Chapter 1

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[1].

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. 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. 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[1].

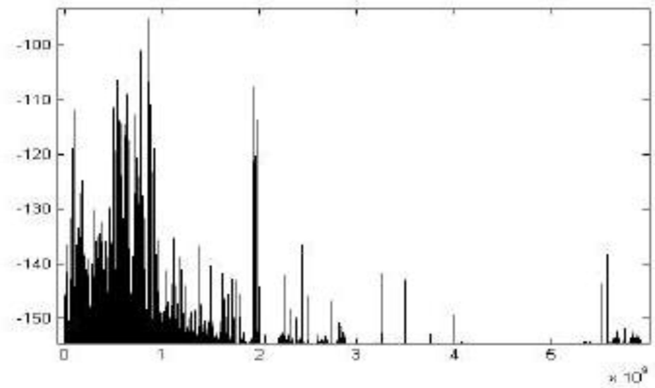


Figure 1.1 Measurement of 0-6 GHz spectrum utilization at BWRC

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).

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[2].

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[2].

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[2].

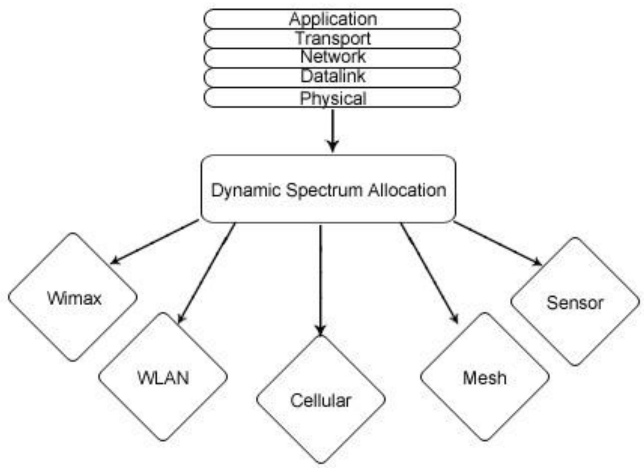


Fig 1.2 Dynamic changes in all Layers

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 [1]. 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.

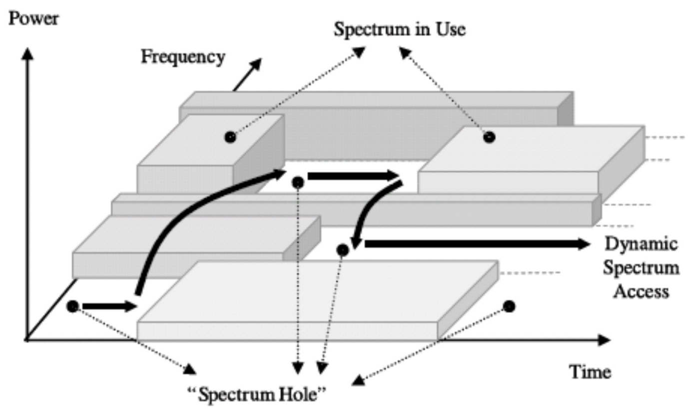


Fig 1.3 Spectrum hole concept

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, which is referred to as the cognitive cycle. The three main steps of the cognitive cycle, shown in Figure.

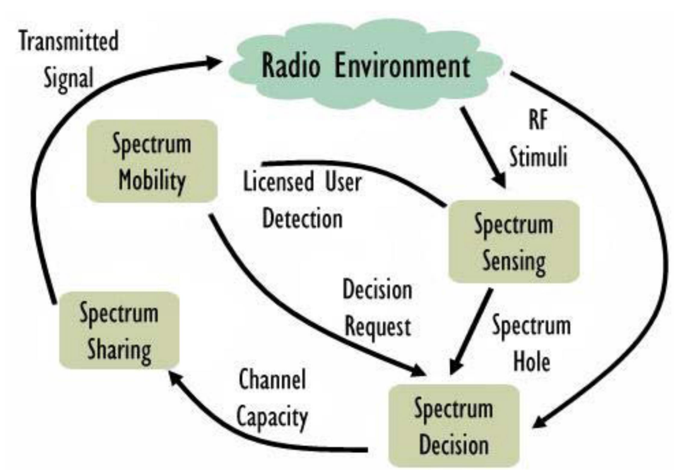


Figure 1.4 Cognitive Cycle

1.3.1 Spectrum sensing

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 [1],[2],[3],[4]. 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.

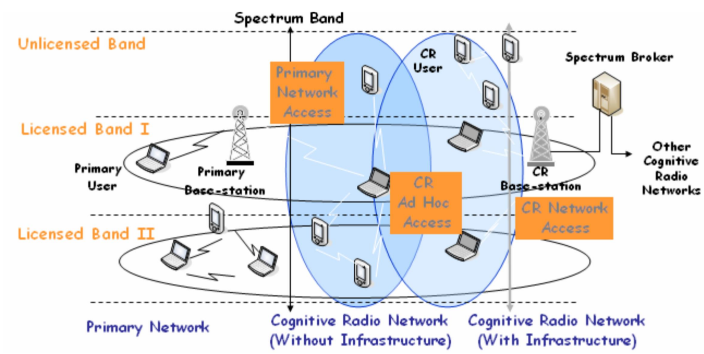


Figure 1.5 Cognitive Radio Network Architecture

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[4].

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[5].

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[4].

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 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. 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. 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

The authors[6] 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 by compressed detection in wideband sensing 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 sensing the signal using compressed wideband sensing technique.

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. Chapter 6 gives the details about compressed sensing, chapter 7 details about the wideband compressed sensing and its application in cognitive radio communications. Chapter 10 keeps the simulation results of the project. Chapter 11 gives the advantages and limitations. Lastly, chapter 12 concludes the research and highlights the future work, which can be done to carry forward this effort.

1.9 Conclusion

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 SURVEY

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.

A CR cannot 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.

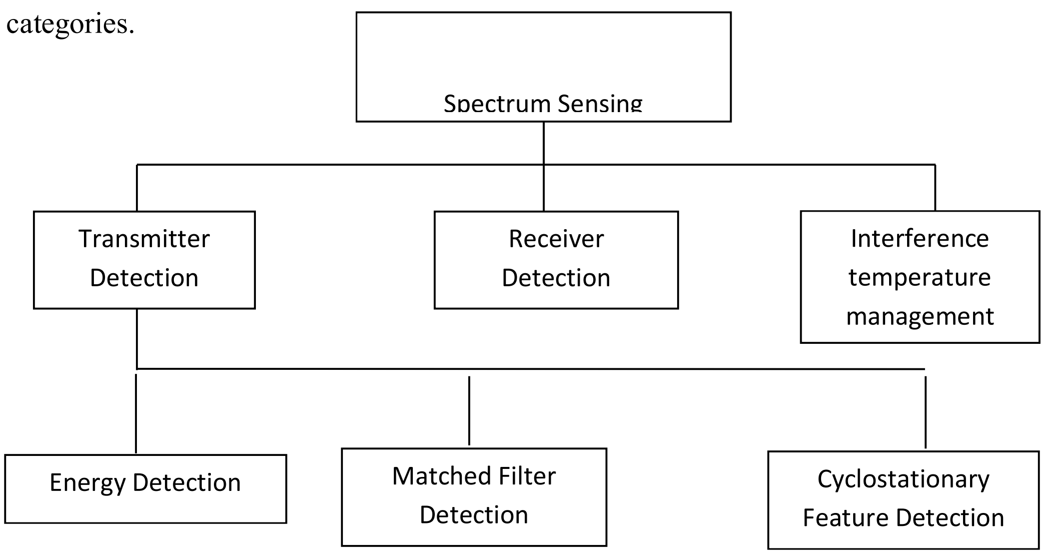


Figure 2.1. Classification of techniques

2.2.**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 that is, the signal received (detected) by the CR (secondary) user is

$$x(t)= n(t)H_0 \quad (1)$$

$$x(t)= hs(t) + n(t)H_1 \quad (2)$$

Where x(t) is the signal received by the CR, s(t) is the transmitted signal of the 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 Detectio
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.

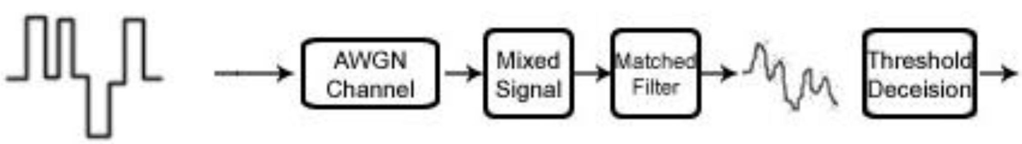


Figure 2.2 Block Diagram of Matched Filter

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 at 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]. The block diagram of the energy detector is as shown in Figure 2.3. 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.

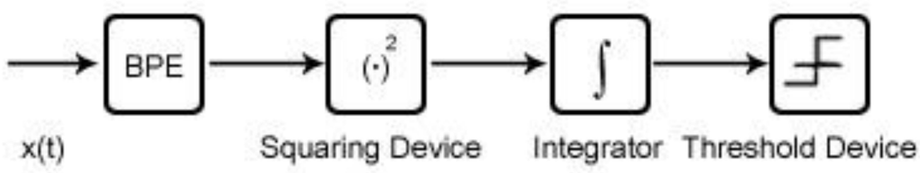


Figure 2.3 Block Diagram of Energy Detector

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]:

$Pd= P(Y>\lambda/H_1)=Qm(\sqrt{2\gamma}, \sqrt{\lambda})$ 2.2

$Pf= P(Y>\lambda/H_0)=\Gamma(m,\frac{\lambda}{2})/\Gamma(m)$ 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 ility of detection 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:

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

signals are characterized as Cyclostationary, since their statistics, mean and autocorrelation 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 the 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 uncertainty in noise power. It cannot differentiate between signal power and a noise power rather 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, exhibits periodicity. These features are detected by analyzing a spectral correlation function. The periodicity is provided for signa

eion 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.

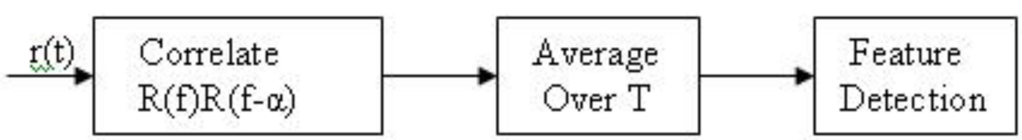


Figure 2.4 Block Diagram of Cyclostationary Feature Detector

Implementation of spectrum correlation function for Cyclostationary feature detection is depicted in Figure 2.4. 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 process in low SNR regimes. ing time, hich 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 signal

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.

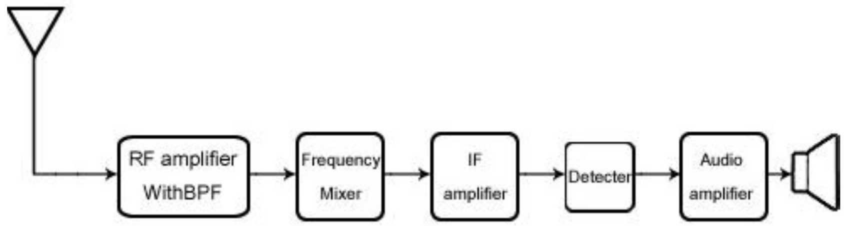
2.2.1.5 Cooperative Vs Non Cooperative The detection behavior can be categorized into two main branches, Non cooperative and cooperative. In noncooperative detection behavior cognitive radio user can detect the signal of primary transmitter by its own observations of cognitive radio users. While in Cooperative 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 users while in distributed mechanism cognitive radio exchange messages with respect to 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 receiver.

2.2.2 Receiver Detection

Now we need such spectrum sensing techniques which are able to remove the problems intransmitter 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.



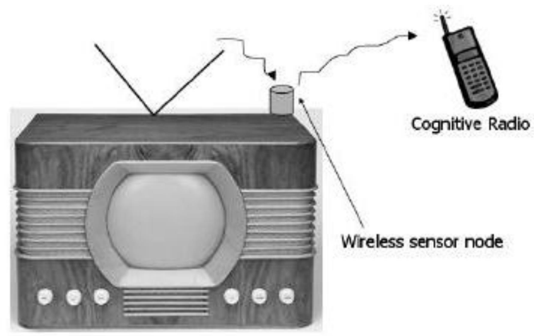
2.5 Architecture of Super heterodyne Receiver

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 ixed with incoming RF signal, it converts it into fixed low IF band. In all of these e leakage, and therefore some of the local oscillator ertainty 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.

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] it was 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 chann n to the CR el the receiver was tuned. It would then relay this information through a separate control channel using a fixed power level. Working of this is shown in Figure 2.5.



2.6 Sensor Nodes Notifying Cognitive Radio [12]

2.2.3 Interference Temperature Management

We can define interference temperature management as measure of the RF power generated by undesired 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 in 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 Conclusion

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.

Chapter 3

DESCRIPTION OF THE PROJECT

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.

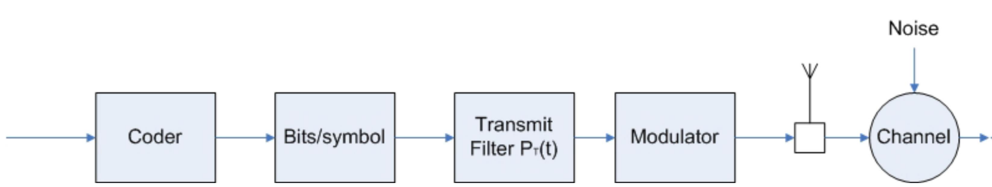


Figure 3.1 Block Diagram of Digital Communication Transmitter

3.4 Problem Decomposition into Modules

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

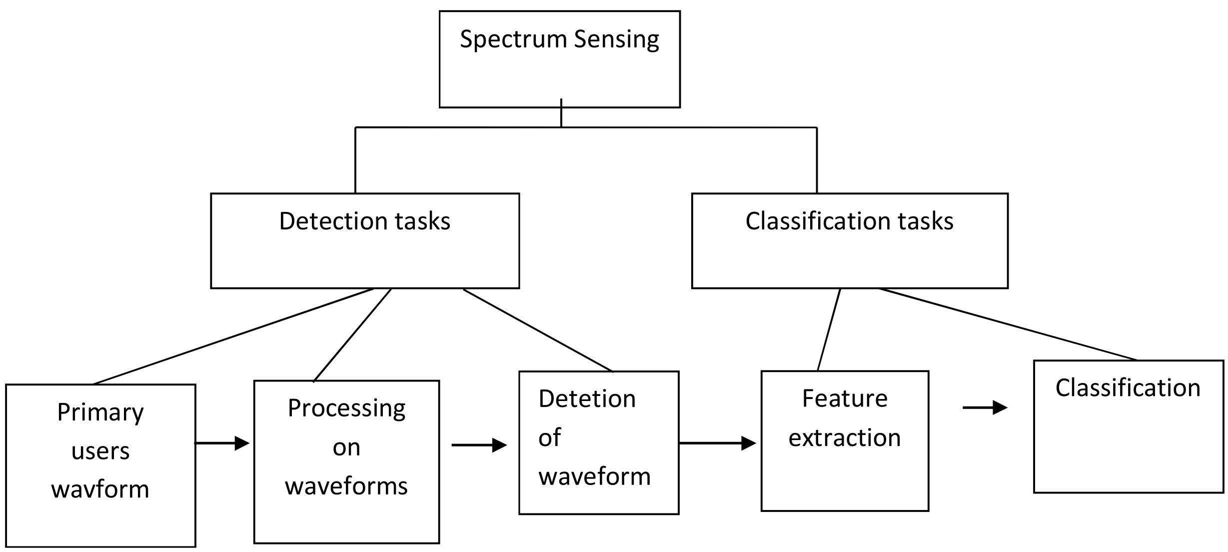


Figure 3.2 System Process Diagram

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.

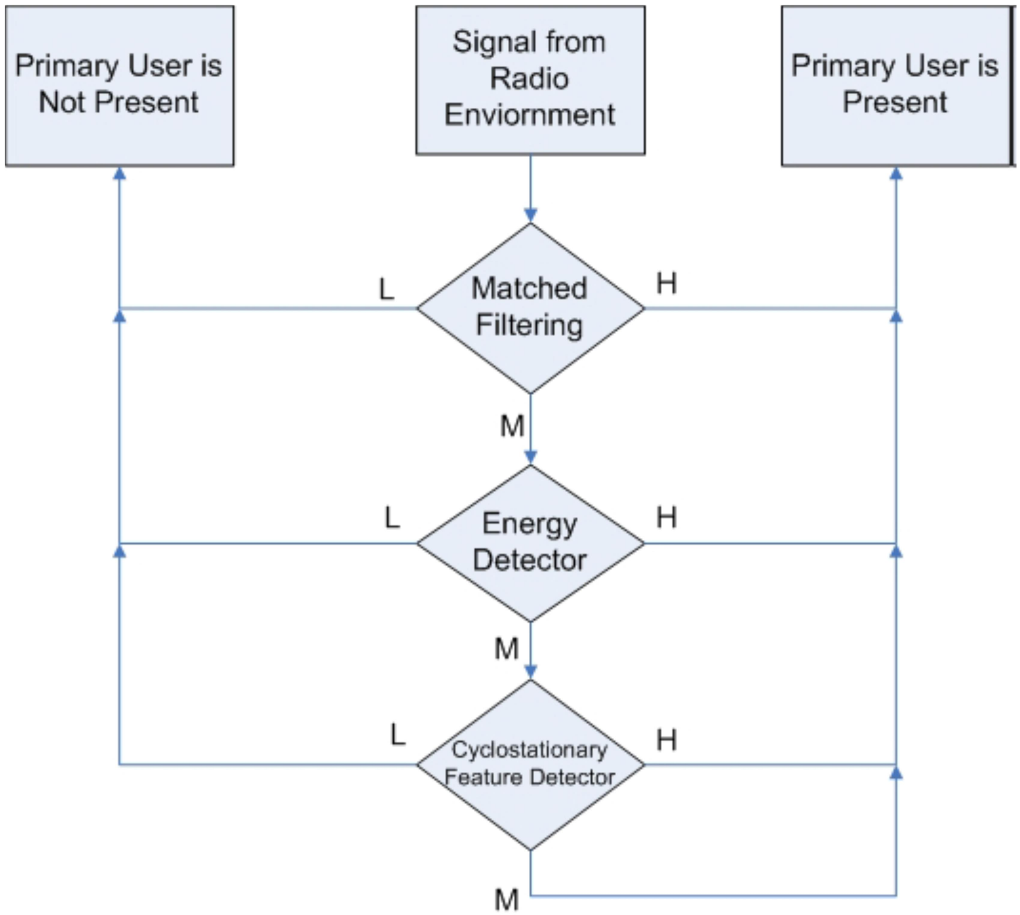


Figure 3.3 Algorithm for minimizing sensing time for detection

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 Conclusion

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 OF SENSING TIME ALGORITHMS

4.1 Introduction

This chapter concentrates on the implementation of spectrum sensing techniques to obtain results for all designed classifiers and subsequent analysis. The overall program structure has been discussed followed by the algorithms.

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 $c(t) = \delta(t)$ which in the discrete domain becomes $c = 1$. If the channel is multipath, e.g., with the impulse response $c(t) = a0\delta(t - t0) + a1\delta(t - t1)$, 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.

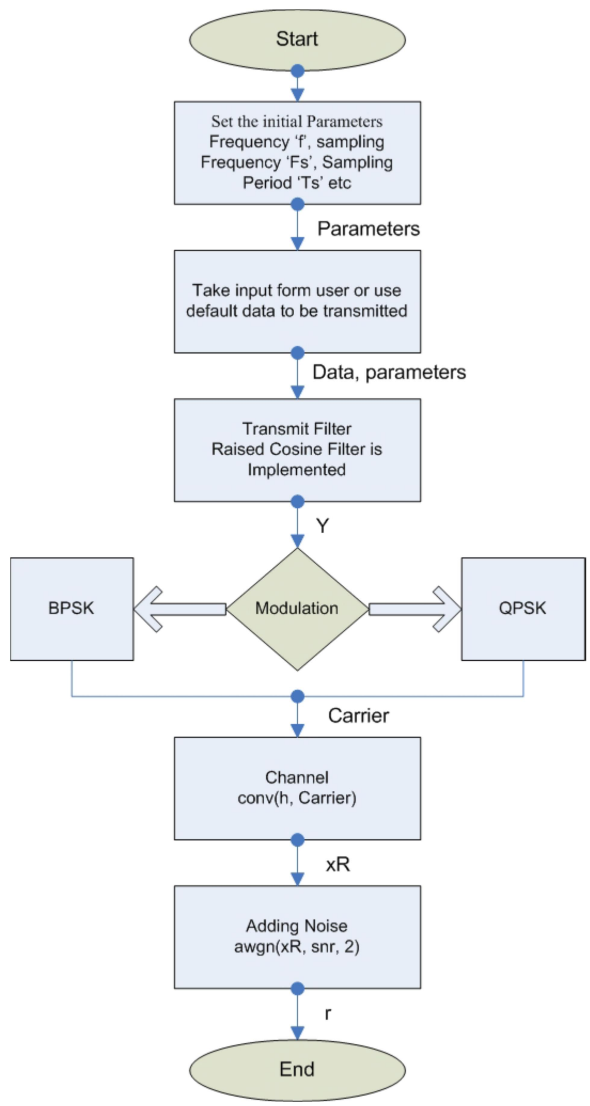


Figure 4.1 Flow chart for Implementation of Primary Transmitter

4.3 Energy Detection

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.

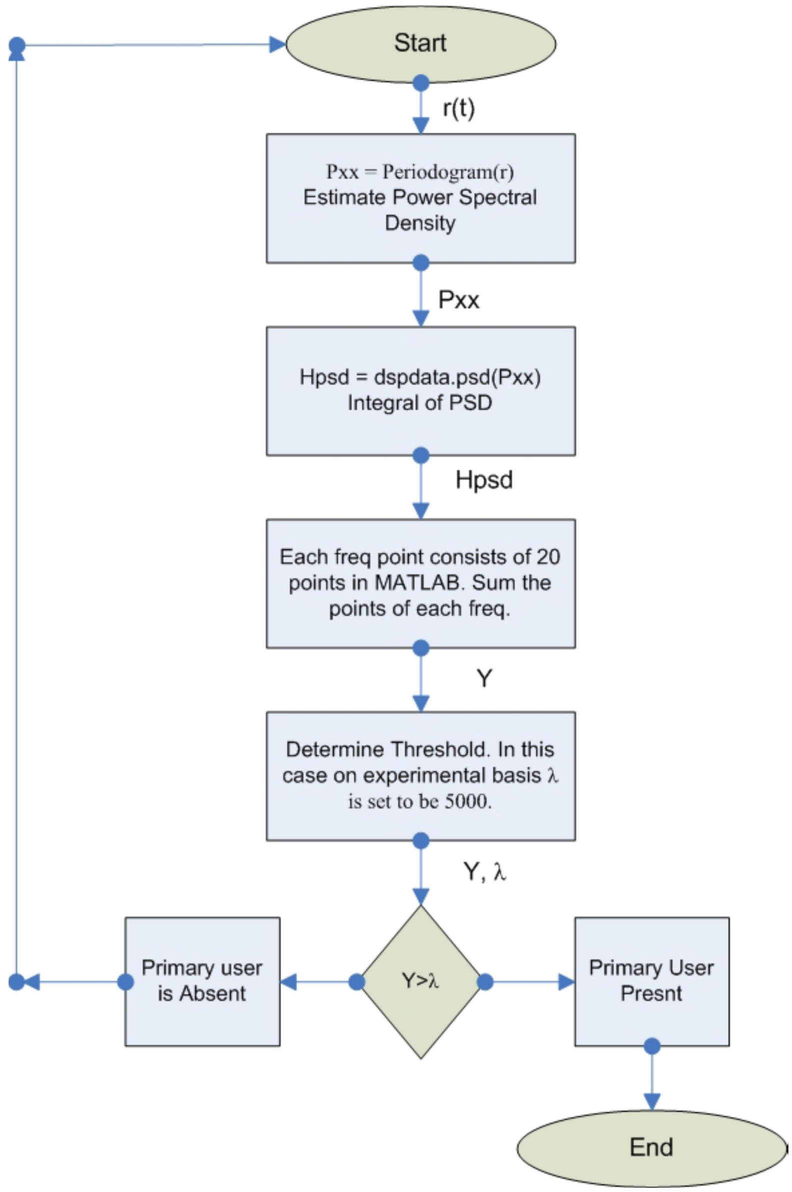


Figure 4.2 Flow chart for Implementation of Energy Detector

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.

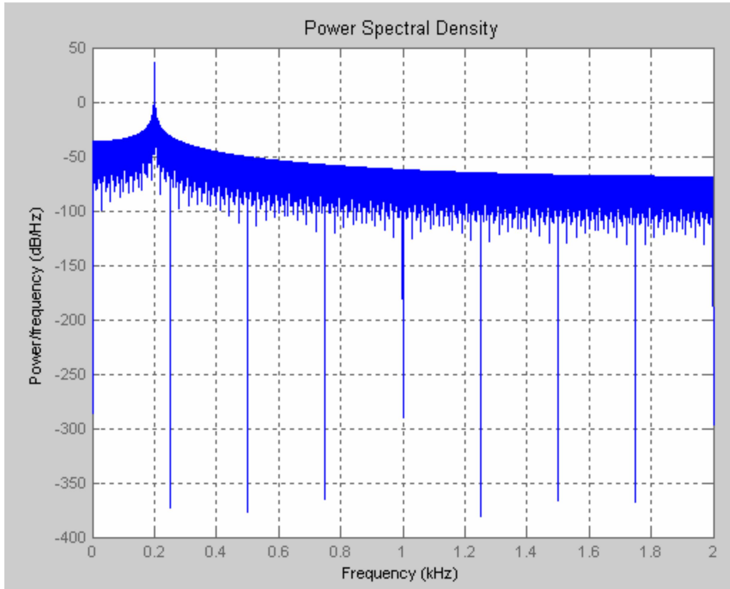


Figure 4.3 Energy Detector Output at SNR 30dB for BPSK when primary user is present at 200Hz

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 4.4. 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.

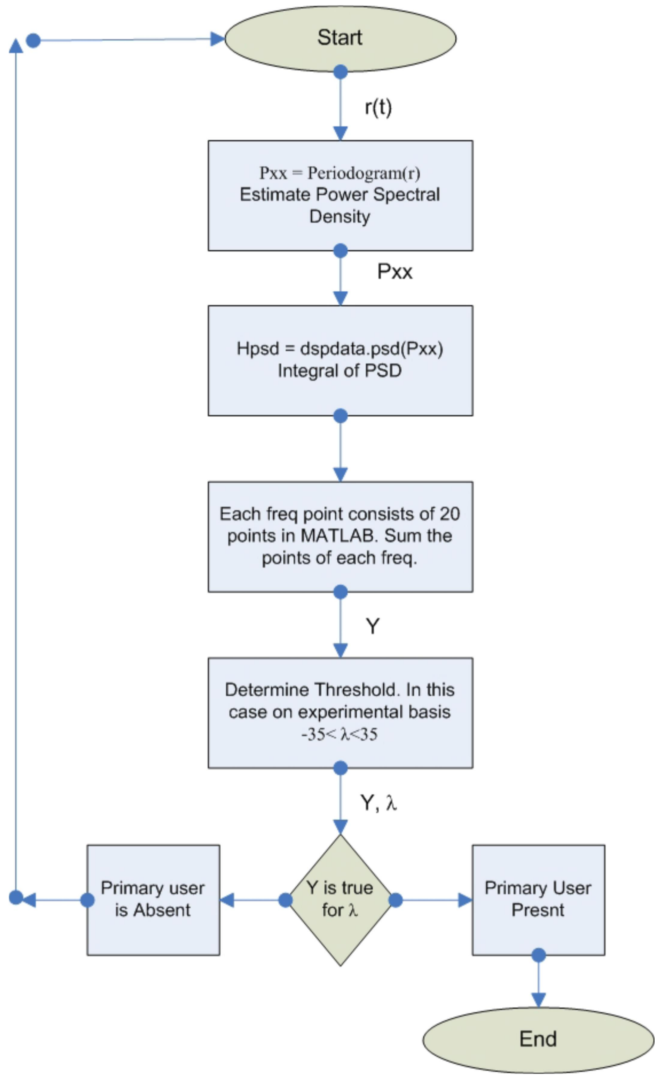


Figure 4.4 Flow chart for Implementation of Matched Filter

For the case of BPSK in which the two pulses are p(t) and –p(t). The correlation coefficient c of these pulses is 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.

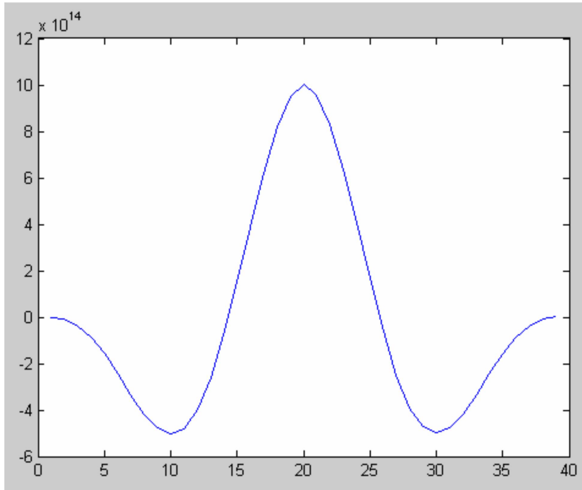


Figure 4.5 Matched Output at SNR 30dB for BPSK Filter

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 4.6. Let r(t) is the received signal which we have to pass from Cyclostationary feature 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 primary signal like operating frequency and modulation technique.

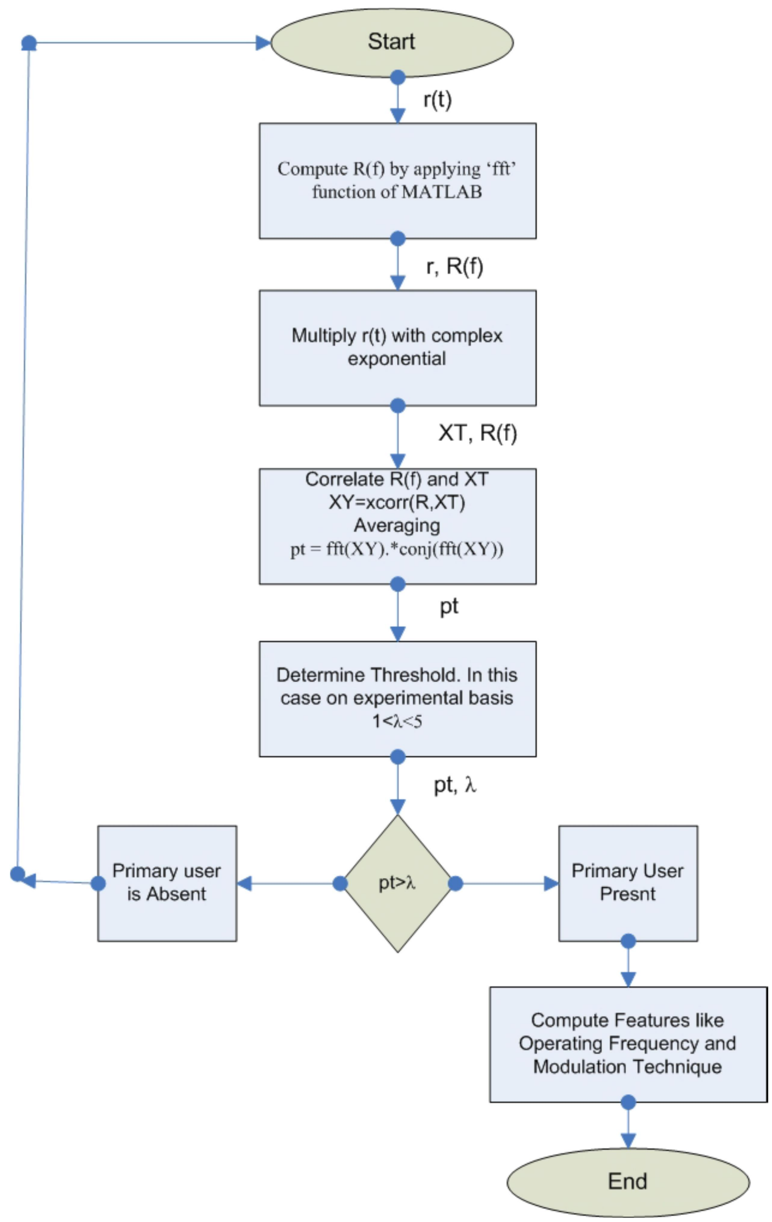


Figure 4.6 Flow chart for the implementation of Cyclostationary Feature Detection

4.6 Conclusion

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

IMPLEMENTATION OF PROBABILITY OF DETECTION ALGORITHMS

5.1 Introduction

In this chapter, we focus attention on the particular task on which the very essence of cognitive radio rests: The probability of detection is of main concern as it gives the probability of correctly sensing for the presence of primary users in the frequency band. Probability of miss-detection is just the complement of detection probability.

5.2. Energy Detection Technique

Energy detector is well known spectrum sensing technique. It is based on the principle that the energy of the received signal to be detected is always higher than the energy of noise. Energy detector is said to be blind signal detector because it ignores the structure of received signal with known threshold. Threshold value can be fixed according to channel condition. Energy Detection over AWGN Channels has analyzed in which ten carrier frequencies were used[6].

Algorithm for energy detection is designed as follows. 1. First we have transmitted signals of primary user.

2. At the receiver, received signal 'y' is calculated by adding all received signals.

3..Then we have estimated power spectrum density of signal 'y' by using periodogram function in MATLAB. The integral of the PSD over a given frequency band computes the average power in the signal over that frequency band.

4. The signal power is then compared with a threshold and if it is above the threshold, then the result of the detector is that a primary user is present.

5. Plot the probability of detection by using Marcumq function.

5.3 Conclusion

The designed test program is written in MATLAB. The program comprises one of the major techniques i.e., Energy Detector.

Chapter 6

COMPRESSED SENSING TECHNIQUE

6.1 Introduction

This chapter concentrates on the compressed sensing and its history, basics, system model and problem statement.We also discuss the advantages over current algorithms in compressed sensing.

6.2 What is meant by compressed sensing?

Compressed sensing (also known as compressive sensing, compressive sampling, or sparse sampling) is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the Shannon-Nyquist sampling theorem. There are two conditions under which recovery is possible.The first one is sparsity which requires the signal to be sparse in some domain. The second one is incoherence which is applied through the isometric property which is sufficient for sparse signals[1 and references therein].

6.3 Overview

A common goal of the engineering field of signal processing is to reconstruct a signal from a series of sampling measurements. In general, this task is impossible because there is no way to reconstruct a signal during the times that the signal is not measured. Nevertheless, with prior knowledge or assumptions about the signal, it turns out to be possible to perfectly reconstruct a signal from a series of measurements. Over time, engineers have improved their understanding of which assumptions are practical and how they can be generalized.

An early breakthrough in signal processing was the Nyquist–Shannon sampling theorem. It states that if the signal's highest frequency is less than half of the sampling rate, then the signal can be reconstructed perfectly. The main idea is that with prior knowledge about constraints on the signal's frequencies, fewer samples are needed to reconstruct the signal.

Around 2004, Emmanuel Candès, Terence Tao, and David Donoho proved that given knowledge about a signal's sparsity, the signal may be reconstructed with even fewer samples than the sampling theorem requires. This idea is the basis of compressed sensing.

6.4 History

Compressed sensing relies on L1 techniques, which several other scientific fields have used historically.In statistics, the least squares method was complemented by the L1-norm, which was introduced by Laplace. Following the introduction of linear programming and Dantzig's simplex algorithm, the L1-norm was used in computational statistics. In statistical theory, the L1-norm was used by George W. Brown and later writers on median-unbiased estimators. It was used by Peter J. Huber and others working on robust statistics. The L1 norm was also used in signal processing, for example, in the 1970s, when seismologists constructed images of reflective layers within the earth based on data that did not seem to satisfy the Nyquist–Shannon criterion.It was used in matching pursuit in 1993, the LASSO estimator by Robert Tibshirani in 1996 and basis pursuit in 1998.There were theoretical results describing when these algorithms recovered sparse solutions, but the required type and number of measurements were sub-optimal and subsequently greatly improved by compressed sensing.[citation needed]

At first glance, compressed sensing might seem to violate the sampling theorem, because compressed sensing depends on the sparsity of the signal in question and not its highest frequency. This is a misconception, because the sampling theorem guarantees perfect reconstruction given sufficient, not necessary, conditions. A sampling method fundamentally different from classical fixed-rate sampling cannot "violate" the sampling theorem. Sparse signals with high frequency components can be highly under-sampled using compressed sensing compared to classical fixed-rate sampling.

6.5 Compressed sensing for wideband spectrum sensing

Compressive sensing theory has also been considered in wideband spectrum sensing techniques. In [11], an analog-to-digital converter has been used to transform the analog received signal into a digital signal by sampling at the Nyquist rate. Next, compressive sampling is applied to the sampled vector to compress it into a smaller vector and then the spectrum is reconstructed by solving an $\ell 1$ norm minimization problem. In [12] the received analog signal is sampled at the information rate of the signal using an analog-to information-converter (AIC). Here, the compressive sensing is embedded in the AIC. The same $\ell 1$ norm minimization method is used to estimate the original spectrum. In both [11,12], wavelet edge detector has been used to detect the channel borders in the estimated spectrum and the detection's performance has been evaluated in terms of mean square error through simulations. It has been shown that MSE performance of [11] outperforms that of [12] for all compression rates, but their detection performances are comparable. In both [11,12], the signal needs to be sampled at the Nyquist rate and then compressed based on its sparsity.

In this paper, we propose a novel method of compressive detection for wide-band spectrum sensing. In the proposed method, the signal is fed into a number of filters, much less than the number of channels within the wide-band spectrum. The energies of the filter outputs are used as the compressed measurement to reconstruct the signal energy in each channel. The energy vector is then compared with a threshold vector to detect the spectrum holes. The effect of noise on the received signal is investigated through simulations. Numerical results suggest that the compressive sensing method enhances the detection performance of the receiver by suppressing the noise energy in the unoccupied bands.

6.6 Compressive Sensing Basics

Compressive sensing is a method to recover signals from far fewer measurements than needed for traditional sampling. Assume that an $N \times 1$ vector x is to be measured. Also suppose that there is a basis Ψ in which x is sparse. Mathematically, x can be written as

$$x = \Psi s \text{ -------- } (1)$$

where the $N \times 1$ vector s is the representation of x in the basis Ψ and has just $Ls \ll N$ non zero elements.Compressive sensing theory states that x can be accurately recovered from $K \ll N$ measurements of the signal. Assume that we use a set of K linear combinations of the signal as the measurement vector y

$$y = \Phi x \text{ --------- } (2)$$

where Φ is the sensing matrix. Then by properly choosing K and Φ, and based on sparsity of the representation of x in the Ψ basis, x can be recovered from y. The value of K depends on N, L_s and a measure of coherence (correlation) between the sensing matrix Φ and the basis matrix Ψ. As the basis matrix is determined by the nature of the problem, choosing a sensing matrix having a low coherence with Ψ will lead to a smaller K. This suggests choosing Φ to be a totally random matrix [13]. If the above conditions apply, then the sparse vector s can be recovered from the measurement vector y through an $\ell 1$ norm minimization

$$\min_{s} \|s\|_1$$
$$\text{Subject to } y = \Phi\Psi s \text{ -------- (3)}$$

6.7 System Model and Problem Statement

Suppose that a total spectrum of W Hz is considered to be shared among a number of primary and secondary users. This can be either an ad-hoc network sharing a total of W Hz spectrumamong its nodes or a secondary network of cognitive radios trying to use the licensed spectrum opportunistically for secondary communication. Assume that each node in the ad-hoc network in the first scenario or each cognitive radio in the second scenario needs a bandwidth of B Hz for the communication. Define $N \triangleq W/B$ to be the number of available channels and denote by fi the center frequency of the ith channel. Also assume that each node is using a wide-band antenna listening to the whole spectrum and providing the node with the wide-band time domain signal x(t).

Each node is also provided with a filter bank $\{H_k(f)\}^{k}_{k=1}$ consisting of $K \ll N$ wide-band filters with a bandwidth equal to the total spectrum W. Alternatively, a $K \times N$ totally random complex matrix Φ can be assigned to the nodes. This matrix is used to design the K filters so that the frequency response of the kth filter at the ith channel is $[\Phi]_{ki}$, or equivalently

$$H_k(f_i) = [\Phi]_{ki},\ k = 1, 2, \ldots K,\ i = 1, 2, \ldots N \text{ ----------- (4)}$$

Here, $H_k(f)$ represents the transfer function of the kth filter. The Φ matrices can be generated once and stored in the nodes (equivalently the filters can be generated and stored). Assume that, the wide-band signal at the input of the node, x(t), is sampled to obtain the time sequence vector x_t. The node then feeds the wide-band signal into the filters and the output at the kth filter is

$$z_k = \mathrm{Conv}(x_t, h_k) \text{ ------------ (5)}$$

where Conv(·, ·) denotes the convolution operation and hk is the impulse response sequence of the kth filter. The energy of the output signal of each filter is then measured to get the $K \times 1$ energy vector y

$$y_k = z_k^H z_k,\ k = 1, 2, \ldots, K \text{ -------------(6)}$$

$$y = [y_1, y_2, \ldots y_K]^T \text{ -------------- (7)}$$

where $(\cdot)^T$ and $(\cdot)^H$ represent transpose and complex transpose of a matrix respectively. Lets denote the portion of the received signal's energy in the ith channel by E_i. Mathematically,

$$E_i = \int_{fi-B/2}^{fi+B/2} Fx(t)df \text{ ---------- (8)}$$

Here $\mathcal{F}$ denotes the continuous Fourier transform of a signal. Suppose that the frequency response of each filter is approximately constant throughout each channel and equals Hk(fi) = Φki for the kth filter and the ith channel. Hence the energy at the output of the kth filter can be represented as

$$y_k = \sum_{i=1}^{N} Hk(fi)^2 E_i \ ; k = 1, 2, \ldots K$$

In the vector form, we can write the above set of equations as

$$y = \bar{\Phi} e \text{ ------------ (9)}$$

where

$$\Phi = \begin{bmatrix} |H1(f1)|2 & |H1(f2)|2 \ldots\ldots\ldots. & |H1(fN)|2 \\ |H2(f1)|2 & |H2(f2)|2 \ldots\ldots\ldots. & |H2(fN)|2 \\ |HK(f1)|2 & |HK(f2)|2 \ldots\ldots\ldots.. & |HK(fN)|2 \end{bmatrix}$$

Here $\bar{\Phi}$ is a matrix whose elements are square absolute values of the elements of the random matrix Φ and e = $[E1,E2, \ldots .EN]^T$ is the vector of energies of the received signal in different channels. The goal of the node is to estimate the length N vector e using the length K measurements vector y.

It is now straightforward to establish the correspondence between our filter-based node design and the compressive sensing theory. We assume that at each node and at each instance of time, only a small portion of the channels are occupied. This is equivalent to assuming that the energy vector e is sparse. Therefore, by properly choosing the number of the filters, K, based on the compressive sensing theory, the channel energy vector e can be recovered from the measurement vector y as

$$e = \text{argmin } \|e\|_1$$

$$\text{Subject to } y = \bar{\Phi} e$$

This is the base for the compressive detection receiver. Each node reconstructs the energy vector e from the vector of measurements y. Next, a threshold is adopted and the values of e are compared with the threshold to decide on the occupancy of the channels. In the cognitive radio scenario, the threshold adopted in each channel depends on the maximum level of interference allowed by the primary user. Assume that the distance from the primary transmitter to the primary receiver is denoted by R. If the guaranteed signal to interference ratio (SIR) for the primary communication is the interference range of the primary receiver, D, can be determined by

$$\frac{\mathrm{PpL(R)}}{PsL(D)+Pb} = \gamma \text{ ----------- } (10)$$

where Pp and Ps are the primary transmitter and the cognitive radio's transmit powers, Pb is the power of background interference at the primary receiver and L(d) is the function of total path loss at distance d [14]. Consequently, the cognitive radio should be able to sense any signal coming from a distance of maximum R + D or equivalently any signal with power equal to or grater than Pmin = PpL(D+R). So in each channel, if Pmin > BNo, where No is the noise spectral density, the threshold should be set above the noise level and below Pmin. Otherwise the cognitive radio is not in the interference range of the primary receiver and can always transmit in the underlying channel. The parameters , R and Pb should be provided by the regulator or the corresponding primary system [14].

6.8 Cooperative Spectrum Sensing in Ad-hoc Networks

The compressive detection method proposed could be adopted by ad-hoc networks for efficient spectrum utilization. Assume a number of nodes communicating within an ad-hoc network and spectrum of W Hz is assigned to the whole network. This spectrum is divided into N service channels and a low bandwidth control channel. The control channel is used to convey control commands such as connection initialization commands and channel occupancy estimation. One-to-one communication is assumed so whenever one node in the network has information to share with another, an empty channel has to be selected and used for the transmission. A major challenge in such scenario is the hidden terminal problem. Suppose that node A wants to transmit data to node B. Node A senses the spectrum and chooses a channel for the transmission. However, if node C which is out of the detection range of A but in the interference range of B, uses the same channel for transmission, then the signals of A and C interfere in B and the transmission fails. In order to prevent the hidden terminal problem, the nodes communicating in an ad-hoc network should cooperate in finding the empty channels. Whenever data is available at one node intended to be sent to another, the destination is also notified through the control channel and then both nodes sense the spectrum and exchange their estimates of the available channels through the control channel. The estimates made at the two nodes might be different since each may pick up signals from close by nodes that are communicating through one of the N channels that are not detected by peer node. Next, based on the two estimates of the occupancy pattern, they agree on one or a number of channels that are empty on the location of both nodes. Exchange of spectrum estimates can be performed by sending N bits over the control channel in which ones show the locations of occupied channels. Upon receiving this decision bit stream, each node can use bitwise OR operation to obtain the channels available at both ends.

To find the thresholds that nodes should adopt in the channel occupancy detection, assume that a minimum frequency reuse distance D is determined for the network. In other words, the same channel can be re-used to connect two other nodes if both are in a distance of at least D from the nodes initially using the channel. Using the same path loss function $L(\cdot)$, the threshold at each channel can be set to = PL(D) where P denotes the maximum transmit power of the nodes. As both nodes detect the channel occupancy using the proposed compressive detection approach, it is guaranteed that no interference or hidden terminal problem occurs.

6.9 Advantages over Current Algorithms

The proposed algorithm has several advantages over the algorithms already suggested in the literature. First, unlike methods suggested in [11,12], in our compressive detection, the frequency domain representation of the signal is not being reconstructed. Instead, just the vector of channel energies is obtained by solving the $\ell 1$ norm minimization. This benefits the complexity of the problem in two aspects. First, the energy vector in our algorithm has exactly N elements and hence the optimization problem has dimension N, while in spectrum reconstruction, the dimension is nN where n is the number of samples per channel and depends on the resolution of the spectrum reconstruction. Second, the optimization variable in spectrum reconstruction is a complex vector. It is shown that the complexity of the $\ell 1$ norm minimization in this case is $O(n^3)$ [ref]. In the proposed energy detection, the optimization variable is a vector of real and nonnegative numbers. Authors of [15] show that in this case, the optimization problem can be solved with linear programming. To compare the complexities of the two methods, as an example, suppose that a spectrum consisting of 100 channels is being sensed. If just two samples per channel are used in the spectrum reconstruction scheme, the proposed method has a lower complexity factor of 80000 ($(nN)^3/N$). It is also worth mentioning that comparing with non wide-band spectrum sensing methods, i.e. channel-by-channel scanning, the proposed method outperforms in complexity in spite of the added compressive sensing algorithm. First, in channel-by-channel scanning, a bank of N narrow-band filters are needed to scan each channel while the proposed method exploits just K << N filters. Second, the filters used in the proposed method are wide-band filters having a much shorter impulse response and hence lower filtering complexity. Considering that our K filters have bandwidth N times larger than a narrow band single channel filter, and the fact that we have only K filters, leads to the conclusion that the filtering complexity of the proposed method over the conventional channel-by-channel scanning is

$$\frac{1}{N} \times \frac{K}{N} = \frac{K}{N^2}$$

Another advantage of the proposed method, is the effect of the compressive sensing algorithm on the performance of the detection in presence of noise. If there is no noise, the energy vector e has lots of zeros and a few nonzero elements representing the occupied channels. This sparse vector hence can be reconstructed based on the compressive sensing theory. In real situations, the energy of the unoccupied channels is BN_o (the noise energy) and therefore e has no zeros. In this case, the reconstructed signal is not an exact copy of the energy vector as the sparsity has changed. Nevertheless, numerical results suggest that as the compressive sensing algorithm searches for a vector with least number of nonzero elements, in the reconstructed energy vector, the noise effect has been suppressed compared to the original energy vector. In other words, as far as a reasonable signal power is present in the receiver, the output of the compressive sensing algorithm has a higher SNR. We hope to be able to report on rigorous analysis of this result in a follow-up paper.

We can evaluate the performance of the compressive detection algorithm through simulations. The input signal to each node, is the wide-band noisy signal which is fed into K different filters and the energy of the output signals are then used in the $\ell 1$ norm optimization problem to obtain the channel energy vector e (10). In the simulations, a spectrum bandwidth of 20 channels is considered and it is also assumed that at each node and at each instance of time, not more than 6 channels are occupied. Measurements show that a minimum of 12 filters (K = 12) is needed for successful reconstruction of the energy vector. Additive white Gaussian noise is added to the received time signal. Fig. 1 illustrates the probability density function (PDF) of the estimated channel energy e for an occupied and an unoccupied channel and the signal to noise ratio of 5 dB. As seen in this figure, the PDF of the detected energies in an occupied channel are very close for K = 15 and K = 12. On the other hand, for K = 10 the mean of the detected energy degrades significantly. This shows the threshold effect of K based on compressive sensing theory. Interestingly, the mean of the unoccupied channel energy, which is the mean of the reconstructed noise energy, decreases with K as far as K remains above the threshold. In other words, the compressive sensing algorithm is suppressing the input noise at the output while keeping the signal almost constant and hence increasing the SNR. This is of course true just if K is above the threshold. As seen in Fig. 6.1, for K = 10 the noise has been actually amplified. Fig. 6.2 depicts the probability of error in channel occupancy detection versus SNR for different number of filters K. As seen in this figure, for number of filters equal and above K = 12, the performance of the detector is almost the same. The degradation is on the other hand apparent when less than 12 filters are used.

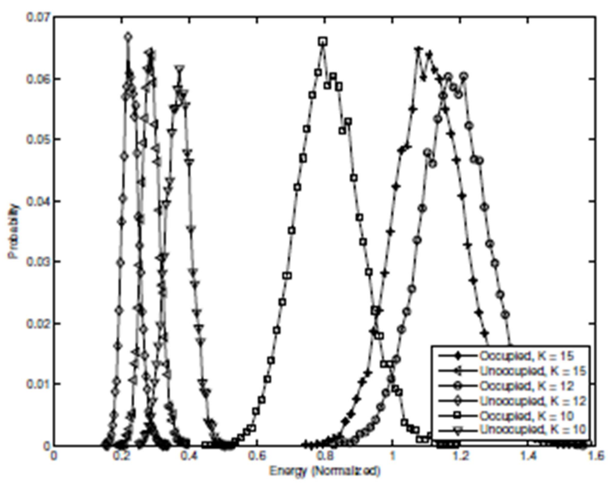


Figure 6.1 PDF of energy in an occupied and an unoccupied channel for different number of filters K

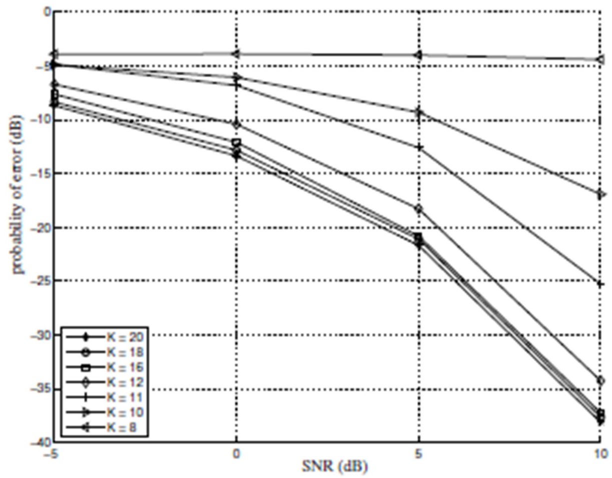


Figure 6.2 Probability of detection error versus SNR for different number of filters

6.10 Conclusion

This chapter gives the basis for the entire project. It provides the literature for developing and implementing the compressed sensing technique to cognitive radio communications.

Chapter 7

COMPRESSED SENSING IN COGNITIVE RADIO COMMUNICATIONS

7.1.Introduction

This chapter deals with the application of Compressed sensing in cognitive radio communications.

7.2 Compressed sensing and cognitive radio

The main functions of a CR are to be aware of its surrounding radio environment, i.e., spectrum awareness, and to utilize the available spectral opportunities effectively, i.e., spectrum exploitation. CS theory states that certain signals can be recovered from far fewer samples or measurements than the samples required by traditional methods[8]. In this approach, a significantly reduced number of measurements is obtained from the incoming data stream and is expected to be reconstructble from these small number of measurements. This method basically combines the following key concepts: (i) sparse representation with a choice of a linear basis for the class of the desired signal, and (ii) incoherent measurements of the considered signal to extract the maximum information using the minimum number of measurements. In sparse signals, most of the signal energy is concentrated in a few non-zero coefficients. Furthermore, to apply the CS theory, it's not necessary for the signal itself to be sparse but can be compressible within sparse representations of the signal in some known transform domain. For example, smooth signals are sparse in the Fourier basis whereas piecewise smooth signals are sparse in the wavelet basis. Although there exist several survey papers in the areas of CR communications covering a wide range of areas such as Spectrum Sensing (SS) , spectrum occupancy measurement campaigns, spectrum management, emerging applications, spectrum decision, spectrum access strategies, CR techniques under practical imperfections, and CR networks, a comprehensive review on the applications of CS in CR communications is given from the literature.

7.3 Compressed sensing and its applications in CR communications

Compressive Signal Processing: Many signal processing problems such as detection, estimation, and classification do not require full signal recovery. The CS theory can be further extended to address the detection, estimation and classification problems. In this context, the most relevant works are the discussions of compressive parameter estimation in [16], [17], compressive detection in [18], [23], [24] and compressive classification in [18], [24], [27], [28]. It is possible to apply standard CS to continuous-valued parameter estimation and the detection of signals in continuous domains but it does not perform well due to the discretization of the sparse domain. CS requires the signal to be sparse over a finite basis whereas the parameters/signals could lie anywhere on a continuum. This problem is known in the literature as a basis-mismatch problem [25], [26]. Further, basis-mismatch problems may arise in many other applications including channel estimation . A comprehensive analysis on the performance of signal classification based on compressive measurements is presented in [27]. The first works where sparsity was leveraged to perform classification with very few random measurements are [18], [24], [27]. In particular, [24] focuses on the compressive detection problem but provides some ideas for extensions to classification. Later, [28] explored the use of a compressed version of the matched filter referred to as the smashed filter. The basic idea of the smashed filter is to implement a matched filter directly in the compressed domain without the requirement of reconstructing the original signal from the compressed measurements. The utility of CS projection observations for signal classification by means of an m-ary hypothesis testing was proposed in [18]. In general, there are many applications where it can be more efficient and accurate to extract information for classification directly from a signal's compressive measurements than first recover the signal and then extract the information.

7.4 Complexity Discussion

One of the main motivations behind using CS in CR communications is that a CS-based CR transceiver can sense wider spectrum with the same sampling requirements or the same spectrum with reduced sampling requirements, thus resulting in cheaper and more energy efficient systems. However, CS-based receivers are relatively complex due to the involved operations in reconstructing the original sparse signal. For the recovery of the original sparse signals, several recovery algorithms such as Greedy Pursuit, matching Pursuit, Orthogonal Matching Pursuit (OMP), Stage wise Orthogonal Matching Pursuit (StOMP), Gradient Pursuit (GP), Tree-based OMP (TOMP), re-weighted l1 minimization, etc. have been proposed in the literature. These algorithms offer different tradeoffs in terms of reconstruction complexity, performance, robustness to noise, as well as the allowable compression ratios for a certain sparsity level of the original sparse signal [19]. Some recovery algorithms are simple to implement, but may require a large number of samples in order to satisfy a desired performance level. For instance, based on the comparative results presented in [19], the algorithms OMP and TOMP are greedy search algorithms which are fast in computation, however, their recovery accuracy is poor and they need a large number of measurements in order to reach a comparable reconstruction performance to BP and reweighted l1 algorithms. On the other hand, BP and re-weighted l1 algorithms provide more accurate solutions but are demanding in terms of computational costs. Thus, in general, there exists a clear tradeoff between the sampling cost and energy saving in computation and it is crucial to balance this tradeoff in order to enhance the overall recovery performance. Another example is that the simple and most commonly used OMP algorithm can be implemented using the following four different methods [20]: (i) naive approach, (ii) Cholesky decomposition, (iii) QR decomposition, and (iv) matrix inversion lemma. These four implementation aspects have different complexities and memory requirements, and depending on the size of the considered problem, any of these four implementations can be the fastest. As the number of samples increases, the computation time of the naive approach becomes much longer than for the other three and for the large problem sizes which require higher number of iterations, the QR decomposition approach appears to be the fastest one [19]. The aforementioned complexity discussion is applicable while carrying out CS-based spectrum sensing using the following steps [34]: (i) acquisition of the compressed samples, (ii) reconstruction of the Nyquist rate signal from the compressed samples, and (iii) spectrum sensing using the reconstructed signal. In this procedure, there have been several attempts to reduce the computational complexity of the employed reconstruction step by utilizing prior information ([20] and references therein). In this regard, authors in [20] have recently proposed a data-assisted non-iteratively reweighted least squares based CS algorithm by exploiting the prior data obtained from a geo-location database in order to reduce the computational complexity of the previously proposed iteratively re-weighted least squares algorithm [21]. However, for signal detection/ estimation/classification problem in CR applications, it's not necessary to reconstruct the entire original sparse signal. The decision on the presence or the absence of PU signals over the considered spectrum can be made based on the compressed measurements only and the reconstruction step of the commonly used CS technique can be completely illuminated, thus reducing the computational complexity [22], [23]. In this context, authors in [22] proposed a Bayesian formulation to estimate the parameters of the sparse signal directly from the compressed measurements and demonstrated that such a Basysian formulation is computationally less expensive, more accurate, and achieves a higher compression rate compared to the traditional non-CS methods such as BP method. Moreover, authors in [22] have shown that in several applications such as detection, estimation and classification, it becomes more efficient and accurate to extract information directly from compressive measurements rather than the traditional approach of first recovering the signal first and then extracting information from the recovered signal.

7.5 Conclusion

Chapter 7 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.

Chapter 8

WIDEBAND SPECTRUM SENSING

8.1 Introduction

In this chapter we give the details about wideband spectrum sensing, its related issues and estimation of parameters related to compressed wideband spectrum sensing technique.

8.2 How in wideband spectrum?

In CR networks, it is desirable for the SUs to identify spectrum opportunities over a wideband spectrum rapidly and accurately. Figure 8.1 depicts the schematic representation of a wideband channel with Nc number of narrowband channels. As reflected in the diagram, some of the channels are occupied and the remaining are idle at a certain time.

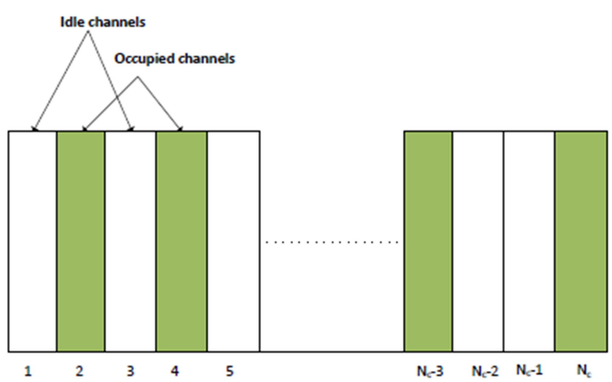


Figure 8.1 Schematic representation of a wideband channel with Nc number of narrowband channels.

Herein, sparsity order is the ratio of the number of occupied channels to the total number of channels.

In this context, a CR should be able to acquire information about which channels are idle over the considered bandwidth in order to use them in an opportunistic way. For this purpose, an SS technique requires the radio to receive a wideband signal through an RF front-end, sample it by a high speed ADC, and subsequently perform measurements for the detection of the PU signals. For the implementation of wideband SS, a CR transceiver needs to have a wideband antenna, a wideband filter and amplifier, and a high speed ADC. The solutions of wideband antennas and wideband filters are available in the literature [35], [36], however, the development of high speed ADC technology is lagging [37], [38] due to the challenges involved in building sampling hardware that operates at a sufficiently high rate [39].The traditional way for detecting spectrum holes over a wideband is to divide the total band into many channels and to perform channel-by-channel sequential scanning [40], which might introduce large latency. Another possible way is to use an RF front-end with a bank of narrow band pass filters. This approach solves the latency problem since multiple channels can be processed simultaneously. However, it is inefficient to implement due to the requirement of numerous RF components. An alternative approach is to directly sense the wide frequency range at the same time, called Wideband Spectrum Sensing (WSS) (see [41] and the references therein).

However, special attention should be paid to the wideband processing which renders high-rate standard ADC costly and even impractical. Clearly, the need to process very wide bandwidth is the most critical challenge for the WSS [42]. To address the aforementioned issues, many researchers have considered CS techniques for wideband SS assuming some sparsity basis. As the wideband spectrum is inherently sparse due to the low percentage of spectrum occupancy, CS becomes a promising technique to reduce the burden on the ADCs in WSS. The important advantage of the CS approach for wideband signal acquisition is that it can increase the overall Dynamic Range (DR) of the acquisition system. In contrast to conventional Nyquist rate sampling systems, CSbased ADCs, also called Analog to Information Converters (AICs) [41] provide an important benefit in reducing the required sampling rate in order to represent the same spectrum. Further, fewer quantization operations are required in CSbased receivers due to the reduction in the number of acquired measurements, thus resulting in significant power savings [42]. Several CS-based approaches have been developed to detect the frequency occupancy of PUs using sub-Nyquist rate samples. CS was first applied to WSS in, where sub-Nyquist rate samples are utilized to detect and classify frequency bands through a wavelet-based edge detector. Further, authors in studied a two-step CS scheme with the aim of minimizing the sampling rate, where the actual sparsity was estimated in the first time slot and the compressed measurements were then adjusted in the second slot. In [44], a sequential CS approach has been proposed where each compressed measurement was acquired in sequence. In this sequential CS approach, observations become available sequentially and the process can be stopped as soon as there is a reasonable certainty of correct reconstruction. This approach does not require knowing how sparse is the signal, and allows reconstruction using the smallest number of samples. The problem of sampling a signal at the minimal rate and reconstructing the original spectrum from the compressive measurements has been discussed in [45]–[47]. Further, power spectrum estimation methods based on sub-Nyquist rate samples were presented in [48], [49], where the spectrum of the uncompressed signal is retrieved by concentrating on the autocorrelation function instead of the original signal itself. Moreover, CS-based correlation matching approaches for identification of the PUs were presented in [50]–[52] in the context of a CR. In [53], an adaptive SS algorithm, which can adaptively adjust compressed measurements without any sparsity estimation efforts, has been studied. Consequently, the wideband signals are acquired block-by-block from multiple mini-time slots, and gradually reconstruct the wideband spectrum using compressed samples until the spectral recovery is satisfactory. In, the performance of a CS-based receiver has been studied with the help of a theoretical analysis of its expected performance with a particular emphasis on noise and DR, and simulation results that compare the CS receiver against the performance expected from a conventional implementation. It has been demonstrated that CS-based systems can potentially attain a significantly large DR since they sample at a lower rate. Consequently, it has been shown that CS-based systems that aim to reduce the number of acquired measurements are somewhat sensitive to noise, exhibiting a 3 dB SNR loss per octave of subsampling similar to the classic noise-folding phenomenon. The sensing performance of a single node may degrade in wireless channels for several reasons such as the hidden node problem, shadowing, multipath fading, and interference/noise uncertainty. To address these issues, cooperative spectrum sensing, in which several nodes collaborate with each other to enhance the overall sensing performance, has been investigated in several works [54]–[57]. Authors in [57] have compared the performance of soft and hard schemes in which a cooperative node forwards multiple bits of the raw data, i.e., soft cooperative scheme, and a single bit related to the decision on spectrum availability, i.e., hard cooperative scheme, to the fusion center, respectively. By incorporating the reporting interval into the frame structure of a cooperative node and independently of the employed local sensing technique, it has been shown that the hard cooperative scheme provides better performance than the soft cooperative scheme for short sensing times and/or a large number of cooperative nodes. In this particular example, compressive sensing can provide benefits while sensing multiple channels over a wider bandwidth by increasing the dynamic range of the ADC and also in reducing the number of cooperative nodes while sensing multiple number of channels [34]. In the case of a soft cooperative scheme, the CS further helps to reduce the cooperative burden as well as the number of cooperative nodes and in the hard cooperative scheme, the CS is more useful for local sensing.

8.3 Wideband Sensing Issues

8.3.1 Dynamic Range and Noise Folding

Dynamic Range (DR) describes the range of the input signal levels that can be reliably measured at the same time. In other words, it's the ability to accurately measure small signals in the presence of the large signals. The DR is a useful parameter for any measurement/acquisition system and it is determined by the following two independent parameters [50]: (i) limitation by noise and (ii) limitation by spurious signals. The DR is defined as the ratio of the full scale amplitude to the peak noise floor and for an N_b bit ADC, it is given by

$$DR = 6.021N_b + 1.763 \text{ dB} \text{ -------- } (6)$$

The above equation is valid only in the time domain without digital filtering and a different expression is needed to define the real achievable dynamic range of the system. For a simple acquisition system without a preamplifier, the DR is mainly limited by the ADC and the DR in (dBFS/√Hz) can be written as [50]

$$DR = SNR + 10 \times \log(fs/2) \text{ -------- } (7)$$

where the SNR is given by

$$SNR = 6.02 \times N_{eff} + 1.76 \text{ ----------- } (8)$$

where fs is the sampling frequency, N_{eff} is the number of ADC effective bits. From practical perspectives, the important advantage of CS for wideband signal acquisition is that it can increase the overall DR of the acquisition system as compared to the conventional Nyquist rate acquisition system within the same instantaneous bandwidth. Due to this advantage, it can reduce the system size, weight, and power consumption, and the monetary cost considerably but at the cost of increasing the noise figure of the system. The exact value of the DR improvement that can be achieved depends on the exact speed and the exact ADC design. Generally, CS-enabled sampling rate reduction can increase the system DR, approximately by one bit (approx. by 6 dB) for every factor of 2 that CS permits the ADC sampling rate to be reduced [126].

If (i) the noiseless input is sparse, (ii) the additive noise is white, and (iii) the CS measurement process satisfies the RIP, then the Recovered SNR (RSNR) is related to the In-band SNR (ISNR), which measures the SNR by including only the noise within the same bandwidth as the signal [49], of the received signal in the following way [51]

$$\frac{1-\gamma}{1+\gamma}\rho \leq \frac{ISNR}{RSNR} \leq \frac{1+\gamma}{1-\gamma}\rho \text{ --------------- } (9)$$

where is the compression factor (decimation rate) and $\delta \in (0, 1)$ is a constant determined by the CS measurement process. The value of must be less than a critical value $\rho_C = B/W$ (B being the instantaneous bandwidth and W being the maximum signal bandwidth) i.e., the degree of sparsity of the input signal. The above ratio can also be written as [49]

$$ISNR/ RSNR \approx 10\log10(\rho) \text{ ------ } (10)$$

From (10), it can be deduced that every time we double the compression factor (i.e., a one octave increase) up to the value of C, the RSNR of the recovered signal decreases by 3 dB. This 3dB/octave SNR degradation depicts an important tradeoff while designing CS-based receivers. The main conclusion is that for a fixed signal bandwidth W/2, there is a practical limit to the instantaneous bandwidth B/2 for which we can obtain a desired RSNR [51]. Although the above noise folding behavior of CS systems imposes a very real cost, the dominant advantage is that it increases the DR of the acquisition system.

8.3.2. Sampling Rate and Sparsity Order

To determine a suitable sampling rate, most existing works implicitly assume that the sparsity order of the underutilized spectrum is known beforehand. However, in practical CR applications, the actual sparsity order level corresponds to the instantaneous spectrum occupancy of wireless users which is time varying in nature. Thus, the actual sparsity level is often unknown and only its upper bound, which can be measured from the maximum spectrum utilization observed statistically over a time period, can be obtained. Hence, in practice, the conservative determination of the sampling rate based on its upper bound can cause unnecessarily high acquisition costs [39]. From the above discussion, it can be noted that the sampling rate depends on the sparsity level and we need to adapt the CS system in such a way that the sampling rate is adaptive in accordance with the dynamic variation of the spectrum occupancy. One method of addressing this aspect to estimate the sparsity order first and then apply the suitable sampling rate based on the estimated sampling rate. In this context, the authors in [52] have proposed a two-step CS approach in which the sparsity order is estimated at the first step by considering sufficiently smaller number of measurements and then the sampling rate corresponding to the estimated sparsity order is applied at the second step to collect additional samples. Subsequently, the reconstruction of the signal spectrum has been carried out using all the collected samples in both steps. Finally, based on this reconstructed signal spectrum, SS decision is made. Another main benefit of CS-based CR transceiver is that the reduction in the sampling rate of an ADC due to CS directly translates into the power savings and it becomes more power efficient solution than the traditional non-CS based transceivers. The power consumed by an ADC increases at a rate of 1.1fs, where fs is the sampling rate of the ADC. For example, an 8-bit flash ADC at 200 Msps consumes 2320mW of power (or 11.6 nJ/sample), while an 8-bit flash ADC at 20 Msps consumes only 150 mW (or 7.5 nJ/sample) [44]. Therefore, in this example, by reducing the sampling rate by a factor of 12.5, one can reduce the power consumption approximately by a factor of 15.5.

8.4 Comparision of CS and non-CS Detectors

Spectrum sensing in a CR involves deciding whether the PU is present or not from the observed signals. Thus, spectrum sensing can be formulated as a binary hypothesis testing problem in the following way

$$y(n) = \begin{cases} w(n) & H0 \\ s(n) + w(n) & H1 \end{cases} \text{ ---------- (13)}$$

where y(n) denotes the received signal at the CR device at the nth sampling instance, s(n) denotes the primary signal and z(n) is the Additive White Gaussian Noise (AWGN). The CR user has to decide if the primary signal is present (H1) or not (H0) from the observations y(n) collected over the sensing duration. In compressive settings, the above detection problem can be written in the following way

$$y = \begin{cases} \emptyset w & H0 \\ \emptyset(s + w) & H1 \end{cases} \text{ ----------- (14)}$$

where y is a ×1 compressive-sampled received signal, $\emptyset$ is k × L compressive matrix, s is an L × 1 PU signal vector, and w denotes the L × 1 AWGN vector. If we already know the value of s during the design of $\emptyset$, the optimal strategy is to choose the value of $\emptyset = s^T$. However, since this knowledge is difficult to obtain in practice for the case of CR applications, the value of $\emptyset$ should be universal and is considered to be a random matrix in most of the existing literature.

With regard to the detection problem (13), there exist several CR techniques in the literature. The main SS techniques are matched filter based detection, Energy Detection (ED), feature-based detection, autocorrelation based detection, covariance based detection, eigenvalue based detection, etc. Corresponding to the hypothesis testing problem in compressive settings represented in (14), a general framework for signal processing of compressed measurements for detection and estimation without reconstructing the original signal has been detailed in. A much more involved analysis for the estimation setting was presented in [32], where the behavior of the achievable estimation performance in the sparse setting has been analyzed. Out of the aforementioned SS techniques, in this paper, we analyze the performance of the following detectors in compressive and non-compressive settings.

• Matched Filter Detection: The matched filter is an optimal detector in the presence of stationary Gaussian noise since it maximizes the received SNR. However, it requires a priori knowledge of the primary signal and the performance may degrade if this information is not accurate. In practice, most wireless systems have pilots, preambles, synchronization words or spreading codes that can be used for the coherent detection.

• Energy Detection: The energy detector is the most common way of spectrum sensing because of its low complexity (computational and implementation). It can be considered as a semi blind technique since it only requires the knowledge of the noise variance and does not rely on any signal feature. The main drawback of the energy detector is its inability to discriminate between sources of received energy (the primary signal and noise) making it susceptible to uncertainties in background noise power, especially at a low SNR.

• Feature-based Detection: If some features of the primary signal such as its carrier frequency or modulation type are known a priori, more sophisticated feature detectors may be employed to carry out spectrum sensing at the cost of increased complexity. Cyclostationary detection and correlation matching detection are particularly appealing because of their ability to distinguish the primary signal from the interference and noise. They can work in a very low SNR region due to their noise rejection capability but sometimes they are computationally complex and requires significantly long observation time.

Next, we present some numerical results about the performance of the aforementioned three types of SS techniques. To analyze the performance in compressive settings, we consider a multi-coset sampling (periodic non-uniform sampler) in which the total number of received samples is divided into blocks, and the same compressive matrix is applied to each block. Figure 8.2 depicts the probability of detection (Pd) versus SNR results for a primary signal in AWGN considering a fixed probability of false alarm Pf = 10−3. From the figure, it can be noted that the matched filter outperforms the simple energy detector since it is able to reliably detect low-power primary signals. The value of in Fig. 8.2 indicates the compression ratio, i.e., the ratio of the number of rows to the number of columns in , defined in Section II, and the value = 1 represents the Nyquist rate sampling, i.e., the conventional non-CS approach. As the value of decreases, i.e., we use more compression, the detection performance of both matched filter and the energy detector with respect to SNR decreases as depicted in Fig. 8.2. This means that there exists a clear tradeoff between the detection performance and the sampling rate for both matched filter and the energy detector. In addition, we provide the performance comparison of correlation matching detectors (which falls under the category of feature-based detection [117]) in CS and non-CS settings in Fig. 8.2.

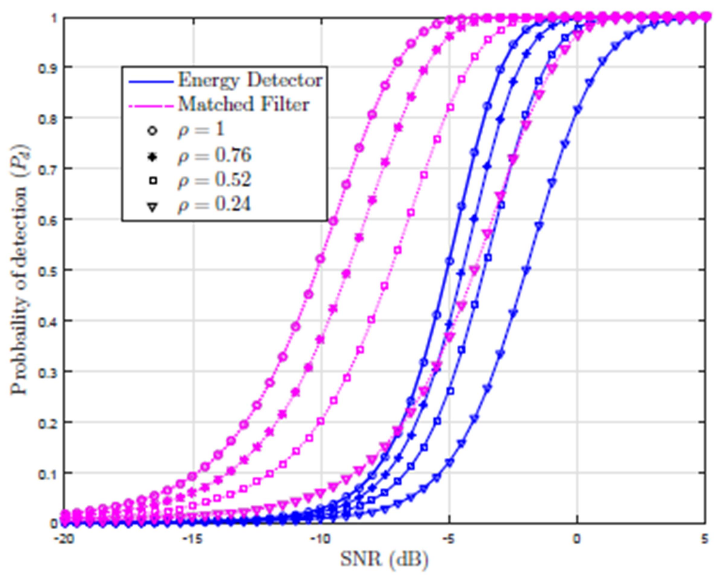
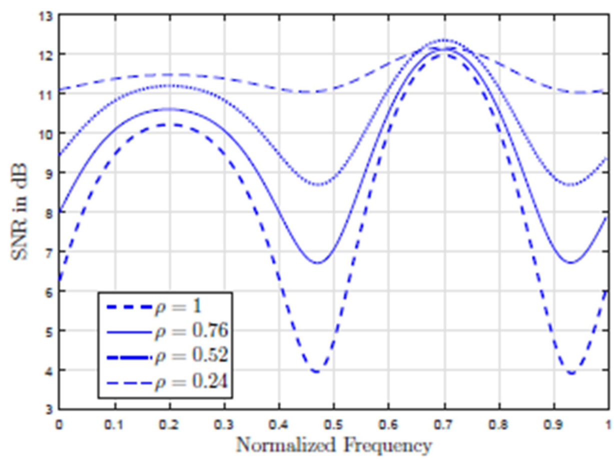
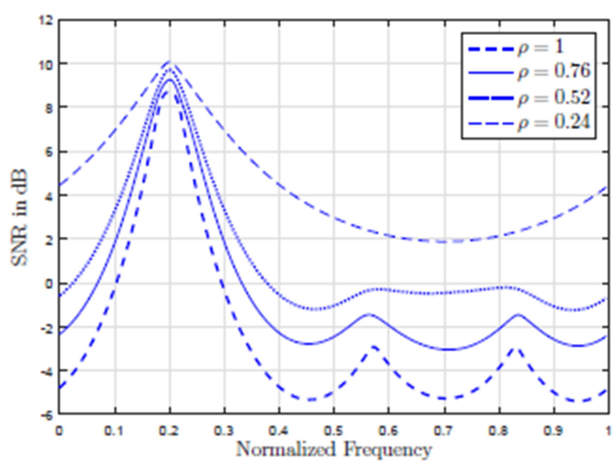


Figure 8.2. Probability of detection versus SNR of the energy detector and matched filter with compressive measurements (Probability of false alarm, Pf = 10−3), Number of Nyquist rate samples=99.

The scenario considers a desired Binary Phase Shift Keying (BPSK) signal with SNR = 10dB at the normalized frequency of 0.2 and a pure-tone interference with SNR = 10dB located at the normalized frequency of 0.7. Figure 8.3(a) uses the Euclidean metric (Frobenius norm) which works as a conventional energy detector, and it can be noted that this approach does not provide a good performance in discriminating interference from the desired signal. On the other hand, the result in Fig. 8.3(b) uses the minimum eigenvalue technique presented in [52],[53] and this method is able to distinguish the desired signal from the interference effectively. Furthermore, the presented results in Figs. 8.3(a) and 8.3(b) show the degradation of the correlation matching-based WSS techniques in terms of the capability of distinguishing the desired signal from the interference with the decrease in the compression ratio = 1, i.e., with more compression. However, in Fig. 8.3(b), it is interesting to note that the power level estimation does not suffer due to compression since the main peak is located at the true frequency with the level close to the SNR value of 10dB.



(a)



(b)

Figure 8.3 Performance of CS-based correlation-matching wideband detector [117], [118]. In the considered scenario, there is a desiredBPSK signal with SNR = 10dB at the normalized frequency of0.2 and there is a pure-tone interference located at the normalized frequency of 0.7 and with SNR = 10dB. The parameter defines the compression rate/ratio with = 1 indicating the Nyquist rate sampling, i.e., no compression. (a) detector based on the traditional Euclidean metric (Frobenius norm), (b) detector based on the minimumeigenvalue technique proposed in [65]

8.5 Compressive signal parameter estimation

As described, a CR may acquire different signal parameters such as SNR, channel, sparsity order, etc. for enabling CR communications. In contrast to the most commonly used spectrum occupancy information required for an interweave CR, the parameters such as SNR, DoA, CSI,etc. will allow the CR to implement underlay CR techniques such as cognitive beam forming [139], cognitive interference alignment [140], Exclusion Zone (EZ), and power control [141]. Due to the practical constraints in the acquisition hardware, the CS-based approach can be utilized to estimate these parameters compressively, leading to the saving in the hardware resources. In the following, we describe the existing contributions which utilized the CS approach in order to acquire these parameters.

8.5.1 Compressive SNR Estimation

In the existing literature, various data-aided and non-data aided SNR estimators have been investigated in the context of traditional legacy based systems (see [142] and reference there in). SNR estimation is helpful for legacy based systems in order to implement adaptive techniques such as handoff algorithms, adaptive bit loading and optimal soft value calculation for improving the performance of channel decoders. In addition to the aforementioned benefits, estimation of primary SNR is useful for CR-based systems in order to implement proper underlay transmission strategies [89]. Existing SNR estimation literature mostly focus on narrowband CR systems [89], [143]–[145] where the application of CS does not provide much benefit. However, in practice, it is highly desirable to estimate the primary SNR over the wideband spectrum in order to utilize the available spectrum opportunities effectively. In this context, authors in [90] recently studied an eigenvalue-based compressive SNR estimation problem for a wideband cognitive receiver utilizing the CS approach. The following two correlated scenarios have been studied considering the equal received power across all the carriers: (i) correlated noise, and (ii) correlated Multiple Measurement Vectors (MMVs). In practice, the correlated noise case may arise due to filtering and oversampling operations. Similarly, the correlated MMV case may arise due to channel correlation or imperfections in frequency selective filters present at the CR node. Figure 7 depicts the normalized Mean Square Error (MSE) versus SNR for the correlated noise scenario for both the compressive and full measurement cases assuming correlation knowledge at the CR receiver [90], [146]. It can be deduced from the figure that the compressive case with the compression ratio = 0.8 has to sacrifice almost 0.3 % estimation error in comparison to the full measurement case at SNR = 1 Db. Furthermore, this estimation error increases with the decrease in the value of , i.e., increase in the compression. On the other hand, the advantage is that ((1 − ρ) ∗ 100) % saving can be obtained in terms of hardware resources in comparison to the full measurement case. Various results on compressive SNR estimation for the correlated noise and correlated MMV cases can be found in [90].

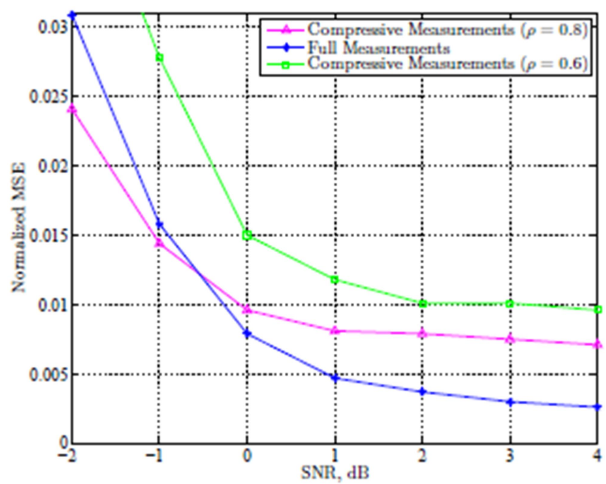


Figure 8.4 Normalized Mean Square Error (MSE) versus Signal to Noise Ratio (SNR) for the correlated noise scenario (sparsity order = 0.6, correlation coefficient = 0.6, N = 100) [90]. In the figure, denotes the compression ratio

8.6 Conclusion

The wideband spectrum sensing and its related issues had been studied and SNR parameter estimation for energy detection was illustrated.

Chapter 9

TOOL FLOW

9.1 Introduction

In this chapter, let us discuss about the software i.e., MATLAB used in our project.

9.2 MATLAB Software

MATLAB (matrix laboratory)is multi-paradigm numerical computing environment and fourth-generation programming language. A proprietary programming language developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in others includingC, C++, Java, Fortran and Python.

Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to computing abilities. An additional package,Simulink,adds graphical multi-domain simulation and model-based design for dynamic and systems. In 2004, MATLAB had around one million users across industry and academia. MATLAB users come from various backgrounds of engineering, science, and economics.

The MATLAB application is built around the MATLAB scripting language. Common usage of the MATLAB application involves using the Command Window as an interactive mathematical shell or executing text files containing MATLAB code. MATLAB is a proprietary product of Math Works, so users are subject to vendor lock-in.[3][35] Although MATLAB Builder products can deploy MATLAB functions as library files which can be used with .NET or Java application building environment, future development will still be tied to the MATLAB language. Each toolbox is purchased separately. If an evaluation license is requested, the Math Works sales department requires detailed information about the project for which MATLAB is to be evaluated. If granted (which it often is), the evaluation license is valid for two to four weeks. A student version of MATLAB is available as is a home-use license for MATLAB, Simulink, and a subset of Math work's Toolboxes at substantially reduced prices.

It has been reported that European Union (EU) competition regulators are investigating whether Math Works refused to sell licenses to a competitor. The regulators dropped the investigation after the complainant withdrew their accusation and no evidence of wrongdoing was found

9.3 Conclusion

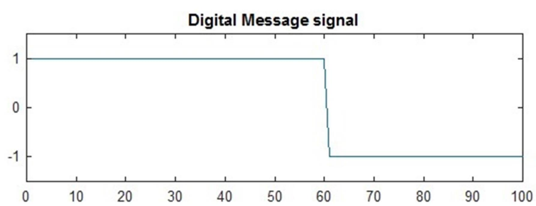
In this chapter, we have discussed about the MATLAB software used in our project.

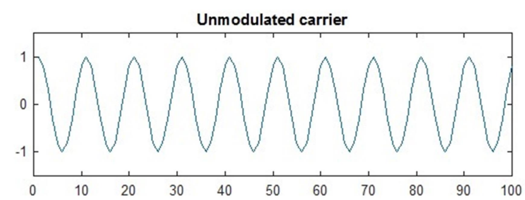
Chapter 10

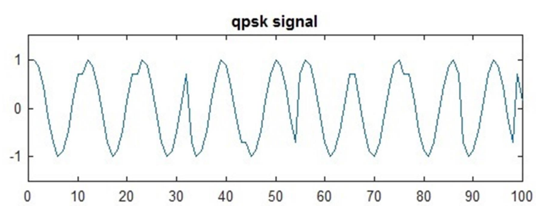
SIMULATION RESULTS

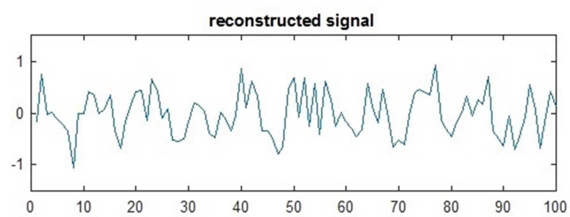
10.1 Simulation graphs for compressed sensing

A random data signal hich is a message signal is modulated by a carrier to produce a QPSK signal and using l1norm minimization technique the signal is reconstructed.The noise in channel can be a additive white Gaussian noise(AWGN) or fading(Rayleigh or racian).The below figures show the MATLAB simulated graphs.









10.2 Simulation Graphs for energy detection

The performance of the detection algorithm can be summarized with two probabilities:

a. probability of detection Pd and
b. probability of missed detection..

Pd is the probability of detecting a signal on the considered frequency when it truly is present. Thus, a large detection probability is desired. Probability of detection can be obtained by averaging the MarcumQ- function over the probability distribution function of SNR.

$$Pd = MarcumQ(\sqrt{2\gamma}, \sqrt{\lambda}).$$

Where γ in (5) corresponds to the SNR of received signal and λ is mean value of received signal Y(t). Figure below shows the graph of SNR versus probability of detection in energy detection technique.

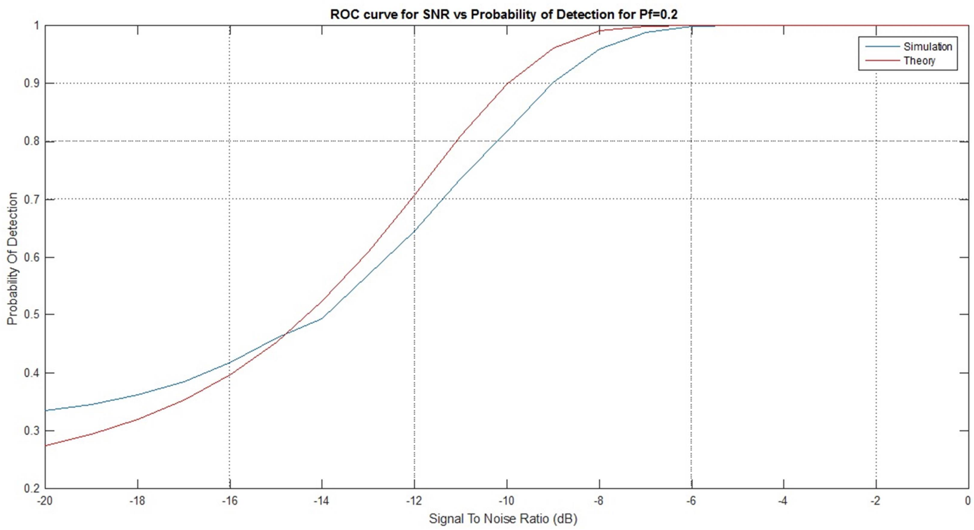
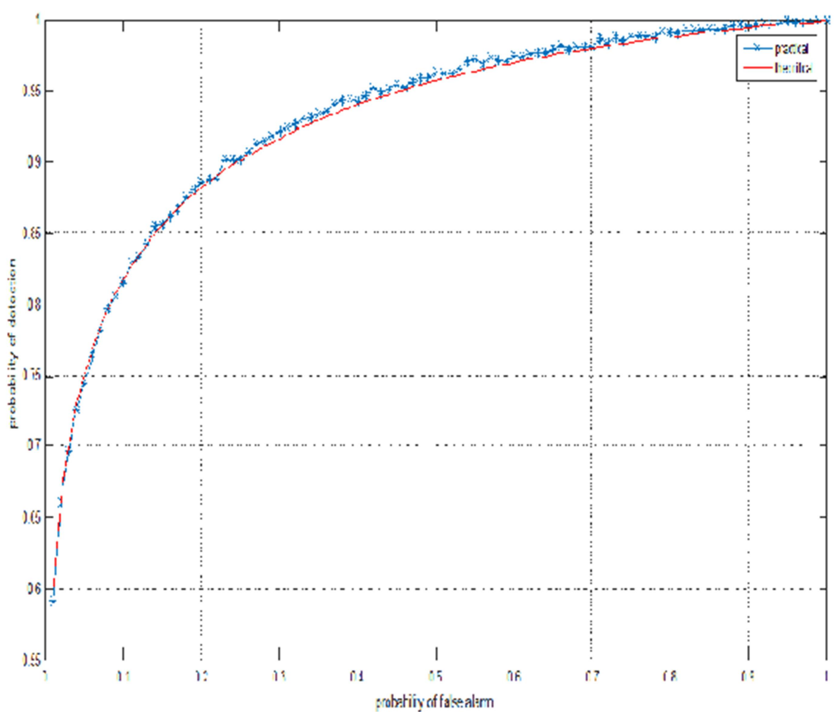


Figure below shows the probability of false alarm versus probability of detection with SNR -10 dB for energy detection technique.



Chapter 11

ADVANTAGES AND LIMITATIONS

11.1 Advantages

Cognitive radio helps

1. Overcome radio spectrum scarcity

-By sensing spectrum utilization (irrespective of channel allocation), cognitive radios can broadcast on unused radio spectrum, while still avoiding interference with the operation of the primary licensee.

2. Avoid intentional radio jamming scenarios

-By sensing channel availability and even predicting the jammer's tactics , cognitive radios can evade jamming by dynamically and preemptively switching to higher quality channels.

3. Switch to power saving protocol

-By switching to protocols that trade off lower power consumption for lower bandwidth, cognitive radios conserve power when slower data rates suffice.

4. Improve satellite communications

- By predicting rain fade and reconfiguring transmitters/receivers for optimum bandwidth, cognitive radios improve communication quality when and where the information is needed most.

5. Improves quality of service (QoS)

- By sensing environmental and inadvertent man-made radio interferences, cognitive radios can select frequency channels with a higher Signal to Noise Ratio (SNR).

11.2 Limitations

1. It suffers in multipath fading and shadowing environments where deep and fast fades of the received signal strength and hidden terminal problem can lead to incorrect spectrum utilization.
2. 2. A longer observation time can allow achieving satisfactory performances, but such a solution is not exploited in practice since fast opportunity detection is desirable in practical CR networks.

Chapter 12

COCLUSION AND FUTURE SCOPE

12.1 Conclusion

CS has been well motivated for CR communications due to the sparse nature of the radio spectrum occupancy in practical wireless systems. In this context, this project has provided a comprehensive review on the applications of CS in CR communications. Starting with the basic principles and the main aspects of the CS technique, this project has identified various application areas such as wideband SS, environmental parameter estimation and REM construction based on the RF parameter to be acquired.

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. Finally the energy detection technique is performed by giving a QPSK signal as its input which is obtained by compressed detection basic pursuit algorithm and various graphs are plotted. By this, even for low SNR values the signal can be detected accurately by using compressed detection technique.

12.2 Future Scope

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).

BIBLIOGRAPHY

[1] S. Haykin, Cognitive radio: brain-empowered wireless communications, IEEE

Journal on Selected Areas in Communications 23 (2) (2005) 201–220.

[2] I.F Akyildiz,W Lee, M.C Vuran, S Mohanty,"Next Generation/Dynamic spectrl access/cognitive radio wireless networks: A survey" Computer Networks 50(2006) 2127-2159, May 2006.

[3] B Saklar,"Digital Communications: Fundamentals and Applications" (2nd Edition) (Prentice Hall Communications Engineering and Emerging Technologies Series).

[4] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation Issues in Spectrum Sensing for Cognitive Radios",in Proc. 38th Asilomar Conference on Signals, Systems and Computers, pp. 772776, Nov. 2004.

[5] A. Sahai, N. Hoven and R. Tandra, "Some Fundamental Limits in Cognitive Radio", in Proc. Allerton Conf. on Comm., Control and Computing 2004.

[6]] H. Tang,"Some Physical Layer Issues of Wideband Cognitive Radio System",in Proc. IEEE DySPAN, pp. 151159, Nov. 2005.

[7] Nisha Yadav, Suman Rathi, Spectrum Sensing Techniques: Research, Challenge and Limitations,Dept. of ECE, Gurgaon Institute of Technology & Management, Bilaspur, Gurgaon, India.

[8] https://en.wikipedia.org/wiki/Compressed_sensing

[9] Z. Quan, S. Cui, A. H. Sayed, and H. V. Poor, "Wideband spectrum sensing in cognitive radio networks," in Communications, 2008. ICC '08. IEEE International Conference on, Beijing,May 2008, pp. 901–906.

[10] R. Lopez-Valcarce and G. Vazquez-Vilar, "Wideband spectrum sensing in cognitive radio: Joint estimation of noise variance and multiple signal levels," in Signal Processing Advances in Wireless Communications, 2009. SPAWC '09. IEEE 10th Workshop on, Perugia, Jun. 2009, pp. 96–100.

[11] Z. Tian and G. B. Giannakis, "Compressed sensing for wideband cognitive radios," in Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on, vol. 4,Honolulu, HI, Apr. 2007, pp. 1357–1360.

[12] Y. L. Polo, Y.Wang, A. Pandharipande, and G. Leus, “Compressive wide-band spectrum sensing,” in Acoustics, Speech and Signal Processing, 2009. ICASSP 2009. IEEE International Conference on, Taipei, Apr. 2009, pp. 2337–2340.

[13] E. J. Candes and M. B. Wakin, “An introduction to compressive sampling,” IEEE Signal ProcessingMagazine, vol. 25, no. 2, pp. 21–30, Mar. 2008.

[14] A. Ghasemi and E. S. Sousa, “Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs,” in Communications Magazine, IEEE, vol. 46, no. 4, Toronto, Ont., Canada, Apr. 2008, pp. 32–39.

[15] D. L. Donoho and J. Tanner, “Sparse nonnegative solution of underdetermined linear equations by linear programming,” Proceedings of the National Academy of Sciences, vol. 102, no. 27, pp. 9446–9451, 2005.

[16] E. J. Candes and T. Tao, “Near Optimal Signal Recovery from Random Projections: Universal Encoding Strategies,” IEEE Trans. Info. Th., vol. 52, no. 12, pp. 5406–5425, Dec. 2006.

[17] S. G. Mallat and Z. Zhang, “Matching Pursuits with Time-Frequency Dictionaries,” IEEE Trans. Signal Process., vol. 41, no. 12, pp. 3397– 3415, Dec. 1993.

[18] J. A. Tropp, “Greed is Good: Algorithmic Results for Sparse Approximation,” IEEE Trans. Info. Th., vol. 50, no. 10, pp. 2231–2242, Oct. 2004.

[19] M. Elad, “Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing”, Springer, 2010.

[20] D. Ramasamy, S. Venkateswaran, and U. Madhow, “Compressive parameter estimation in AWGN,” IEEE Trans. Signal Process., vol. 62, no. 8, pp. 2012–2027, 2014.

[21] M. Wakin, “Manifold-based signal recovery and parameter estimation from compressive measurements,” 2008, Available: http://arxiv.org/abs/1002.1247.

[22] J. Haupt, R. Castro, R. Nowak, G. Fudge, and A. Yeh, “Compressive sampling for signal classification,” Proc. Asilomar Conf. Signals, Syst. Comput., Pacific Grove, CA, USA, Oct. 2006.

[23] Zhi Tian, E. Blasch, Wenhua Li, Genshe Chen, and Xiaokun Li, “Performance evaluation of distributed compressed wideband sensing for cognitive radio networks,” in 11th International Conference on Information Fusion, pp.1-8, June 30-July 3 2008.

[24] B. L. Sturm, and M. G. Christensen, "Comparison of orthogonal matching pursuit implementations," in Proc. 20th European Signal Process. Conf. (EUSIPCO), pp. 220-224, Aug. 2012.

[25] Z. Qin, Y. Gao, and C. G. Parini, "Data-Assisted Low Complexity Compressive Spectrum Sensing on Real-Time Signals under Sub- Nyquist Rate," in IEEE Transactions on Wireless Communications, vol. PP, no. 99, pp.1-1, doi: 10.1109/TWC.2015.2485992.

[26] D. Wipf, and S. Nagarajan, "Iterative Reweighted l1 and l2 Methods for Finding Sparse Solutions," in IEEE J. Sel. Topics Signal Process., vol. 4, no. 2, pp. 317-329, April 2010.

[27] S. Hong, "Direct spectrum sensing from compressed measurements," in IEEE Military Commun. Conf., pp. 1187-1192, Oct. 31-Nov. 3, 2010.

[28] M. Davenport, P. Boufounos, M. Wakin, and R. Baraniuk, "Signal processing with compressive measurements," IEEE J. Sel. Topics in Signal Process., vol. 4, no. 2, pp. 445–460, 2010. M. Duarte, M. A. Davenport, M. Wakin, and R. G. Baraniuk, "Sparse signal detection from incoherent projections," in IEEE ICASSP, May2006.

[29] Y. Chi, L. Scharf, A. Pezeshki, and A. Calderbank, "Sensitivity to basis mismatch in compressed sensing," in IEEE Trans. Signal Process., vol. 59, no. 5, May 2011, pp. 2182–2195.

[30] G. Tang, B. Bhaskar, P. Shah, and B. Recht, "Compressed sensing off the grid," IEEE Trans. Info. Th., vol. 59, no. 11, pp. 7465–7490, Nov. 2013. T. Wimalajeewa, H. Chen, and P. Varshney, "Performance limits of compressive sensing-based signal classification," in IEEE Trans. Signal Process., vol. 60, no. 6, June 2012, pp. 2758–2770

[31] M. Davenport, M. Duarte, M. Wakin, J. Laska, D. Takhar, K. Kelly, and R. Baraniuk, "The smashed filter for compressive classification and target recognition," in Proc. SPIE, San Jose, CA, Jan. 2007.

[32] A. Goldsmith, S. Jafar, I. Maric, and S. Srinivasa, "Breaking spectrum gridlock with cognitive radios: An information theoretic perspective," Proc. IEEE, vol. 97, no. 5, pp. 894 –914, May 2009.

[33] M. Davenport, J. Laska, J. Treichler, and R. Baraniuk, "The pros and cons of compressive sensing for wideband signal acquisition: Noise folding versus dynamic range," IEEE Trans. Signal Process., vol. 60,no. 9, pp. 4628 –4642, Sept. 2012.

[34] Y. Wang, A. Pandharipande, Y. Polo, and G. Leus, “Distributed compressive wide-band spectrum sensing,” in Info. Theory and Applications Workshop, Feb. 2009 , pp. 178–183.

[35] M.-H. Yoon, Y. Shin, H.-K. Ryu, and J.-M. Woo, “Ultra-wideband loop antenna,” Electronics Letters, vol. 46, no. 18, pp. 1249–1251, Sept. 2010.

[36] Z.-C. Hao and J.-S. Hong, “Highly selective ultra wideband bandpass filters with quasi-elliptic function response,” IET Microwaves, Antennas Propag., vol. 5, no. 9, pp. 1103–1108, June 2011.

[37] R. Walden, “Analog-to-digital converter survey and analysis,” IEEE J.Sel. Areas in Commun., vol. 17, no. 4, pp. 539 –550, Apr. 1999

[38] M. Ariaudo and et al, “Green radio despite Dirty RF front-end,” EURASIP J. on Wireless Commun. and Networking, vol. 146, Apr.2012.

[39] H. Sun, A. Nallanathan, C.-X. Wang, and Y. Chen, “Wideband spectrum sensing for cognitive radio networks: a survey,” IEEE Wireless Commun., vol. 20, no. 2, pp. 74–81, Apr. 2013.

[40] M. Kim and J. Takada, “Efficient Multichannel Wideband Spectrum Sensing Technique Using Filter Bank,” Proc. IEEE Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC), pp. 1014–1018, Sept. 2009.

[41] H. Sun, W.-Y. Chiu, J. Jiang, A. Nallanathan, and H. Poor, “Wideband spectrum sensing with sub-Nyquist sampling in cognitive radios,” IEEE Trans. Signal Process., vol. 60, no. 11, pp. 6068 –6073, Nov. 2012.

[42] D. Cabric and R. Brodersen, “Physical layer design issues unique to cognitive radio systems,” in Proc. Int. Symp. Personal, Indoor and Mobile Radio Commun., vol. 2, Sept. 2005, pp. 759 –763 Vol. 2.

[43] J. Laska, S. Kirolos, M. Duarte, T. Ragheb, R. Baraniuk, and Y. Massoud, “Theory and implementation of an analog-to-information converter using random demodulation,” in Proc. IEEE Int. Symp. Circuits and Systems, May 2007, pp. 1959–1962.

[44] J. Laska and et al, “Compressive sensing for dynamic spectrum access networks: Techniques and tradeoffs,” in Proc. IEEE Symp. New Frontiers in DySPAN, May 2011, pp. 156–163.

[45] D. Malioutov, S. Sanghavi, and A. Willsky, “Compressed sensing with sequential observations,” in Proc. IEEE Int. Conf. Acoustics, Speech and Signal Process., Apr. 2008, pp. 3357 –3360.

[46] M. Mishali, Y. Eldar, O. Dounaevsky, and E. Shoshan, "Xampling:Analog to Digital at sub-Nyquist Rates," IET Cir. Dev. and Systems, vol. 5, no. 1, pp. 8–20, Jan. 2011.

[47] M. Mishali and Y. Eldar, "Blind MultiBand Signal Reconstruction: Compressed Sensing for Analog Signals," IEEE Trans. Signal Proces., vol. 57, no. 3, pp. 993–1009, 2009.

[48] C. Yen and X. Tsai, Y. Wang, "Wideband Spectrum Sensing Based on Sub-Nyquist Sampling," IEEE Trans. Signal Process., vol. 61, no. 12, pp. 3028–3040, June 2013.

[49] M. A. Lexa, M. E. Davies, J. S. Thompson, and J. Nikolic, "Compressive Power Spectral Density Estimation," in Proc. Inter. Conf. on Acoustics, Speech and Sig. Process. (ICASSP), pp. 3884–3887, May 2011.

[50] D. Ariananda and G. Leus, "Compressive Wideband Power Spectrum Estimation," IEEE Trans. Signal Process., pp. 4775–4788, Sept. 2012.

[51] Z. Quan, W. Zhang, S. Shellhammer, and A. Sayed, "Optimal Spectral Feature Detection for Spectrum Sensing at Very Low SNR," IEEE Trans. Commun., vol. 59, pp. 201–212, Jan. 2011.

[52] E. Lagunas and M. Najar, "Spectral Feature Detection with sub-Nyquist Sampling for Wideband Spectrum Sensing," IEEE Trans. Wireless Commun., Mar. 2015.

[53] E. Lagunas and M. Najar, "Sparse Correlation Matching-Based Spectrum Sensing for Open Spectrum Communications", EURASIP J. Advances in Signal Process., vol. 31, Feb. 2012.

[54] H. Sun, W.-Y. Chiu, and A. Nallanathan, "Adaptive compressive spectrum sensing for wideband cognitive radios," IEEE Commun. Letters, vol. 16, no. 11, pp. 1812 –1815, Nov. 2012.

[55] H. Chen X. Chen and W. Meng, "Cooperative communications for cognitive radio networks-from theory to applications," IEEE Comm. Surveys & Tutorials, vol. 16, no. 3, pp. 1180-1192, 2014.

[56] S. K. Sharma, S. Chatzinotas, and B. Ottersten, "Cooperative spectrum sensing for heterogeneous sensor networks using multiple decision statistics," in Proc. 10th Int. Conf. Cognitive Radio Oriented Wireless Networks (CROWNCOM), Apr. 2015.

[57] M. Eslami, F. Torkamani-Azar, and E. Mehrshahi, “A Centralized PSD Map Construction by Distributed Compressive Sensing,” in IEEE Communications Letters, vol. 19, no. 3, pp. 355-358, March 2015.

[58] S. Althunibat, R. Palacios, and F. Granelli, “Performance Optimisation of Soft and Hard Spectrum Sensing Schemes in Cognitive Radio,” IEEE Communications Letters, vol. 16, no. 7, pp. 998-1001, July 2012.

[59] Z. Tian, “Compressed wideband sensing in cooperative cognitive radio networks,” in Proc. IEEE Global Telecommun. Conf., Nov. 2008, pp.1–5.

[60] J. Halamek and et al, “Dynamic range and acquisition system,” Measurement Science Review, vol. 1, no. 1, pp. 71–74, 2001.

[61] J. R. Treichler, M. A. Davenport, J. N. Laska, and R. G. Baraniuk, “Dynamic range and compressive sensing acquisition receivers,” in Defense Applications of Signal Process. (DASP), July 2011, pp. 1–7.

[62] Y. Wang, Z. Tian, and C. Feng, “Sparsity order estimation and its application in compressive spectrum sensing for cognitive radios,” IEEE Trans. Wireless Commun., vol. 11, no. 6, pp. 2116 –2125, June 2012.

[63] E. Candes and B. Recht, “Exact low-rank matrix completion via convex optimization,” in Proc. 46th Annual Allerton Conf. on Communication, Control, and Computing, Sept. 2008, pp. 806–812.

[64] J. Meng, W. Yin, H. Li, E. Houssain, and Z. Han, “Collaborative spectrum sensing from sparse observations using matrix completion for cognitive radio networks,” in Proc. IEEE Int. Conf. ICASSP, pp. 3114-3117, Mar. 2010.

[65] Application of Compressive Sensing in Cognitive Radio Communications: A Survey Shree Krishna Sharma, Member, IEEE, Eva Lagunas, Member, IEEE,Symeon Chatzinotas, Senior Member, IEEE and Bj¨orn Ottersten, Fellow, IEEE

[66] S. K. Sharma, S. Chatzinotas, and B. Ottersten, “Compressive SNR estimation for wideband cognitive radio under correlated scenarios,” in Proc. IEEE Wireless Commun. and Networking Conf. (WCNC), Apr. 2014, pp. 713–718.

[67] S. K. Sharma, S. Chatzinotas, and B. Ottersten, “Transmit beamforming for spectral coexistence of satellite and terrestrial networks,” in Proc. 8th Int. Conf. Cognitive Radio Oriented Wireless Networks (CROWNCOM), July 2013, pp. 275–281.

[68] S. K. Sharma, S. Chatzinotas, and B. Ottersten, “Interference alignment for spectral coexistence of heterogeneous networks,” EURASIP J. Wireless Commun. and Networking, vol. 46, 2013.

[69] S. K. Sharma, S. Chatzinotas, and B. Ottersten, “Cognitive beamhopping for spectral coexistence of multibeam satellites,” Int. J. Satellite Commun. and Networking, Mar. 2014.

[70] A. Ijaz, A. Awoseyila, and B. Evans, “Improved snr estimation for BPSK and QPSK signals,” Electronics Letters, vol. 45, no. 16, pp. 858–859, July 2009.

[71] T. Tian, H. Iwai, and H. Sasaoka, “Pseudo BER based SNRestimation for energy detection scheme in cognitive radio,” in Proc. IEEE 75th Veh. Technol. Conference (VTC Spring), May 2012, pp. 1–5.

[72] S. K. Sharma, S. Chatzinotas, and B. Ottersten, “Eigenvalue based sensing and SNR estimation for cognitive radio in presence of noise correlation,” Proc. IEEE Trans. Veh. Technol., vol. 62, no. 8, pp. 1–4, 2013.

[73] S. K. Sharma, “Interweave/Underlay Cognitive Radio Techniques and Applications in Satellite Communication Systems”, Ph.D. dissertation, University of Luxembourg, Luxembourg, 2014, http://orbilu.uni.lu/handle/10993/18973.

APPENDIX 1

COMPRESSED DETECTION MATLAB SCRIPT

Matlab code for l1norm minimization

%QPSK signal generation

```
close all;

clear all;

clc;

msg=round(rand(1,20));

data=[];

fs=10000;

%t=0:.01:.99;

t=0:1/fs:0.01;

fc=1000;

c=cos(2*pi*fc*t);%carrier signal & it's a matrix of length 1X100(bcoz for each t, there's a
c).let fc=10hz

% chan=ricianchan(1/fs,100,1)

% chan=rayleighchan(1/fs,100);

for i=1:20

   if msg(i)==0

       d=-1*ones(1,10);

     else

       d=ones(1,10);

   end;
```

```
 data=[data d];   %data is created only for plotting.it has no application in the following for
loop

end;

disp('length of t,c,data');

a=[length(t);length(c);length(data);];disp(a);

qpsk=[];

for i=1:2:20

   if msg(i)==1 && msg(i+1)== 0

      qpsk=[qpsk cos(2*pi*fc*t+(pi/4))];

   else if msg(i)==0 && msg(i+1)==0

      qpsk=[qpsk cos(2*pi*fc*t+(3*pi/4))];

      else if msg(i)==0 && msg(i+1)==1

      qpsk=[qpsk cos(2*pi*fc*t+(5*pi/4))];

         else if msg(i)==1 && msg(i+1)==1

      qpsk=[qpsk cos(2*pi*fc*t+(7*pi/4))];

            end;

         end;

      end;

   end;

end;

% plot(qpsk);

modsig=[];

for i=1:100:1000
```

```
    for j=1:10
        p=qpsk(i+j);
        modsig=[modsig p];
    end;
end;
%fadedsig=filter(chan,qpsk);
% fadedsig=filter(chan,qpsk);
subplot(321);
plot(data);axis([0 100 -1.5 1.5])
title('Digital Message signal');
%plot('fadesig');
subplot(323);
plot(modsig);axis([0 100 -1.5 1.5])
title('qpsk signal');
subplot(322)
plot(c);axis([0 100 -1.5 1.5])
title('Unmodulated carrier');
%l1 norm minimization
N=100;
% number of spikes in the signal
%  T = 20;
T=3;
% number of observations to make
```

```
%  K = 120;
K=30;
x=modsig;
x=x';
x1=x;
% stem(x1);
% x = zeros(N,1);
 q = randperm(N);
 x(q(1:T)) = sign(randn(T,1));
 x=modsig;
% A = randn(K,N);%additive white gaussian noise
 A = randn(K,N)+j*randn(K,N); % rayleigh fading
A = orth(A')';
y = A*x1;
 xp = A'*y;
subplot(324);
plot(xp);
axis([0 100 -1.5 1.5])
title('reconstructed signal');
D=abs(x1-xp).^2;
MSE1=sum(D(:))/numel(x);
% MSE1 = mse(x1, xp);
% MSE1 =  mean((x1 -xp).^2);
```

```
display([' Mean Squared Error: ' num2str(MSE1)]);

SNR1 = snr(x1,xp);display([' SNR1: ' num2str(SNR1)]);

% SNR1 = (abs(x.^2))./(abs(MSE1.^2));

% SNRdB= 10 * log10( SNR1 );

% display([' SNR1: ' num2str(SNR1)]);
```

APPENDIX 2

ENERGY DETECTION MATLAB SCRIPT

MATLAB Code of Energy detector

Probability of false alarm vs Probability of detection Plot:

```
%%%narrow band signal detection%%%%

clc
close all
clear all
L=512;
 %qpsk signal
N=8;
T=1/N;
Fs=512*2;
Ts=1/Fs;
fc=Fs/8;
data= [-1 -1 1  1 -1 1  1 -1];
        data1=ones(T/Ts,1)*data;
        data2=data1(:);
        bs1=data(1:2:length(data));
        symbols=ones(T/Ts,1)*bs1;
        Isymbols=symbols(:);
        bs2=data(2:2:length(data));
        symbols1=ones(T/Ts,1)*bs2;
        Qsymbols=symbols1(:);
        twopi_fc_t=(1:Fs/2)*2*pi*fc/Fs;
        %phi=45*pi/180;
        phi=0;
        a=1;
        cs_t=a*cos(twopi_fc_t+phi);
        sn_t=a*sin(twopi_fc_t+phi);
        cs_t=cs_t';
        sn_t=sn_t';
```

```
        si=cs_t.*Isymbols;
        sq=sn_t.*Qsymbols;
        sumiq=si+sq;
        s1=sumiq;
        %-------------------------------------
        K=512;
        for h=1:length(K)
            disp('Creating measurment matrix...');
           A = randn(K(h),L);
           A = orth(A')';
           disp('Done.');
           z = A*s1;
        end
%% Simulation to plot Probability of Detection (Pd) vs. Probability of False Alarm (Pf)
        snr_dB = -9.2;
  % SNR in decibels
snr = 10.^(snr_dB./10); % Linear Value of SNR
Pf = 0.01:0.01:1;
for m = 1:length(Pf)
    m
    detect = 0;
for kk=1:10000 % Number of Monte Carlo Simulations
n = randn(1,K);
 sig = sqrt(snr).*z; % Real valued Gaussina Primary User Signal
 y = sig' + n; % Received signal at SU
 energy = abs(y).^2; % Energy of received signal over N samples
 energy_fin =(1/K).*sum(energy); % Test Statistic for the energy detection
 thresh(m) = (qfuncinv(Pf(m))./sqrt(K))+ 1; % Theoretical value of Threshold, refer, Sensing
Throughput Tradeoff in Cognitive Radio, Y. C. Liang
 if(energy_fin >= thresh(m))  % Check whether the received energy is greater than threshold,
if so, increment Pd (Probability of detection) counter by 1
     detect = detect+1;
 end
end
```

```
Pd(h,m) = detect/kk;
end
plot(Pf,Pd,'*-')
%plot(Pf,Pd,'--r',Pf,Pd,'-ok')
grid on
hold on
%% Theroretical expression of Probability of Detection; refer above reference.
% thresh = (qfuncinv(Pf)./sqrt(K))+ 1;
 Pd_the = qfunc(((thresh - (snr + 1)).*sqrt(K))./(sqrt(2).*(snr + 1)));
 plot(Pf, Pd_the, 'r')
%Pd_the = qfunc((qfuncinv(Pf)-sqrt(K).*snr)./(sqrt(2.*snr+1)));
% plot(snr_dB, Pd_the,'r')
%xlabel('Probability of false alarm');
xlabel('probability of false alarm');
ylabel('probability of detection');
grid on
hold on
legend('practical','theoritical');
```

SNR Vs Probability of detection Plot:

```
%%%%%narrow band signal detection%%%%

clc

close all

clear all

L = 512;
%qpsk signal
N=8;
T=1/N;
Fs=512*2;
Ts=1/Fs;
fc=Fs/8;
data= [-1 -1 1  1 -1 1  1 -1];
```

```
data1=ones(T/Ts,1)*data;
data2=data1(:);
bs1=data(1:2:length(data));
symbols=ones(T/Ts,1)*bs1;
Isymbols=symbols(:);
bs2=data(2:2:length(data));
symbols1=ones(T/Ts,1)*bs2;
Qsymbols=symbols1(:);
 twopi_fc_t=(1:Fs/2)*2*pi*fc/Fs;
%phi=45*pi/180;
phi=0;
a=1;
cs_t=a*cos(twopi_fc_t+phi);
sn_t=a*sin(twopi_fc_t+phi);
cs_t=cs_t';
sn_t=sn_t';
si=cs_t.*Isymbols;
sq=sn_t.*Qsymbols;
sumiq=si+sq;
s1=sumiq;
%-------------------------------------
K=512;
for h=1:length(K)
    disp('Creating measurment matrix...');
   A = randn(K(h),L);
   A = orth(A')';
   disp('Done.');
   z = A*s1;
end
L = 1000;
 snr_dB=-20:1:0;
snr= 10.^(snr_dB./10);
 for i=1:length(snr_dB)
    Detect=0;
```

```
   Pf=0.2;
    for kk=1:10000 % Number of Monte Carlo Simulations
         %-----AWGN noise with mean 0 and variance 1-----%
       n = randn(1,K);
       %-----Real valued Gaussian Primary User Signal------%
       sig = sqrt(snr(i)).*z;
       y = sig' + n; % Received signal at SU
       Energy = abs(y).^2; % Energy of received signal over N samples
         %-----Computation of Test statistic for energy detection-----%
       Test_Statistic =(1/K).*sum(Energy);
        %-----Theoretical value of Threshold-----%
       Threshold = (qfuncinv(Pf)./sqrt(K))+ 1;
        if(Test_Statistic >= Threshold)  % Check whether the received energy is greater than
threshold, if so,(Probability of detection) counter by 1
          Detect = Detect+1;
       end
end
       Pd(i) = Detect/kk;
       Pm(i)=1-Pd(i);
       Pd_the(i) = qfunc(((Threshold - (snr(i) + 1)).*sqrt(L))./(sqrt(2).*(snr(i) + 1)));
       Pm_the(i)=1-Pd_the(i);
end
 plot(snr_dB,Pd);
 hold on
 plot(snr_dB,Pd_the,'r');
 grid on
 title('ROC curve for SNR vs Probability of Detection for Pf=0.2')
 xlabel('Signal To Noise Ratio (dB)');
 ylabel('Probability Of Detection');
legend('Simulation','Theory');
```