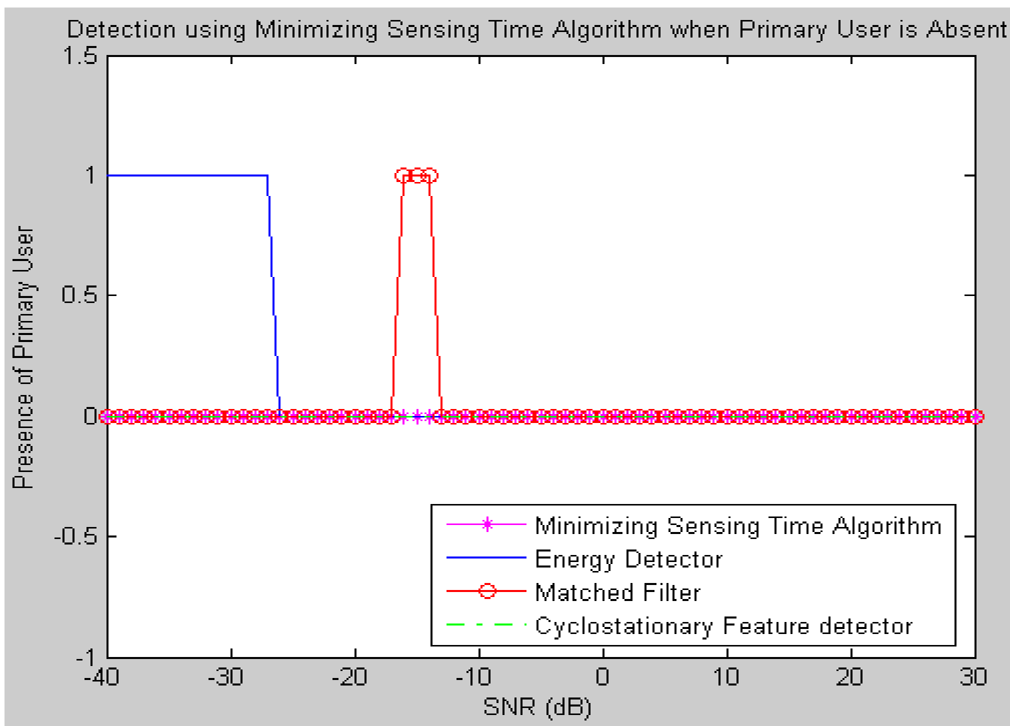


Figure 5.6 Comparison of Algorithm based detection with Transmitter detection Techniques at different SNR values when primary user is absent

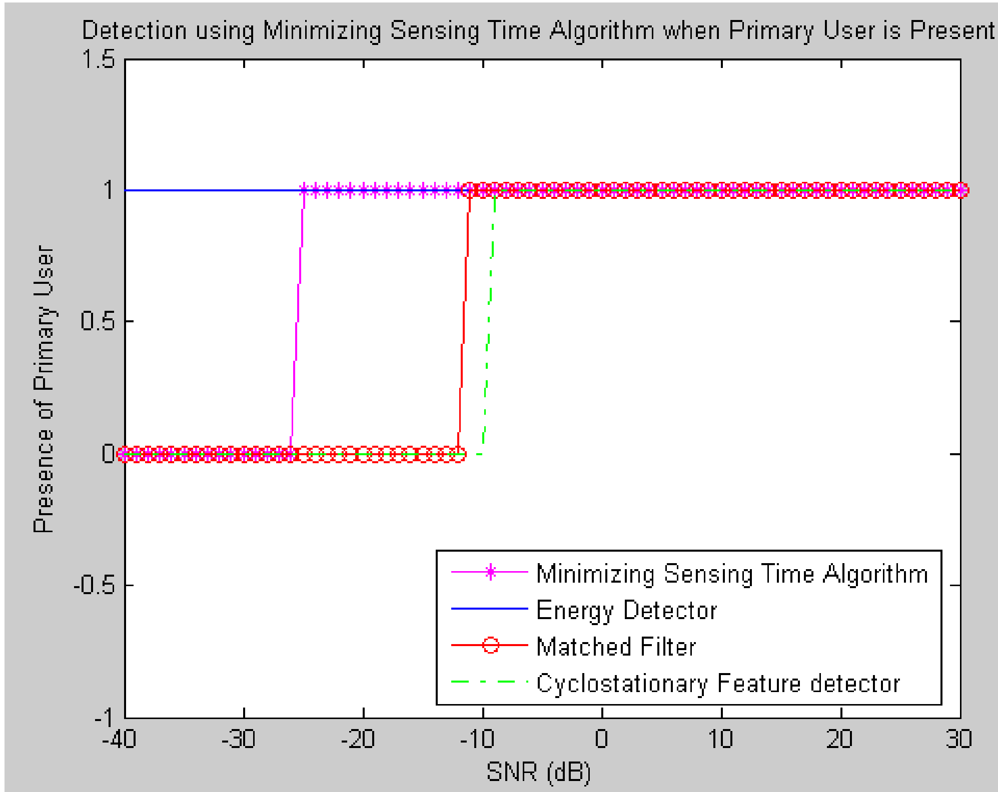


Figure 5.7 Comparison of Algorithm based detection with Transmitter detection Techniques at different SNR values when primary user is present

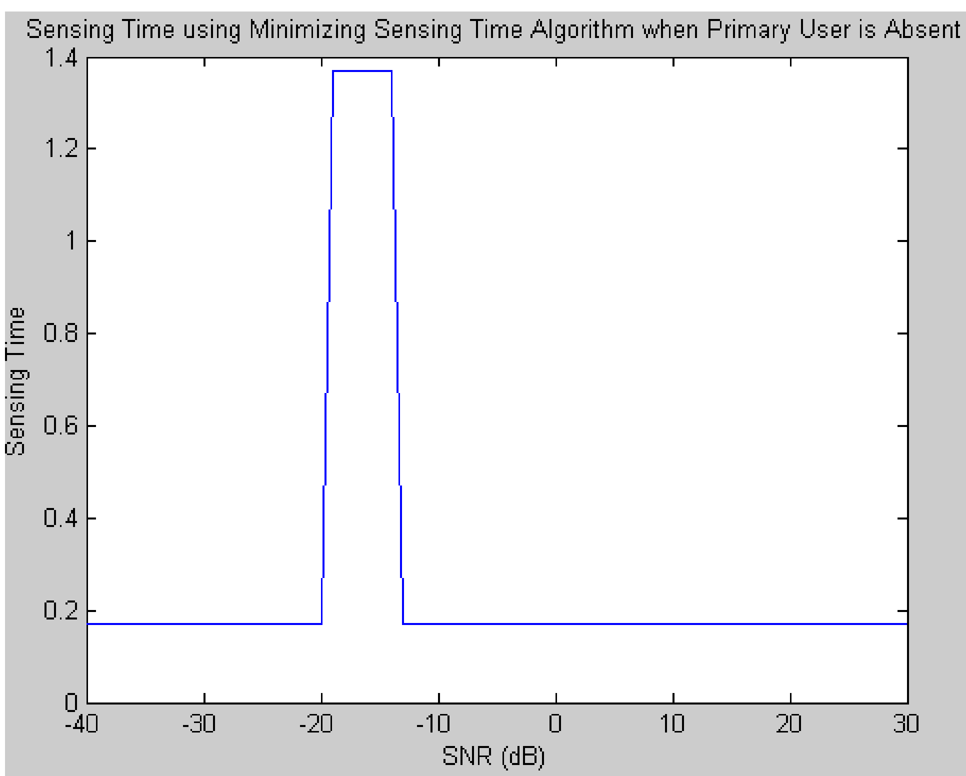


Figure 5.8 Sensing time under Different SNR values when primary user is absent

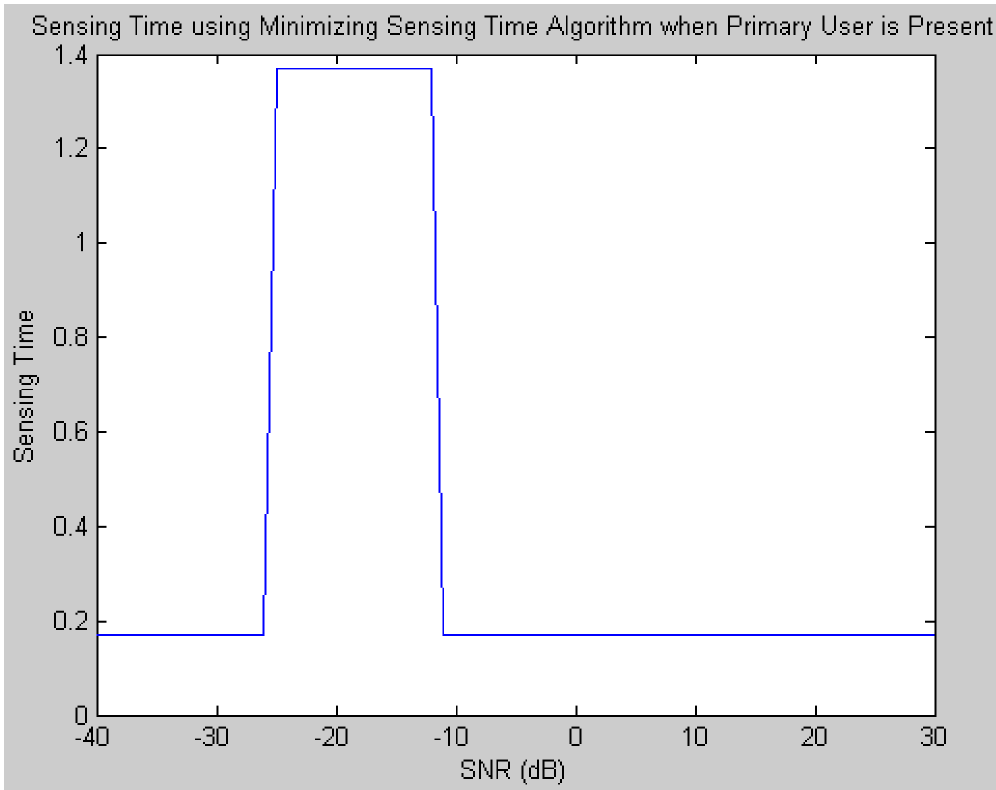


Figure 5.9 Sensing time under Different SNR values when primary user is present

Figure 5.8 shows sensing time required when primary user is absent. Results shows that most of the time it will get results by using matched filter only. But in some cases under low SNR conditions it has to consult with energy detector. Hence, sensing time increases for that period of time. Sensing time can further increase if it has to consult with cyclostationary feature detection.

Figure 5.9 shows sensing time required when primary user is present. Results shows that most of the time it will get results by using matched filter only. But in some cases under low SNR conditions it has to consult with energy detector. Hence, sensing time increases for that period of time. Sensing time can further increase if it has to consult with cyclostationary feature detection.

5.4 Fuzzy Logic Based Detection

To achieve reliable results fuzzy logic based spectrum sensing is introduced discussed in section 3.4. Now instead of having binary decisions we have three outcomes of each technique i.e. 'L' means primary user is not present, 'H' means primary user is present and 'M' means that technique is not sure about presence or absence of primary user.

Figure 5.10 shows the comparison of fuzzy based detection with transmitter detection techniques when there is no primary user present. Figure shows that it will give better results then energy detection but under low SNR conditions cyclostationary feature detection gives better result then it. Figure 5.11 shows the comparison of fuzzy based detection with transmitter detection techniques when there primary user is present. Figure shows that it will give better results then matched filter and cyclostationary feature detection under very low SNR conditions energy detector gives better result then it because energy detector can't distinguish between noise and signal power.

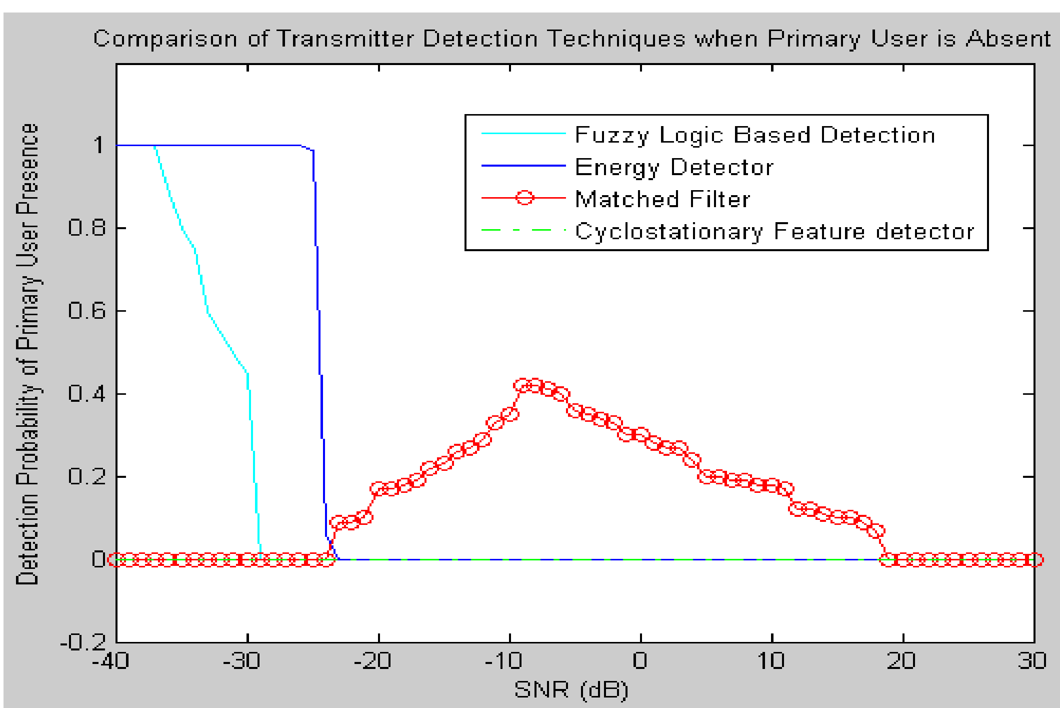


Figure 5.10 Comparison of Transmitter Detection Techniques & Fuzzy based Detection when Primary User is absent

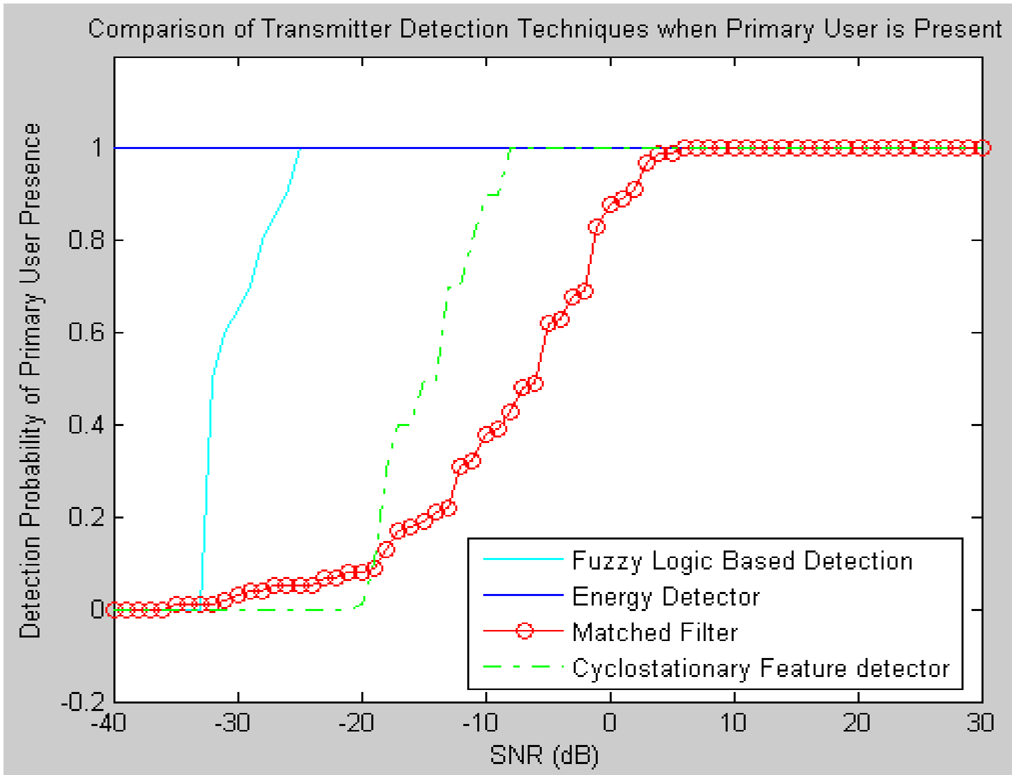


Figure 5.11 Comparison of Transmitter Detection Techniques & Fuzzy based Detection when Primary User is present

5.5 Analysis of Results

The reliable spectrum sensing is successfully done by using fuzzy logic, even though complexity of the system increases. Sensing time can also be minimized by using proposed algorithm, even though there may be errors in the sensing because of low SNR values in energy detector. The results of sensing time rely heavily on the system.

Figure 5.12 shows the comparison of algorithmic based detection and fuzzy based detection when primary user is absent. Under low SNR conditions fuzzy based detection give false detections but algorithm based detection gives 100% results. Hence, in this case algorithm based detection is best sensing mechanism as it takes less computation time as compared to fuzzy based detection.

Figure 5.13 shows the comparison of algorithmic based detection and fuzzy based detection when primary user is present. Under low SNR conditions both of them gives false detections but still fuzzy based detection is better at some values of low SNR also. Hence, in this case if reliability is important then fuzzy based detection gives better results and if sensing time is important then algorithm based detection is a good choice.

Comparing these two mechanisms with respect to sensing time, it is concluded that fuzzy based detection is computationally very expensive. Computation time of algorithm based detection is variable depending upon the results of individual transmitter detection technique and prior knowledge of primary user's waveform.

Hence, if the sensing time is important then algorithm based detection is good choice and if sensing results are important then fuzzy based detection should be used.

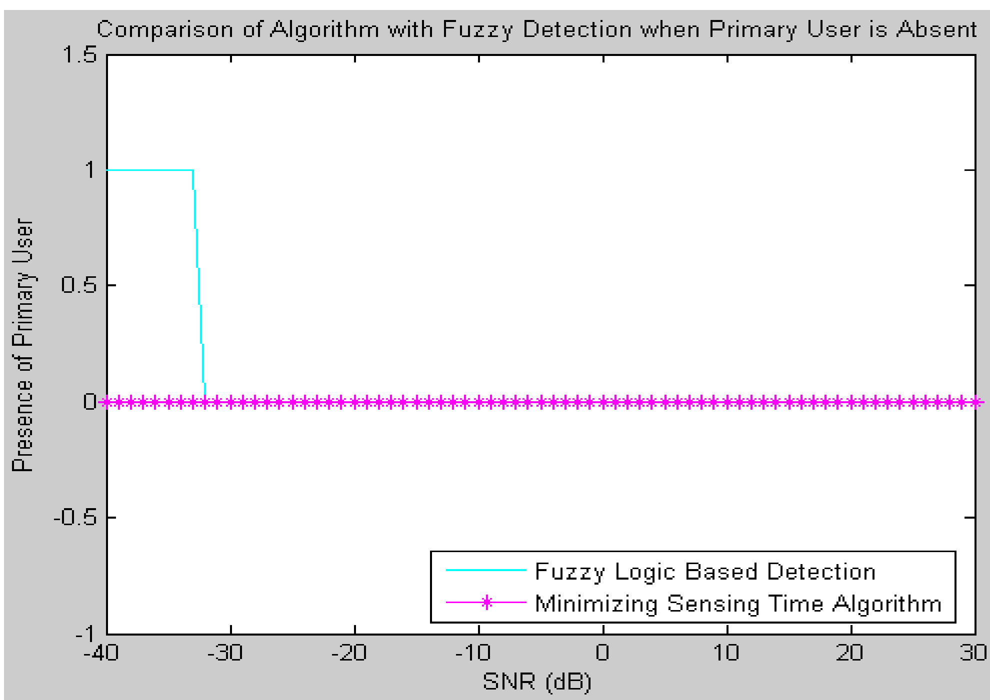


Figure 5.12 Comparison of Algorithm Based Detection & Fuzzy based Detection when Primary User is absent

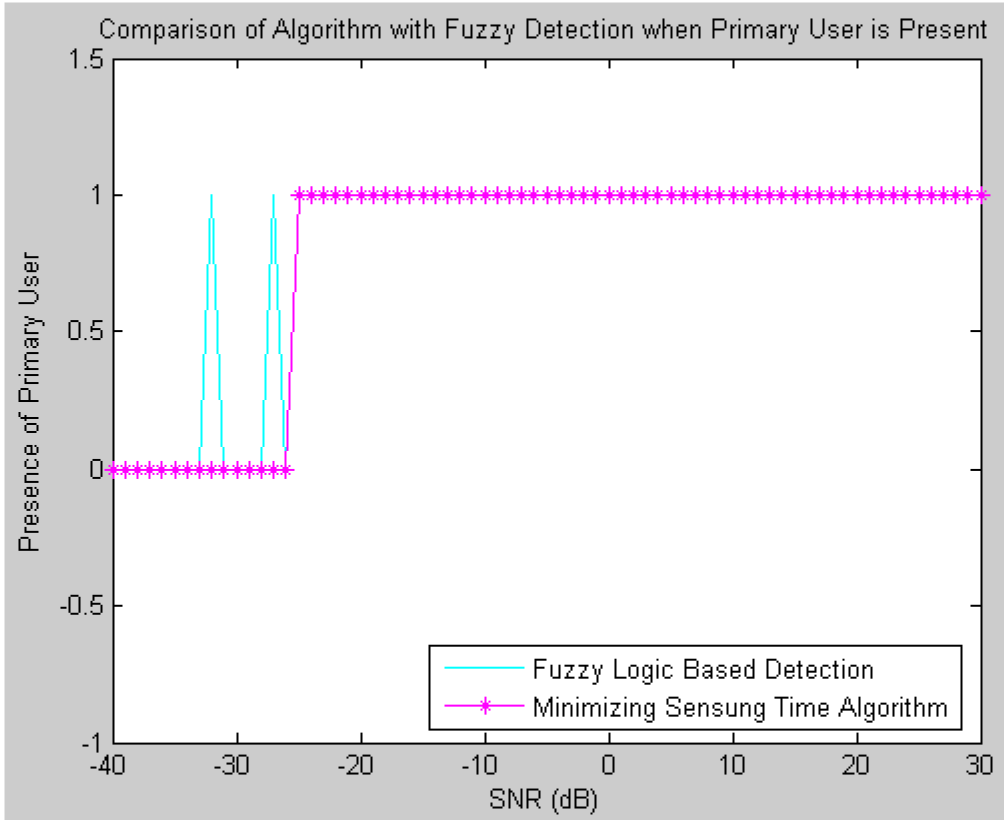


Figure 5.13 Comparison of Algorithm Based Detection & Fuzzy based Detection when Primary User is present

5.6 Summary

This chapter provides the results of the applied technique on various types of primary user's waveforms. The result analysis clearly shows that the algorithm based detection approach has been proved to be highly successful in spectrum sensing for cognitive radio networks. The approach of having used a rule based detector for spectrum sensing using all transmitter detection techniques has made the overall system robust. In the end, the fuzzy based detection is implemented for the spectrum sensing and compared with individual techniques based on the performance.

Chapter 6

CONCLUSION

6.1 Overview

As the demand of radio spectrum increases in past few years and licensed bands are used inefficiently, improvement in the existing spectrum access policy is expected. Dynamic spectrum access is imagine to resolve the spectrum shortage by allowing unlicensed users to dynamically utilize spectrum holes across the licensed spectrum on noninterfering basis.

This research was aimed towards the detection and classification of primary user's waveform in cognitive radio networks. The primary requirement of a spectrum sensing system is its real time processing and decision making. The proposed methodology has been implemented on a desktop PC and requires MATLAB support for simulation. Its implementation can be done on FPGA kit or DSP processor.

First all the transmitter detection techniques are compared on the basis of three metrics: Sensing Time, Detection Sensitivity and ease of implementation. By comparing these techniques it is concluded that cyclostationary feature detection gives best results but take long computation time compared to other techniques.

A fuzzy logic based algorithm named as minimizing sensing time algorithm and improving reliability is proposed which gives very good results at high SNR values. But under worst situation, when it has to consult with cyclostationary feature detection, it will take very long computation time.

The fuzzy logic based detection in the proposed framework is a bottleneck as it is computationally very expensive, but it will give reliable results. However, since accurate detection is to be predicted, therefore the computational time can be sacrificed to accuracy of detection. Moreover for actual implementation, the technique can be implemented on real time processing hardware.

Finally it is concluded that every detection technique has an SNR threshold below which it will fail to operate robustly. So by using the results of different techniques at the same time better results can be obtained.

In this thesis main issues associated with spectrum sensing techniques are highlighted. Performance of these spectrum sensing techniques limits due to uncertainty in the noise level.

6.2 Future Work

Most of the research on spectrum sensing is mainly focused on reliable sensing to meet the regulatory requirements. One of the important areas for the research is to focus on user level cooperation among cognitive radios and system level cooperation among different cognitive radio networks to overcome the noise level uncertainties. In this work, the noise level uncertainties are catered by a proper combination of spectrum sensing techniques.

Another area for research is cross layer communication in which spectrum sensing and higher layer functionalities can help in improving quality of service (QoS).

Annex 1

MATLAB Code of Primary Transmitter

The MATLAB script ‘transmitter.m’, presented below, simulates two types of Primary transmitter for Spectrum Sensing in Cognitive Radio Networks, one using BPSK modulation technique and other using QPSK modulation technique. The code is self-explanatory and consists of following parts.

Parameters

The system parameters are set in this part. The parameters are: (i) the operating frequency, ‘freq’; (ii) the sampling frequency, ‘Fs’; (iii) number of samples per symbol period, ‘L’; (iv) the sampling period, ‘Ts’; (v) roll-off factor for the (square-root) raised cosine filters, ‘alpha’; (vi) N+1 is the length of the square-root raised cosine filter, ‘N’; (vii) standard deviation of channel noise, ‘sigma_v’; (viii) channel impulse response, ‘h’.

Source

This is any piece of information (a text file, a sampled speech signal, a coded image, ……) that is converted to sequence of bits. In the MATLAB script ‘transmitter.m’, this sequence is stored in a vector called ‘pt_dt’.

MATLAB script transmitter.m: Primary Users Transmitter

```
close all;
clear all;
%
%    PARAMETERS
%
freq = 200;        %operating frequency
Fs = 20*f;     %sampling frequency
L=100;          % Number of samples per symbol period
Ts = 1/Fs;       % Sampling period
T = Ts:Ts:1/f;
alpha=0.5;      % Roll-off factor for the (square-root) raised cosine filters
N=8*L;          % N+1 is the length of the square-root raised-cosine filter.
sigma_v=0;      % Standard deviation of channel noise
```

```
h=1;          % Channel impulse response

%
%SOURCE: Take input data from user for transmission
%

pt_dt = input('Data you want to send:','s');
R = isempty(pt_dt);

        if R == 1
                pt_dt = 'Waleed Ejaz';
        else
                pt_dt = pt_dt;
        end
        display(pt_dt);
        RR = double(pt_dt);
        bb = 1;
        Rp = dec2bin(RR,7);
        [TA TC] = size(Rp);

        for  ll = 1:1:TA
                for  lg = 1:1:TC
                 msg(bb) =  Rp(ll,lg);
                bb = bb + 1;
                end
        end

rt = 1;  ht = 1;
        for ls = 1:1:TA
                for ll = 1:2:(TC-1)
                Inp_msg(rt,(ht:ht+1)) = Rp(ls,(ll:ll+1));
                rt = rt + 1;
                end
        end
        %
        % Transmit Filter
        %

        pT=f_sr_cos_p(N,L,alpha);     % Transmit filter:
        xT=conv(f_expander(msg,L),pT);  % Transmit signal

        %
        %  Modulation
        %
        display('Select Type of Modulation');
        display('1. BPSK');
        display('2. QPSK');
        Mod_Type = input('Plz Enter the Type of Modulation:','s');
        Carrier = [];
```

```
%
% BPSK Modulation
%
        if (Mod_Type=='1')
        display('Binary PSK');
        for ii = 1:1:length(T)
        car1(ii) = sin((2*pi*freq*T(ii)));             %CARRIER TO BE TRANSMITTED
        end

        for ii = 1:1:length(xT)
                if xT(ii) == '0'
                car = -1*car1;
         else
                car =  1*car1;
         end
        Carrier  = [Carrier car];
        end

%
% QPSK Modulation
%

        else if(Mod_Type=='2')
        for ii = 1:1:length(T)
        car1(ii) = sin((2*pi*freq*T(ii))+360); %CARRIER TO BE TRANSMITTED
        car2(ii) = sin((2*pi*freq*T(ii))+90); %CARRIER TO BE TRANSMITTED
        car3(ii) = sin((2*pi*freq*T(ii))+180); %CARRIER TO BE TRANSMITTED
        car4(ii) = sin((2*pi*freq*T(ii))+270); %CARRIER TO BE TRANSMITTED
        end

        for ii = 1:1:length(Inp_msg)
                if Inp_msg(ii) == '00'
                car = car1;
                        else if Inp_msg(ii) == '01'
                        car = car2;
                                else if Inp_msg(ii) == '10'
                                car = car3;
                                        else if Inp_msg(ii) == '11'
                                        car = car4;
                                        end
                                 end
                        end
                end
         Carrier  = [Carrier car];
        end
   end % end of if
end %end of else if
```

```
%
%     CHANNEL
%

xR=conv(h,Carrier);
xR=xR+sigma_v*randn(size(xR)); % Received signal
```

Transmit filter

This a square-root raised-cosine filters with roll-off factor α. Here, α is set equal to 0.5. In the real world, the transmit signal is continuous time. Since in computer simulation, we can only have sampled signals, we approximate continuous-time signals by a dense grid of samples. Here, we have L = 100 samples per symbol period. The function 'sr_cos p' generates a square-root raised-cosine pulse, for the transmit filter, pT(t). The next line in the code, expands the transmit symbols and lowpass filters the result by passing it through pT(t).

Modulation

Modulation is done to generate an RF (radio frequency) signal for transmission through channel. Here we use BPSK (Binary Phase Shift Keying) and QPSK (Qaurdrature Phase Shift Keying) to modulate the signal.

Channel

This is characterized by an impulse response c(t) and an additive noise. Here, we have chosen c(t) = δ(t) which in the discrete domain becomes c = 1. If the channel is multipath, e.g., with the impulse response c(t) = a0δ(t −t0) + a1δ(t − t1), it has the equivalent discrete domain c = [zeros(N0,1); a0; zeros(N1,1); a1], where N0 and N1 are t0 and t1 in unit of Ts. The channel noise is assumed to be Gaussian with the standard deviation 'sigma_v'.

MATLAB Code of Energy detector

The MATLAB script ‘energydetector.m’, presented below, simulates the Energy Detector for Spectrum Sensing in Cognitive Radio Networks. The code is self explanatory and consists of following parts.

Periodogram

Power Spectral Density (PSD) estimate via periodogram method. Pxx = PERIODOGRAM(X) returns the PSD estimate of the signal specified by vector X in the vector Pxx. By default, the signal X is windowed with a BOXCAR window of the same length as X. The PSD estimate is computed using an FFT of length given by the larger of 256 and the next power of 2 greater than the length of X.

dspdata.psd

The power spectral density (PSD) is intended for continuous spectra. The integral of the PSD over a given frequency band computes the average power in the signal over that frequency band. In contrast to the mean-squared spectrum, the peaks in this spectrum do not reflect the power at a given frequency. See the avgpower method of dspdata for more information. A one-sided PSD contains the total power of the signal in the frequency interval from DC to half of the Nyquist rate. A two-sided PSD contains the total power in the frequency interval from DC to the Nyquist rate.

Threshold

Finally the output of the integrator, Y is compared with a threshold values to decide whether primary user is present or not. There is another possibility in which energy detector is not sure about whether the primary user is present or not. So, we have two thresholds $\lambda 1$ and $\lambda 2$.

MATLAB Script energydetection.m

```
   Pxx = periodogram(xR);
    Hpsd = dspdata.psd(Pxx,'Fs',Fs);
    plot(Hpsd)

 fre=[]; o=1;
 len=65537*0.5;
 n_len= floor(len/2000);

for p=1:n_len:1980*n_len
    fre(o)=sum(Pxx(p:p+n_len));
    o=o+1;
end
sa=[];
count=0;

for w=1:1:length(fre)
    if(fre(1,w)>5000)
       count=count+1;
       sa= [sa w];
    end
end

count_m=0;
if(count>=1)
    E(1,1)=1;
else if(count==0)

            E(1,2)=1;


    end
end
```

MATLAB Code of Matched Filter

The MATLAB script ‘matchedfilter.m’, presented below, simulates the Matched Filter for Spectrum Sensing in Cognitive Radio Networks. The code is self-explanatory and consists of the following parts:

Local Carrier

For the matched filter prior knowledge of primary user waveform is required. Therefore a local carrier is generated using local oscillator.

Cross Correlation

xcorr estimates the cross-correlation sequence of a random process. Autocorrelation is handled as a special case. The true cross-correlation sequence is

$$R_{xy}(m) = E\{x_{n+m} y_n^*\} = E\{x_n y_{n-m}^*\} \qquad \text{(A-1)}$$

where xn and yn are jointly stationary random processes, $-\infty<n<\infty$, and E {·} is the expected value operator. xcorr must estimate the sequence because, in practice, only a finite segment of one realization of the infinite-length random process is available.

Threshold

Finally the output of the correlated signals, Y is compared with a threshold values to decide whether primary user is present or not. There is another possibility in which matched filter is not sure about whether the primary user is present or not. So, we have two thresholds λ1 and λ2.

MATLAB Script matchedfilter.m

```
 for ii = 1:1:length(T)
car1(ii) = sin((2*pi*f*T(ii))+360); %CARRIER TO BE TRANSMITTED
car2(ii) = sin((2*pi*f*T(ii))+90); %CARRIER TO BE TRANSMITTED
car3(ii) = sin((2*pi*f*T(ii))+180); %CARRIER TO BE TRANSMITTED
car4(ii) = sin((2*pi*f*T(ii))+270); %CARRIER TO BE TRANSMITTED
end
```

```
res1= xcorr(xR(1:20),car1)* 10^14;
res2= xcorr(xR(1:20),car2)* 10^14;
res3= xcorr(xR(1:20),car3)* 10^14;
res4= xcorr(xR(1:20),car4)* 10^14;


r1=sum(res1);
r2=sum(res2);
r3=sum(res3);
r4=sum(res4);

if((r1>-35 && r1<35)&& (r2>-35 && r2<35) && (r3>-35 && r3<35) && (r4>-35
&& r4<35))
    M(1,1)=1;%Primary user is not present
else
    M(1,2)=1;%Primary user is present
end
```

MATLAB Code of Cyclostationary Feature Detector

The MATLAB script 'cyclostationary.m', presented below, simulates the Cyclostationary Feature Detector for Spectrum Sensing in Cognitive Radio Networks. The code is self-explanatory and consists of the following parts:

Correlation and Averaging

We assume that received signal is cyclostationary i.e. its mean and autocorrelation are periodic functions of time. Hence, correlation of received signal with its shifted version is obtained. Shifting of receive d signal is done by multiplying it with ejα. The time average of correlated factor is computed.

Thresholding

If the correlation factor is greater than certain threshold then it means that there is a primary user in radio environment. There is another possibility in which cyclostationary feature detector is not sure about whether the primary user is present or not. So, we have two thresholds λ1 and λ2.

MATLAB Script cyclostationay.m

```
Fup = 4*f;
Fdwn = -Fup;
resol = 1;
Delf = Fdwn;
shfT = 1/Fs:1/Fs:((length(Carrier)*(1/Fs)));

for ii = 1:1:((2*Fup)/resol)

   XT = Carrier.*exp(j*2*pi*Delf*shfT);
   XY = xcorr(Carrier,XT);
   YT = fft(XY).*conj(fft(XY));
   pt(ii) = sum((YT));
   Delf = Delf + resol;

end
```

```
Fscal = Fdwn:resol:Fup;
 plot(Fscal(1,(1:end-1)),(pt));


[freq freq_indx] = max(pt(1,((end/2)+(end/4):end)));

freqy = Fscal(1,(length(pt)/2)+(length(pt)/4)+freq_indx-1);
freqy/2
if((freq_indx>=1 && freq_indx<=5) && freq>1)
        C(1,1)=1;

    else
            C(1,2)=1;

    end
```

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