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"CYCLOSTATIONARY FEATURES BASED LOW COMPLEXITY MUTLIRESOLUTION SPECTRUM SENSING FOR COGNITVE RADIO APPLICATIONS"

by

BAKHIT AMINE ADOUM

The undersigned certify that they have read, and recommend to The Postgraduate Studies Programme for acceptance this thesis for the fulfillment of the requirements for the degree of Master of Science in Electrical and Electronics Engineering.

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UNIVERSITI TEKNOLOGI PETRONAS

"CYCLOSTATIONARY FEATURES BASED LOW COMPLEXITY MUTLIRESOLUTION SPECTRUM SENSING FOR COGNITVE RADIO APPLICATIONS"

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Bakhit Amine Adoum

A Thesis

Submitted to the Postgraduate Studies Programme

as a Requirement for the Degree of

MASTER OF SCIENCE

ELECTRICAL AND ELECTRONICS ENGINEERING

UNIVERSITI TEKNOLOGI PETRONAS

BANDAR SRI ISKANDAR

PERAK

November, 2010

DECLARATION OF THESIS

Title of thesis	CYCLOSTATIONARY FEATURES BASED LOW COMPLEXITY MULTIRESOLUTION SPECTRUM SENSING FOR COGNTIVE RADIO APPLICATIONS

I, BAKHIT AMINE ADOUM,

hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTP or other institutions.

Witnessed by

Bakhit Amine Adoum	Assoc. Prof. Dr. Varun Jeoti
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Date:	Date:

Dedicated

To the Soul of My Mother

To My Father &My Brothers

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ABSTRACT

The demand for variety of services using wireless communication has grown remarkably in the past few many years, consequently causing an acute problem of spectrum scarcity. Today, it is one of the most challenging problems in modern wireless communication. To overcome this, the concept of cognitive radio has been proposed and this technology is fast maturing.

The first and foremost function a cognitive radio must do is to sense the spectrum as accurately as possible and do it with least complexity. Among many techniques of spectrum sensing, the Multi-resolution Spectrum Sensing (MRSS) is a popular technique in recent literature. Various multi resolution techniques are used that include wavelet based spectrum estimation and spectral hole detection, wavelet based multi-resolution in analog domain and multi-resolution multiple antenna based detection. However, the basic idea is the same - the total bandwidth is sensed using coarse resolution energy detection, then, fine sensing is applied to the portion of interest. None of these techniques, however, use multi-resolution sensing using cyclostationary features for cognitive radio applications which are more reliable but computationally expensive.

In this thesis, we suggest a cyclostationary features based low complexity multi-resolution spectrum sensing for cognitive radio applications. The proposed technique discussed in this thesis is inspired by the quickness of multi-resolution and the reliability of cyclostationary feature detection. The performance of the proposed scheme is primarily evaluated by its complexity analysis and by determining the minimum signal-to-noise ratio that gives 90% probability of correct classification. Both subjective and objective evaluation show that the proposed scheme is not only superior to the commonly used energy detection method but also to various multi-resolution sensing techniques as it relies on the robustness of cyclostationary feature detection. The results found are encouraging and the proposed algorithms are proved to be not only fast but also more robust and reliable.

ABSTRAK

Permintaan untuk komunikasi wayarles telah berkembang luar biasa dalam beberapa tahun terakhir, sehingga menyebabkan masalah kekurangan spektrum akut. Hari ini, adalah salah satu masalah yang paling mencabar dalam komunikasi wayarles moden. Untuk mengatasi hal ini, konsep kognitif radio telah dicadangkan dan teknologi ini adalah mudah jatuh tempo. Yang pertama dan terutama fungsi kognitif radio harus anda lakukan adalah merasakan spektrum seakurat mungkin dan melakukannya dengan kompleksitas terendah. Diantara banyak teknik penginderaan spektrum, spektrum multi-resolusi penginderaan adalah teknik yang popular dalam sastera terkini. Berbagai kaedah pengesanan isyarat telah dicadangkan untuk multi-resolusi penginderaan yang merangkumi, tetapi tidak terhad kepada, sebagai berikut: estimasi spektrum dan spektrum wavelet berdasarkan pengesanan lubang, wavelet berdasarkan multi-resolusi dalam domain analog, beberapa antena multi-resolusi pengesanan berasaskan. Namun, idea asasnya adalah sama - total bandwidth merasakan menggunakan resolusi kasar, kemudian halus penginderaan dilaksanakan pada bahagian bunga. Tidak ada teknik ini, bagaimanapun, dengan menggunakan multi-resolusi penginderaan menggunakan ciri-ciri cyclostationary untuk aplikasi radio kognitif yang lebih handal.

Dalam tesis ini, kami menyarankan beberapa ciri cyclostationary berasaskan spektrum resolusi multi-sensing untuk aplikasi radio kognitif. Teknik yang dicadangkan dibahas dalam tesis ini terinspirasi oleh kelajuan multi-resolusi dan kehandalan ciri pengesanan cyclostationary. Prestasi dari skim yang dicadangkan dievaluasi dengan menggunakan kebarangkalian klasifikasi benar dan analisis kompleksitas. Keputusan kajian menunjukkan bahawa prestasi yang lebih baik adalah dicapai dengan skim yang dicadangkan terutama dalam rejim SNR rendah.

Kedua-dua langkah penilaian subjektif dan objektif menunjukkan bahawa skim yang dicadangkan tidak hanya unggul dengan kaedah pengesanan tenaga yang umum digunakan, tetapi juga untuk pelbagai resolusi penginderaan multi-teknik sebagai hal

itu bergantung pada kekokohan pengesanan ciri cyclostationary. Keputusan yang ditemui adalah menggalakkan dan algoritma yang dicadangkan ternyata tidak hanya cepat, tetapi juga lebih kuat dan dapat diandalkan.

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LIST OF ABBREVIATIONS

ADC	Analog-to-Digital Converter
AGC	Automatic Gain Controller
AM	Amplitude Modulation
Amp	Amplifier
ASK	Amplitude Shift Keying
ASIC	Application -specific-integrated circuit
AWGN	Additive White Gaussian Noise
BW	Bandwidth
CA	Conventional autocorrelation
CDF	Cumulative distribution function
CEA	Consumer Electronics Association
CPE	Customer premise equipment
CR	Cognitive Radio
DCS	Digital cellular suystem
DSP	Digital Signal Processing
DVB-T	Digital Video Broadcasting – Terrestrial
DWT	Discrete Wavelet Transform
DWPT	Discrete Wavelet Packet Transform
Fc	Carrier Frequency
FCC	Federal Communication Commission
FM	Frequency Modulation
Fs	Sampling frequency
FFT	Fast Fourier Transform

FPGA	Field programmable gate array
GPS	Global Positioning System
GLONASS	Global Navigation Satellite
IEEE	Institute of Electrical and Electronics Engineering
LPF	Low pass filter
LNA	Low noise amplifier
MAC	Media Access Control layer
MCMC	Malaysian Communications and Multimedia Commissions
MFN	Multiple Frequency Network
MRSS	Multi-resolution Spectrum Sensing
N_0	Thermal Noise Power spectrum density
N	Noise power
Ns	Number of Samples during Sensing Time
NF	Noise factor
FFT	Fast Fourier Transform
FAM	FFT accumulation method
NLA	Non Linear Amplifier
NPRM	Notice Proposed Rule Making
MR	Multi-resolution
MRSS	Multi-resolution Spectrum Sensing
OFDM	Orthogonal Frequency Division Multiplex
PDC	Personal Digital Cellular
PSD	Power spectrum density
PUs	Primary Users
P_c	Probability of correct classification
PLL	Phase Locked Loop
P_{fa}	Probability of false alarm
QAM	Quadrature Amplitude Modulation
Q(x)	Complementary Cumulative Distribution Function
RF	Radio Frequency
RFE	Radio Front-End
R^{α}_{x}	Cyclic autocorrelation

SCD	spectral cyclic density
SCF	Spectral Correlation function
$S^{\alpha}_{x}(f)$	Spectral Correlation Function
SDRs	Software Definite Radios
SFN	Single Frequency Network
SNR	Signal to Noise Ratio
STFT	Short Time Fourier Transform
SUs	Secondary User
TS	Test statistic
TV	Television
UHF	Ultra High Frequency
VHF	Very High Frequency
WIS	Windowed Integrated Sampler
VCO	Voltage Controlled-Oscillator
WRAN	Wireless Regional Access Network
WG	Working Group
λ	Decision Threshold

CHAPTER 1

INTRODUCTION

This chapter presents the introduction of the thesis. It explains the basic information of cognitive radio system, the motivation, the objective and methodology of the work, contributions that have been made and lastly the thesis organization.

1.1 Background and Motivation

The demand of radio frequency spectrum is increasing rapidly to support the user needs in wireless communication. RF spectrum is scarce and requires efficient utilization from a cost point of view.

The Federal Communication Commission (FCC) frequency allocation chart indicates multiple allocations over all of the frequency bands as shown in Figure 1.1 [1]. Thus, within the current regulatory framework, a spectrum is scarce resource, at least at frequencies below 3 GHz, which are particularly valuable due to their favorable propagation characteristics. The actual measurements that are shown in Figure 1.2 have been taken for 0 - 2.5 GHz frequencies over a period of 10 minutes, showing the low utilization of radio spectrum [2].

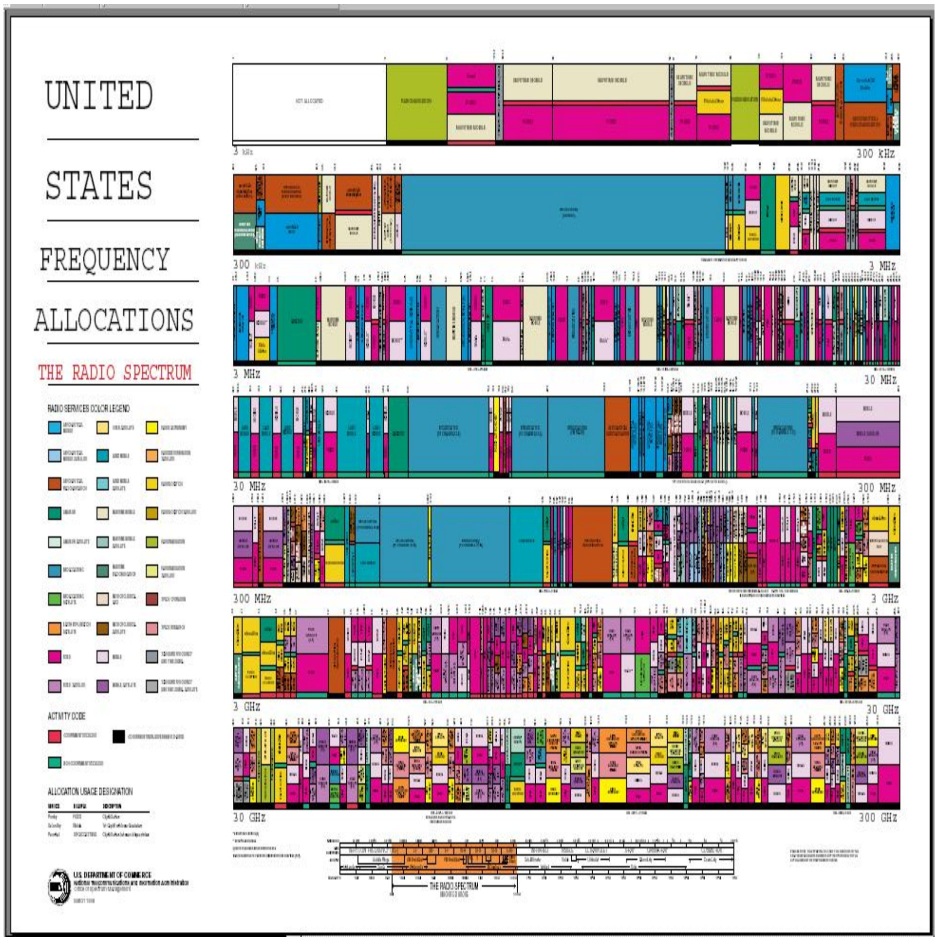


Figure 1.1: Current FCC spectrum allocation

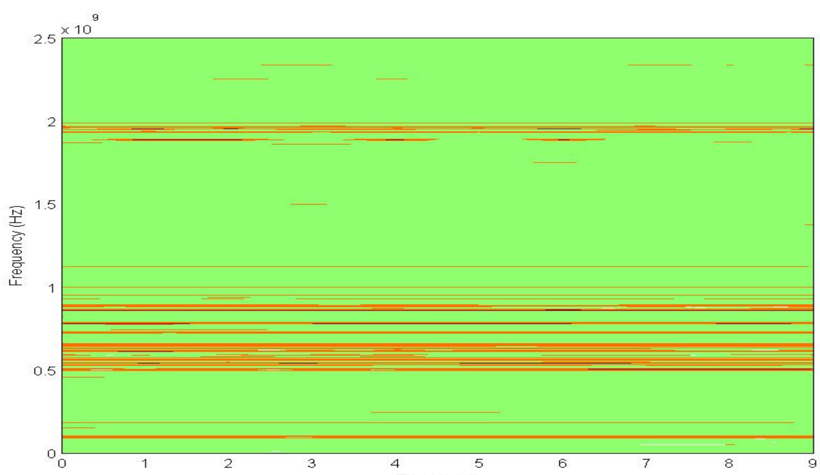


Figure 1.2: Spectrum use of 0-2.5 GHz frequencies over 10 minutes

The cognitive radio (CR) technology thus aims to offer the best way to utilize the radio spectrum. The basic meaning of a cognitive radio is that it is a radio that can sense and react to its operating environment. Cognitive radio is an emerging wireless technology, very helpful in improving the use of spectrum resources and also to reduce the engineering and planning time. Frequency of operation, transmitter power and modulation are just a few of operating parameters that can automatically be adjusted in a cognitive radio system.

The cognitive radio terminology was created by Mittolla [3] and refers to a smart radio which has the ability to sense the external environment, learn from history and make intelligent decisions to adjust its parameters according to the current state of the environment. However, no commonly accepted definition of CR exists yet, mainly because different people or organizations have various views on or expectation of CR [4] [5] [6]. For example the Virginia Tech CR research groups views CR as an adaptive radio that is capable of the following:

- awareness of its environment and its own capabilities,
- goal-driven autonomous operation,
- understanding or learning how its actions impact its goal, and
- recalling and correlating past actions, environments and performance.

The U.S. Federal Communication Commission (FCC) views CR as “a radio that can change its transmitter parameters based on interaction with the environment in which it operates”. The majority of cognitive radios will probably be Software Defined Radios (SDRs) but neither having software nor being field programmable are requirements of a cognitive radio [7].

Cognitive radio technologies have recently received much attention for two reasons: flexibility and potential gains in spectral efficiency. They can rapidly change their transmission parameters and schemes, listen to the spectrum as well as quickly adapt to different spectrum policies.

Cognitive radios are able to sense the spectrum band to see whether it is being used by the licensed user. However, this sensing operation may be made difficult due to degraded wireless channel, which has prompted concerns from licensed users of the spectrum.

Cognitive radio is a much wider concept than a software defined radio and currently a very active research area that attracts serious research works around the world [8][9][10][11], especially after IEEE 802.22 working group for CR was established which was the first wireless standard based on CR. There are two serious problems affecting CR deployment.

- Spectrum scarcity with the increasing applications of wireless communication nowadays, while at the same time, the distributed spectrum is seriously wasted. Unlicensed bands are often left so crowded while licensed bands are often left unused.
- The importance of improving spectrum utilization and the promising CR as a solution which requires better spectrum sensing using reliable sensing techniques.

This research work mainly focuses on the spectrum sensing problem in the context of IEEE 802.22 WRAN CR when Digital Video Broadcasting-Terrestrial (DVB-T) single frequency networks and FM wireless microphone signals are the primary users (PUs). The spectrum sensing techniques can be formulated as the detection theory or binary hypothesis, i.e. either the radio spectrum is occupied, or the radio spectrum is not occupied. The spectrum sensing techniques are: matched filter, energy detector, cyclostationary feature and multi-resolution spectrum sensing. The matched filter is considered an optimal detector but it requires a perfect knowledge of the PU_s signals at the physical and medium access control layers. The energy detector is the simplest and lowest complexity but it cannot recognize signal features, so it cannot be used to distinguish between different signal types. The cyclostationary feature is reliable but it requires extra-computation. The multi-resolution spectrum sensing is fast but is not reliable.

Among these techniques of spectrum sensing the multi-resolution spectrum sensing is a popular technique due to its ability to detect quickly the free band. Various signal detection methods have been proposed for multi-resolution. None of these techniques, however use multi-resolution sensing using cyclostationary feature for cognitive radio application which is more reliable.

1.2 Objectives of the Research

This thesis considers DVB-T single frequency networks and wireless microphone signals as the primary services in the context of WRAN 802.22. Broad objective of the work is to propose a method of spectrum sensing that combines the quickness of multi-resolution and the reliability of cyclostationary feature detector. Specifically, the main objectives of this thesis can be summarized as follows:

- To design a radio front-end (RFE) compliant with the multi-resolution technique (MR) for wideband sensing receivers for cognitive radio application.
- To design and develop a multi-resolution sensing strategy and algorithm for CR application to detect and identify the location of the PUs within the wideband of interest, and thereby, the spectrum holes.
- To identify the unoccupied spectrum within the given DVB-T bandwidth when only a wireless microphones with 200 KHz bandwidth uses that channel. This is with the purpose so the rest of the channel can be used by the cognitive radio.
- To suggest solutions and enhancements found during the research.

1.3 Scope of the Thesis

This thesis limits its scope to study, analyze, simulate and discuss the proposed multi-resolution spectrum sensing approach in an AWGN environment only in terms of the complexity and sensitivity of the technique. The hardware implementation of the proposed method of spectrum sensing therefore is out of the scope and will be left as future work to analyze the comparison of the hardware implementation complexity of the proposed multi-resolution spectrum sensing approach.

1.4 Methodology of the Research

According to the above outlined problem statement and research objectives, a clear view of spectrum sensing problem is not available in the context of IEEE 802.22 WRAN for cognitive radio without calculating the power levels of PU_s at SU receiver. The evaluation of spectrum sensing is mainly based on its sensitivity i.e. the minimum signal to noise ratio (*SNR*) at which the spectrum sensing is able to achieve the required probability of correct classification (P_c). So, the noise floor at radio front end (RFE) should be estimated and combined with the calculated signal powers to obtain the received SNRs at the input of the spectrum sensing algorithm. The MATLAB® is used to simulate the primary user's signals and also to obtain the overall performance of the proposed method of spectrum sensing. Noise is assumed to be white Gaussian noise (WGN) with zero mean and $\sigma_w{}^2$ variance where σ_w is standard deviation of the noise statistics. In order to evaluate the performance of the proposed algorithm, two performance measures are considered: probability of correct classification $\left(P_c\right)$ to determine the sensitivity, i.e., minimum SNR for 90% classification reliability and complexity. Furthermore, effects of noise uncertainties are also considered. The sensitivity of the proposed multi-resolution scheme is computed assuming DVB-T or wireless microphone signal as the weakest signal. As multi-resolution schemes are required to carry out multi-resolution an-extra computation compared to non multi-resolution schemes, they may not prove efficient for all scenario of spectrum occupancy. Keeping this in mind, various occupancy scenarios are analyzed to determine the range and scenarios of occupancy over which the proposed scheme is superior. The following six cases have been analyzed:

- Case 1: 25% of the radio spectrum is densely populated by the primary users.
- Case 2: 25% of the radio spectrum is populated by the primary users in distributed manner.
- Case 3: 50% of the radio spectrum is densely populated by the primary users.

- Case 4: 50% of the radio spectrum is populated by the primary users in distributed manner.
- Case 5: 80% of the radio spectrum is densely populated by the primary users.
- Case 6: 80% of the radio spectrum is populated by the primary users in distributed manner.

These cases are able to capture the different information within the wideband of interest.

The steps for performance evaluation are as follows:

- Determine the threshold value for fixed probability of false alarm (P_{fa}) for the sensing algorithm by using cumulative distributive function *(CDF)* of the test statistics when only noise exists at the input of the detector under noise uncertainty.
- Apply the proposed algorithm to the received signal with AWGN under noise uncertainties of 0, 1 and 2 dB.
- Analyze the complexity of the proposed technique in comparison with that of fixed energy detector, brute-force cyclostationary feature detector and multi-resolution spectrum sensing (MRSS) based on energy detector.
- Evaluate the performance of the proposed algorithm using the probability of correct classification (P_c).

1.5 Research Contributions

The main contributions of this research work are:

- Proposal of a compliant RF front-end for the proposed wideband sensing receivers for cognitive radio application.
- Novel low-complexity multi-resolution spectrum sensing strategy and algorithm for cognitive radio application with the following attributes:
    - It performs coarse resolution sensing by computing the energy of the lower sub-band and only the sub-band with larger energy is used for fine resolution sensing.

- It performs spectral correlation function (SCF) only for the channel indices with small and negligible sub-band energy.
- It identifies the empty band while wireless microphone with 200 KHz is present in a given band.

1.6 Thesis organization

This dissertation is organized as follows; Chapter 1 discusses the background and motivations, specific objectives and the scope of this research, summarizes the original contributions and overviews the organization of this dissertation.

Chapter Two gives an overview of the related topic of the research. First of all, the topic on cognitive radio is reviewed. Then, the history of software defined radio (SDR) is reviewed, including the research and application and this is followed by the primary users system. Some of the most related techniques to our work like the Discrete Wavelet Transform, Parseval's theorem for DWT, and Cyclostationarity features are described. Finally, survey of multi-resolution spectrum sensing architecture is presented

Chapter Three introduces the problem formulation of the proposed multi-resolution spectrum sensing. The RFE architecture is proposed for a WRAN sensing receiver suitable for cognitive radio application. It is followed by the technique itself and then, we mainly focus on the methodology for performance evaluation.

Chapter Four presents the specific results. In particular, it shows the probability of correct classification of the proposed algorithm assuming DVB-T as the weakest signal in different scenarios. It is then followed by obtaining the same assuming wireless microphone as the weakest signal. Then, it analyzes various scenarios mentioned in the methodology. It presents the power spectrum of the simulated primary user (PUs) signals for each of those scenarios. It presents, step by step at a fixed SNR, the application of the proposed technique for spectrum sensing for the first scenario, and summarily repeats the same for other scenarios. Then, it analyzes the complexity of the proposed scheme for each scenario. It evaluates the performance of the proposed multi-resolution approach for each scenario using the probability of the correct classification under noise uncertainties of 0, 1 and 2dB. Finally, it evaluates the performance of the technique in comparison to those of fixed energy detector, MRSS energy detector and brute force SCF.

Chapter Five, concludes the thesis and summarizes the important findings and contributions and also provides recommendations for future research.

CHAPTER 2

BACKGROUND THEORY AND LITERATURE REVIEW

2.1 Introduction

This chapter gives an overview of the related topic of research. First of all, the overview of cognitive radio is reviewed. Then, the history of software defined radio (SDR) is reviewed, including the research and application and this is followed by the primary users system. Some of the most related techniques to our work like the Discrete Wavelet Transform, Parseval's theorem for DWT, and Cyclostationarity features are described. After that, survey of multi-resolution spectrum sensing architecture is presented. It is seen that the work undertaken in this thesis of accurately sensing incumbent DVB-T single frequency network and analog FM wireless microphones using the proposed methods of spectrum sensing has not been developed before.

2.2 Cognitive Radio Overview

Cognitive Radio (CR) was first introduced to the radio community in 1999 by Joseph Mitola and Gerald Q. Maguire.Jr. in [12] as an extension of an SDR, which served to improve the overall performance of the radio in relation to its interaction with the spectrum using a cognitive cycle, as shown in Figure 2.1. In [12], Mittola describes that cognitive radio "is a goal driven framework in which the radio autonomously observes the radio environment, infers context, assesses alternatives, generates plans, supervises multimedia services, and learns from its mistakes." At the same time other definitions have been developed from research groups across the SDR community, the two components that are most often considered core feature of the CR involve awareness of the RF environment and adaptation and /or learning algorithms to improve the performance of the radio.

A cognitive Radio (CR) is a Software Defined Radio that traditionally senses its environment, tracks changes, and reacts upon its findings. A cognitive radio is an autonomous unit in a communication environment that frequently exchanges information with the networks; it is able to access as well with other cognitive radios. From our point of view, a CR is a refined SDR [12]. The basic idea behind a cognitive radio is the utilization of unused frequency bands of a primary or licensed user by a secondary or unlicensed user without causing harmful interference to the primary user's communication and providing the required QoS for the secondary users (SUs). If we scan a portion of radio spectrum we would find that some frequency band are largely unoccupied most of the time while some other frequency bands are only partially occupied and the remaining frequency band are heavily used. The measurements taken at Berkeley Wireless Research Center shows this uneven usage of spectrum between 0-6 GHz as illustrated in Figure 2-1 we can see that the spectrum utilization is heavy below 3 GHz. Actually, measurements taken shows that the utilization in 3-4 GHz frequency band is 0.5 % while it drops to 0.3% in 4 -5 GHz band [13]. Thus, we can say that the spectrum is not actually scarce but it is not utilized efficiently. Cognitive Radios are proposed to sense this uneven usage of the spectrum and identify a vacant frequency band and automatically decide to access this vacant spectrum.

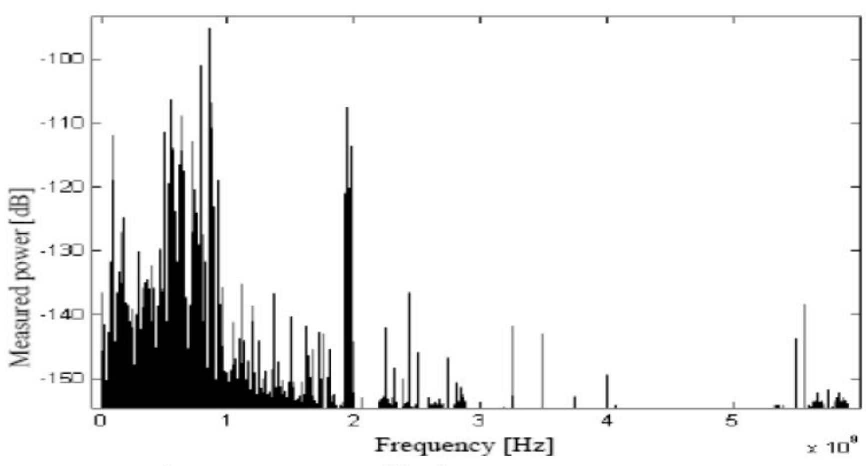


Figure 2.1: Spectrum Utilization Measurement at BWRC

Table 2.1: Frequency utilization

Frequency (GHz)	0-1	1-2	2-3	3-4	4-5	5-6
Utilization%	54.4	35.1	35.1	.25	.128	4.6

Table 2.1 above reveals the spectrum utilization from the 0-6 GHz band. The lower frequency band is crowded while at higher frequencies utilization is not adequate. We call these regions as spectrum holes or white space.

Frequency ranges are restricted to licensed users only and at any particular time or location which are underutilized.

FCC was interested in making these white spaces to be freely used by unlicensed users for the best spectrum utilization because of the growth in the 802.11/Wi-Fi unlicensed consumer devices market which is estimated to billions of US dollars per year [14].

In May 2004, FCC released a report [15] in which it took an initiative which allows the use of this underutilized spectrum to unlicensed users (Users that are not being served by the primary license holders) to operate in television spectrum increase where the spectrum is not in use. For all that, these unlicensed users should not create harmful interference to the licensed user and at times the licensed user wants to transmit its signal the unlicensed user should vacate the spectrum and should look for some other free space. This could be achieved by incorporating "Cognitive radios" to sense unused spectrum.

Table 2.2: Unlicensed consumer device market

(Source [14]: CEA comments, Docket 02-135, September 30, 2002)

Product	Penetration	Number per household	Total Installed Base (millions)
Cordless phones	81.0%	1.50	130.01
Garage door openers	40.8%	1.29	56.26
Wireless routers	NA	NA	1.14
Remote Control Toys	19.5%	2.61	54.47
Toy walkie-talkies (not FRS)	15.1%	1.85	29.81
Baby Monitors	10.5%	1.38	15.52
Home security systems	18.0%	1.10	21.21
Key Entry Systems for cars	26.5%	1.40	39.71

2.2.1 Functions of Cognitive Radio

A cognitive cycle is shown like Figure 2.2 which contains all the important tasks performed by cognitive radio.

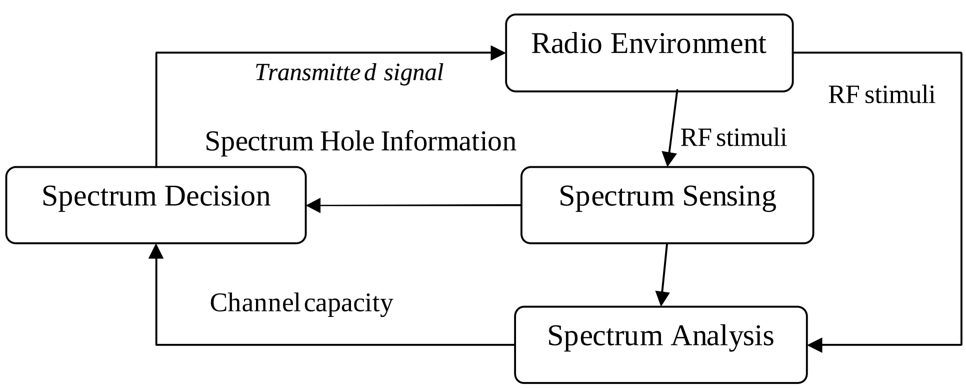
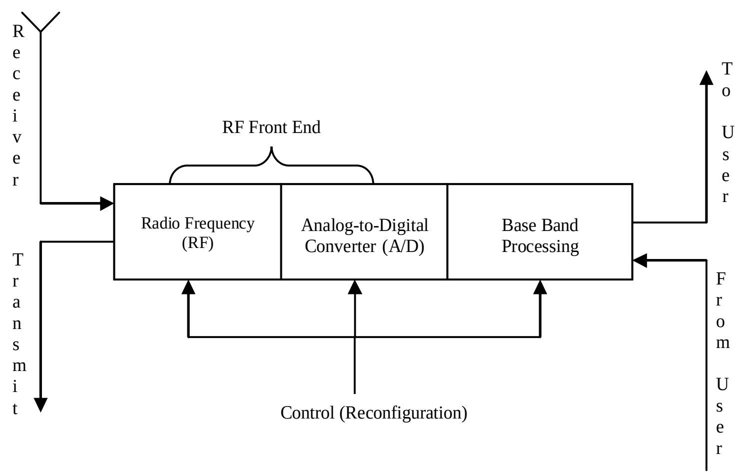


Figure 2.2: Cognitive cycle

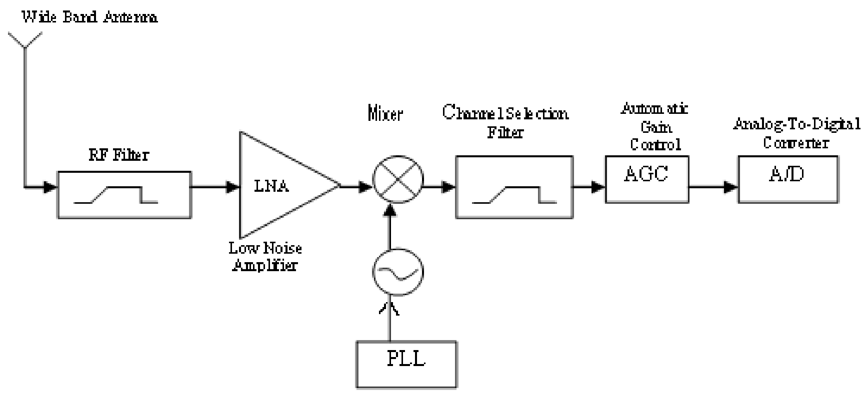
The major function of the cognitive radio is spectrum sensing which detects unused spectrum and shares it without harmful interference with other users. Cognitive Radio is designed to be aware of and can sense its environment. Now the practical design problem is to reliably detect the presence of another user on processing the wide bandwidth (multi-Gigahertz).

2.2.2 Physical Architecture of Cognitive Radio

The architecture of a Cognitive Radio Transceiver is like that shown in Figure 2.3(a) [16]. The main components of cognitive radio transceivers are the RF front-end and the base-band processing unit. Each component can be reconfigured via a control bus to adapt to the time varying RF environment.



a)



b)

Figure 2.3: Physical architecture of the cognitive radio [16] and [17]: (a) Cognitive radio transceiver (b) wideband RF/analog front-end architecture.

In the radio front -end the received signal is amplified, mixed and analog to digital converted (A/D). In the base band processing unit, the signal is modulated or demodulated and encoded or decoded. The base-band processing unit is essentially similar to existing transceivers. However, the novelty of the cognitive radio is the RF front-end. The novel characteristic of the cognitive radio transceiver is the wide band sensing capability of the RF front-end. This function is mainly related to RF hardware technologies such as wideband antenna, power amplifier and adaptive filter. RF hardware for cognitive radio should be able to tune to any part of a large range of frequency spectrum. Also such spectrum sensing enables measurements in a real time manner of spectrum information from the radio environment. Generally a wideband front-end architecture for cognitive radio has the following structure as shown in Figure 2.3 (b) [16].The components of cognitive radio RF front-end are as follows:

- RF filter: the RF filter selects the desired band by band pass filtering the received RF signal.
- Low noise amplifier (LNA): The LNA amplifies the desired signal while simultaneously minimizing the noise component.
- Mixer: In the mixer, the received signal is mixed with a locally generated RF frequency and converted to the base-band or the intermediate frequency (IF).

- Voltage controlled-oscillator (VCO): The VCO generates a signal at a specific frequency for a given voltage to mix with the incoming signal to base-band or an intermediate frequency.
- Phase locked loop: The PLL ensures that the signal is locked on a specific frequency and can also be used to generate precise frequencies with a fine resolution.
- Channel selection filter: The channel selection filter is used to select the desired channel and to reject the adjacent channel. There are two types of channel selection filters [18]. The direct conversion receivers that use a low pass filter for the channel selection; on the other hand the super heterodyne receivers adopt a band pass filter.
- Automatic gain control (AGC): The automatic gain control maintain the gain or output power level of an amplifier constant over a wide range of input signal levels.

In this architecture, a wide band signal is received through RF front-end, sampled by a high speed analog–to-digital converter (A/D) and measurements are performed for the detection of the licensed user signal. However there exist some limitations on developing the cognitive radio front-end.

The wideband RF antenna receives signal from various transmitters operating at different power levels, bandwidths and allocations. As a result, the RF front-end should have the capability to detect a weak signal in a large dynamic range. The front-end design will also maximize the dynamic range of signals that the receiver can process through automatic gain control. However, this capability requires a multi-GHz speed A/D with high resolution, which might not be infeasible [16] [19].
The requirement of multi-GHz speed A/D converters necessitates the dynamic range of the signal to be reduced before the A/D conversion. This reduction can be achieved by filtering strong signal. Since strong signal can be located anywhere in the white spectrum range, tunable notch filters are required for the reduction [16]. Another approach is to use multiple antennas such that the signal filtering is performed in the spatial domain rather than in spectral domain. Multiple antennas can receive signals selectively using beam-forming techniques [19].

The key challenge of physical architecture of cognitive radio is an accurate detection of weak signals of licensed users over a wide spectrum range.

2.2.3 Cognitive Capability

Cognitive capability is defined as the ability of the radio technology to sense the information from its radio environment. This capability can not simply be realized by monitoring the power in some frequency bands of interest but more sophisticated techniques are required in order to capture the temporal and spatial variations in the radio environment and avoid interference to other users. Through this capability, the portion of the spectrum that is unused at a specific time or location can be identified. Consequently the best spectrum and appropriate operation parameters can be selected.

The cognitive capability of a cognitive radio enables interaction with its environment in a real time manner to determine appropriate communication parameters and adapt to the dynamic radio environment. The tasks required for adaptive operations in an open spectrum can be found in [20] [21] [22], which are referred to as the cognitive cycle. The overview of the main steps of the cognitive cycle is provided in this section: spectrum sensing, spectrum analysis and spectrum decision. The main steps of the cognitive cycle are as follows [23].

- Spectrum sensing: A cognitive radio senses the available spectrum bands, captures their information, and then detects the spectrum holes.
- Spectrum analysis: The characteristics of the fraction of spectrum or spectrum holes that are detected through spectrum sensing are estimated.
- Spectrum decision: A cognitive radio determines the appropriate parameters such as data rate, the transmission mode and the bandwidth of the transmission. Then the appropriate radio frequency is chosen according to the spectrum characteristics and user requirements. Once the operating frequency range is determined, the communication can be performed over this frequency range. To our knowledge, the radio environment changes over time and space, the cognitive radio should have information about the changes of the radio environment. If the current

frequency range in use becomes unavailable, the spectrum mobility function is performed to provide a seamless transmission.

2.2.4 Reconfigurability

Reconfigurability refers to the capability of adjusting operating parameters for the transmission on the fly without any modification on the hardware components. This capability of cognitive radio enables interaction with its environment to adapt easily to the dynamic radio environment. The reconfigurable parameters that can be incorporated into cognitive radio are as explained below [75]:

- Operating frequency: A cognitive radio is capable of changing its frequency in use. Based on the information obtained about the radio environment, the most suitable operating frequency can be determined and the communication can be dynamically performed on this appropriate operating frequency.
- Modulation: A cognitive radio should reconfigure the modulation method adaptive to the user's requirements and channel conditions. For example, the data rate is more important than the error rate, in the case of delay sensitive applications. Thus, the modulation method that enables the higher spectral efficiency should be selected. Conversely, the loss sensitive application focuses on the error rate, which necessitates modulation schemes with low bit error rate.
- Transmission power: Transmission power can be reconfigurable within the power constraints. Power controls enable dynamic transmission power configuration within the permissible power limit. If higher power operation is not necessary, the cognitive radio reduces the transmission power to a closer level to allow more users to share the spectrum and to decrease the interference.
- Communication technology: A cognitive radio can also be used to provide interoperability among different communication systems.

The transmission parameters of cognitive radio can be reconfigured not only at the beginning of a transmission but also during the transmission. According to the radio spectrum characteristics, these parameters can be reconfigured such that the cognitive radio is switched to a different spectrum band, the transmitter and receiver parameters are reconfigured and the appropriate protocol parameters and modulation schemes are used.

2.3 Software Defined Radio Receiver Review

The software defined radio architecture was first envisaged by Mitola in 1995[24]. The signal from DC to radio frequency is digitized by an ADC directly, and all the signal processing is done in the DSP.

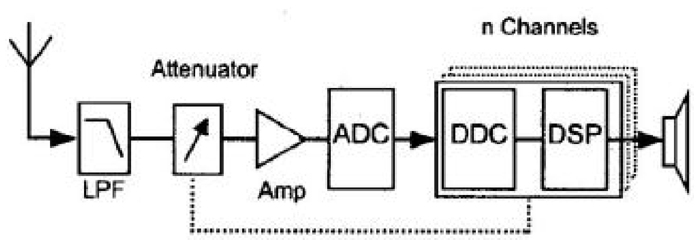


Figure 2.4**:** Ideal software defined radio architecture [25]

The only realization of this kind of SDR is the UK DERA which dealt with frequency from 3MHz to 30MHz in 2000[26]. This Mitola type ideal software radio is limited by the ADC's technology.

An anti-aliasing pre-filter is adopted in Toshiba's SDR receiver [27] for PDC (Personal Digital Cellular) at 1.5 GHz and DCS (Digital Cellular System) at 1.9 GHz applications. The bandwidth of this receiver is 10MHz covering over 50 channels. With the principle of sub-sampling, a GPS (Global Positioning System)/GLONASS (Global Navigation Satellite System) receiver is published [28], which also used a pair of RF pre-filters after LNA to attenuate the wideband LNA noise. The sub-sampling combined with analog decimation technology was applied [29] from the point of view of saving power consumption. To avoid the use of an anti-aliasing pre-filter, which limits the flexibility of the receiver, a quadrature charge sampling circuits with built-in anti-aliasing by means of windowed integration sampler (WIS) is introduced [74] at an IF of 100MHz. In industry, this technology was exploited by Texas Instruments in its Bluetooth and GSM receiver. However, the need to rely on the RF pre-select filter make it limited to narrowband applications.

The detail explanation about the advantages and limitations of the above schemes can be referred to [25], in which, Abidi also introduced an SDR architecture being able to tune to any channel from 800MHz to 6GHz as shown in Figure 2.5. In this receiver, zero-IF architecture ensures the high flexibility and low image rejection requirement. A second-order RC filter is driven by the mixer to eliminate the RF pre-select filter, which is to achieve the full anti-aliasing function. It also relaxes the linearity requirement for the subsequent stages and, by means of decoupling the sampler and mixer, simplifies the complement of the mixer with high 2nd order linearity and low flicker noise required by zero-IF architecture. The sampler is placed immediately after the RC filter and leaves the rest of the filter in discrete-time domain for the robust operation purpose.

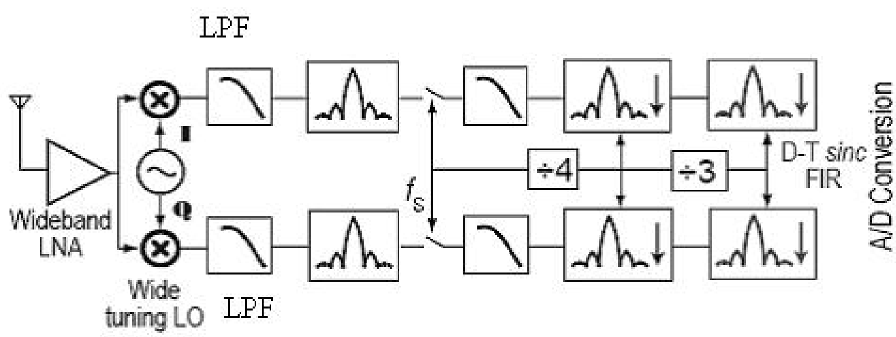


Figure 2.5: Abidi’s SDR receiver architecture[25]

The above architectures aim to detect the arbitrary channels, which is the standard function of software defined radio. Nowadays, the most popular SDR technology can be found in IEEE 802.11a/b and Bluetooth. However, the detected bandwidths are typically 20MHz with the carrier frequency at hundreds of Megahertz or several

Gigahertz. Hence, the advantage of a software-defined radio is its flexibility in operating frequency, power, and bandwidth.

A software defined radio provides, an ideal platform for the realization of CR [12]. It is expected that Cognitive radio will evolve from current SDR and adaptive radio by adding more and more cognition features, such as comprehensive simulation awareness and learning capability.

2.4 Primary Users and Their Characteristics

In this section DVB-T single frequency networks and wireless microphone signals are studied. These will be considered in Chapter 3 specifically in the context of the proposed technique that can be used for detecting them in a low SNR regime.

2.4.1 Wireless Microphone System

A wireless microphone is an audio transmission service. As the name implies, the microphone is used without a physical cable connecting it to the amplifying equipment or sound recorder which allows greater freedom of movement for the speaker. The main application of a wireless microphone is to provide real-time high quality audio transmission over short distances up to 300 m. Wireless Microphones are classified as low power auxiliary stations and are considered as licensed secondary of the TV spectrum. Wireless microphones operate on vacant TV channels based on frequency planning and coordination. Many older wireless microphone systems operate in VHF while most modern systems operate in a UHF TV band [30]; the same spectrum that the WRANs will use. The operation in the U.S. is regulated by the FCC under part 74 of the code of Federal Regulations (47cfr74). In other countries, operation is regulated by different agencies, but with technical characteristics that are generally similar to those that apply in the U.S. Besides wireless microphones, there are wireless in ear Monitors, IFB monitors, wireless intercoms and wireless assist video devices (WAVDs) using “vacant” TV channels. The maximum transmission power depends on the operating band; for VHF it is 50 mW and 250 mW for UHF [31]. Most units operate with 10 – 50 mW output power.

All wireless microphone systems use analog FM modulation, although other types are permitted. The occupied bandwidth (*B*w) is less than 200 KHz. Most systems utilize the full bandwidth to maximize the audio quality.

2.4.2 Wireless Microphone Characteristics

The wireless microphone signal can be represented as an FM signal in the form of Eq. (2.1).

$$x_{FM}(t) = A_c \cos\left(2\pi f_c t + 2\pi f_\Delta \int_0^t m(\tau) d\tau\right) \tag{2.1}$$

where f_c is the central frequency of wireless microphones signal in a TV spectrum, f_Δ is the frequency deviation, $m(\tau)$ is the message signal and A_c is the amplitude of the carrier signal.

Table 2.3 shows the parameters for wireless microphone signal

Table 2.3: Wireless microphone signal parameters

Parameters	
Wireless microphone bandwidth	200 KHz
Sampling frequency	256MHz
Wireless microphone frequency deviation	15KHz
Carrier frequency f_c	4, 12, 28, 36MHz

2.4.3 DVB-T System- Development

Digital Video Broadcast Terrestrial DVB-T is the latest technology for digital broadcasting television which soon will replace the existing technology, analogue broadcasting television. The standard for DVB-T, maintained by DVB Project, is EN 300 744 (version 1.5.1, 2004/11). All the DVB-T system worldwide must comply with this standard (including transmitting and receiving ends). The DVB-T Transmitter model is shown in Figure 2.6.

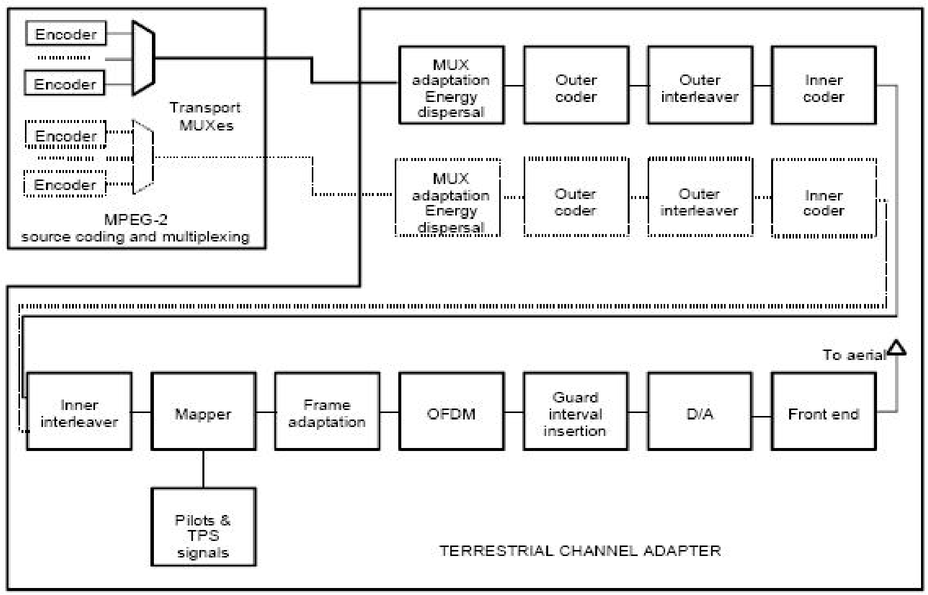


Figure 2.6: DVB-T System Model (ETSI EN 300 744 v.1.5.1 pp 10)

In DVB-T, there are 2 available modes based on the subcarriers which are 2K (1705 subcarriers) and 8K (6817 subcarriers). Both of the modes have trade offs, in 2K mode the tolerance against time-variant fading is four times better compare to 8K mode (due to the symbol duration in 2k mode being one fourth that of 8K) meanwhile 8K mode can be used to combat effectively the multipath channels with very long delays [32]. Hence, 2K mode is more common to use in Single Frequency Network (SFNs). 2K mode is selected in this thesis due to the above reason.

Besides 2K and 8K modes, as specified in [33], there are two available modulation modes of DVB-T, either its hierarchical or non-hierarchical modulation. The hierarchical modulation provides a means by which the MPEG-2 bit stream can be divided into two parts. One stream, the high priority (HP) stream, is heavily protected against noise and interference, whereas the second, low priority (LP) stream is much less well protected [34]. The differences between these two are described in Figure 2.7. Based on [34], by using the hierarchical mode the HP stream could achieve a coverage increase of 8.4% while the LP stream coverage area would decrease of 2.7% compared to the non-hierarchical mode.

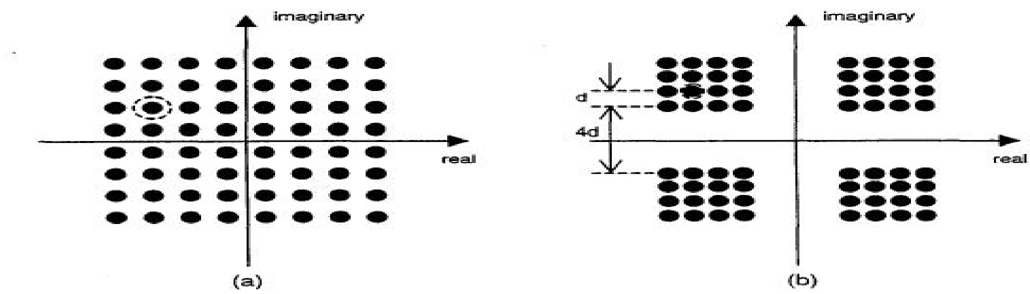


Figure 2.7: Constellation of 64-QAM DVB-T signals. a) Non-hierarchical b) Hierarchical

For Malaysia, the MCMC or Malaysian Communications and Multimedia Commission has decided that the operating frequency for DVB-T is from 510 MHz to 798 MHz with an 8 MHz channel [35].

2.4.4 DVB-T Single Frequency Network (SFN) principle

This section deals with principles and properties of single frequency networks of digital video broadcast terrestrial television transmitters. Digital video broadcasting can be performed in so-called single frequency network (SFNs). Reception of more delayed signals from several transmitters working in the single frequency network can be utilized even for improvement of the power efficiency of transmitters [36]. Let's assume that in the analyzed SFN:

- A number of transmitters DVB-T operate,
- All transmitters operate at the same frequency,
- These transmitters operate with the same and exact time synchronous digital data multiplex.

2.4.4.1 DVB-T System Characteristic

The DVB-T system has two modes of operation, namely 2K AND 8K modes, allowing different levels of QAM modulation. We assume that the primary user is a DVB-T signal using 16 QAM-OFDM modulation and 1705 carriers which corresponds to mode 2K [37]. The DVB-T primary signal is transmitted in frames; each frame is formed by 68 OFDM symbols. Each OFDM symbol contains a set of 1705 carriers and it is transmitted with a symbol duration (T_s) of 280 μs.

The transmitted DVB-T signal in one frame is given by equation (2.2)

$$s(t) = \mathrm{Re}\left\{ e^{j2\pi f_c t} \sum_{l=0}^{67} \sum_{k=K_{\min}}^{K_{\max}} c_{l,k} \psi_{l,k}(t) \right\} \tag{2.2}$$

where $$\psi_{l,k}(t) = \begin{cases} e^{j2\pi \frac{k'}{T_U}(t-\Delta-l.T_S)}, & lT_S \le t \le (l+1)T_S \\ 0, & else \end{cases}$$

where k' is the carrier index relative to the center frequency $k' = k - \frac{(\mathrm{K}_{\max} - K_{\min})}{2}$, T_U is the inverse of the carrier spacing and Δ is the duration of the guard interval.

The Numerical values for the DVB-T parameters for the 2 K mode is shown in Table 2.4.

Table 2.4: Numerical values for the DVB-T parameters for the 2 K mode

Parameter	**2 K mode**			
Elementary period T	7/64 μs			
Number of carriers K	1,705			
Value of carrier number $K_{\min}$	0			
Value of carrier number $K_{\max}$	1,704			
Duration T_U	224 μs			
Carrier spacing $\frac{1}{T_U}$	4,464 Hz			
Spacing between carriers $K_{\min}$ **and** $K_{\max}\ \frac{(K-1)}{T_U}$	7.61 MHz			
Allowed guard interval $\frac{\Delta}{T_U}$	1/4	1/8	1/16	1/32
Duration of symbol part T_U	2,048xT 224 μs			
Duration of guard interval Δ	512xT 56 μs	256xT 28 μs	128xT 14 μs	64xT 7 μs
Symbol duration $T_S = \Delta + T_U$	2,560xT 280 μs	2,304xT 252 μs	2,176xT 238 μs	2,112xT 231 μs

2.5 Theoretical Background of Spectrum Sensing

An important requirement for cognitive radio is the ability to sense the presence of spectral holes. A cognitive radio is designed to be aware of and sensitive to the changes in its surroundings. The spectrum sensing enables the cognitive radio to adapt to its environment by detecting spectrum holes. The spectrum sensing is an application of a detection theory. The final decisions can be binary hypothesis, i.e., either the radio spectrum is occupied, or the radio spectrum is not occupied. The wireless scenario used in the simulations section will contain a DVB-T primary user that the operating frequency ranging from 0-128MHz with an 8 MHz channel. In this scenario some bands are occupied for certain period of time and some others are not occupied.

The most efficient way to detect spectral holes is to detect the primary users that are receiving data within the communication range of the secondary user. In reality however, it is difficult for a cognitive radio to have a direct measurement of a channel between a primary receiver and a transmitter.

The most recent research work in cognitive radio focuses on primary transmitter detection by spectrum sensing based on local observation of secondary users. Thus, if, e.g., a licensed user is transmitting on a spectral resource that resource could in principle be used by a SU if that SU was certain that there were no primary receivers listening. However, in most applications the focus is usually on the primary transmitter detection because the secondary user can not reliably detect primary receivers. Of course, the secondary usage of the spectrum could be done in principle when appropriate agreements have been set up between the license owners of the spectrum (i.e. primary users) and secondary users.

This research work will mainly focus on transmitter detection. There exist several different approaches for transmitter detection which may be used in different sensing scenarios. The most well known methods for spectrum sensing include, but are not limited to the following methods: matched filter (MF) based spectrum sensing, energy based spectrum sensing, cyclostationary feature based spectrum sensing, and multi-resolution spectrum sensing. These will be described below.

2.5.1 Matched Filter Based Spectrum Sensing

The matched filter detector is considered an optimal detector [38] since it maximizes the received SNR. It requires perfect knowledge of the PU_s signals at the physical and medium access control layers. This knowledge includes modulation type and order, bandwidth, operating frequency, pulse shaping, packet format and other information needed for demodulation. In addition, timing and carrier synchronization with the PU signal are also required for the demodulation process. The matched filter performs poorly if this information about the PU_s signals is not accurate. The main advantage of the matched filter is that a high processing gain is achieved within less time. However, within the context of cognitive radio spectrum sensing the significant drawback of the matched filter is that a dedicated receiver is needed for each primary licensed system [16]. If $x(n)$ is completely known to the receiver then the optimal detector for this case is [38].

$$TS = \begin{cases} \sum_{n=0}^{N-1} y(n)x(n) \leq \gamma & H_1 \\ \sum_{n=0}^{N-1} y(n)x(n) > \gamma & H_0 \end{cases} \tag{2.3}$$

here γ is the detection threshold and TS is the test statistic. When TS is less than γ, the decision test statistic is the hypothesis H_1 and when TS is greater than γ the decision test statistic is the hypothesis H_0. The numbers of samples required for optimal detection are

$$N = \left[Q^{-1}(P_D) - Q^{-1}(P_{FD})\right]^2 (\gamma_b) \tag{2.4}$$

$$= O(\gamma_b)^{-1}$$

where P_D , P_{FD}, Q and γ_b are the probabilities of detection ,false detection, complementary cumulative distribution and signal to noise ratio (SNR) respectively.

Thus the number of samples required for optimal detection is $O(1/\gamma_{\mathrm{b}})$.

2.5.2 Energy Detector Based Spectrum Sensing

The energy detector is the simplest and lowest complexity based on the energy measurement [39] [40]. It has suited the blind detection for the detection of free band, since no prior information of the signal property is required. Its test statistic is based on the energy measurement and is given by,

$$TS = \frac{1}{N_s}\sum_{n=1}^{N_s}\left(y[n]\right)^2 \tag{2.5}$$

This is measured and averaged over N_s samples. To apply this test statistics, the PU signal occupying bandwidth B is first down-converted and sampled at the Nyquist rate $f_s = 2B$. The test statistic TS is compared with threshold λ, to decide whether a PU is present or not. If the test statistic $TS\rangle\lambda$; then the primary user signal is present in the band under sensing. Otherwise the band is empty. For large numbers of samples N_s [39], the probability of detection P_d and the probability of false alarm P_{fa} are given by,

$$P_{fa} = Q\left(\frac{\frac{\lambda}{\sigma_w^2} - N_s}{\sqrt{2N_s}}\right) \tag{2.6}$$

$$P_d = Q\left(\frac{\frac{\lambda}{\sigma_w^2+\sigma_x^2} - N_s}{\sqrt{2N_s}}\right) \tag{2.7}$$

where $Q(x)$ is the right-tail probability or also called the complementary cumulative distribution function. For given $SNR, \gamma_c = \frac{\sigma_x^2}{\sigma_w^2}$, the minimum number of samples N_s required to achieve the target P_d and P_{fa} is given by [38],

$$N_s = 2\left[\left(Q^{-1}(P_{fa}) - Q^{-1}(P_d)\right)\gamma_c^{-1} - Q^{-1}(P_d)\right]^2 \tag{2.8}$$

Some works have been done which apply this type of detector to the problem of spectrum sensing:

- [41] developed FM wireless microphone signal detector based on power density (*PSD*) estimation. The performance of this detector was also studied.
- In [42], the power level at the output of FFT of the received signal is compared with a threshold to identify the used TV channels. FFT is performed on the sequence sampled at 45 KHz around the centered TV carrier frequency.

2.5.2.1 Computational Complexity of energy detector Based Spectrum Sensing

The energy detector is well known for its simplicity in terms of implementation and the computation required. The energy detector requires $4N$ real multiplications and $2(2N-1)$ real additions [43]. In addition, when the DWPT db5 wavelet filtering is performed not to the final level but to n level, n and is much smaller than the data N where n is the level of decomposition of discrete wavelet packet transform, the complexity of DWPT is $3*N*n$ [57]. The proposed MRSS technique is the combination of energy and cyclostationary feature detectors. The equation of energy detector will be used in chapter 3 to calculate the computational complexity of the proposed MRSS scheme.

While the energy detector is simple and can be implemented easily and efficiently, it has some disadvantages stated hereunder:

- Its performance is susceptible to noise uncertainty [44].
- It can not recognize signal features, so it can not be used to distinguish between different signal types.
- It is not effective for signals whose signal power has been spread over a wideband.

2.5.3 Cyclostationary Feature Based Spectrum Sensing

In this section the theory of cyclostationarity is introduced. Some works that have been done which apply this type of detector to the problem of spectrum sensing are reviewed. Finally, the complexity of the cyclostationarity feature block is presented.

2.5.3.1 Cyclostationarity Theory

Generally, data symbols are modeled as stationary random processes. However, communication signals are in general coupled with carriers, pulse trains, repeating sequences or cyclic prefixes or other intended signals that cause hidden periodicity. These communication signals have distinct features and are classified as cyclostationary random processes instead of stationary random processes as in the radiometric methods. It is defined that a process, say $x(t)$, is said to be cyclostationary in the wide sense if its mean and autocorrelation are periodic with some period T[45].

$$m_x(t+T) = m_x(t) \tag{2.9}$$

$$R_x\left(t+T+\tau/2, t+T-\tau/2\right)=R_x\left(t+\tau/2, t-\tau/2\right) \tag{2.10}$$

since $R_x(t+T+\tau/2, t+T-\tau/2)$ is a function of two independent variables, t and τ, is periodic in t with period T for each value of τ. We can express it as a Fourier series as

$$R_x\left(t+\tau/2, t-\tau/2\right)=\sum_{\alpha} R_x^{\alpha}(t) e^{j2\pi\alpha t} \tag{2.11}$$

for which $\left\{R_x^{\alpha}(t)\right\}$ are the Fourier coefficients

$$R_x^{\alpha}(t)=\frac{1}{T}\int_{-\frac{z}{2}}^{\frac{z}{2}} R_x\left(t+\tau/2, t-\tau/2\right) e^{-j2\pi\alpha t}\,dt \tag{2.12}$$

$R_x^{\alpha}(t)$ is referred to as the cyclic autocorrelation (CA) function, and α is called the cyclic frequency parameter. For $\alpha=0$, CA is the conventional autocorrelation function. The conventional power spectral density function is defined as the Fourier transform of the CA by the following expression:

$$PSD=F\left\{R_x(t)\right\} \qquad (2.13$$

In contrast with that, the Fourier transform of the CA function is defined as the cyclic spectral density function:

$$S_x^{\alpha}(f)=\sum_{j=-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-j2\pi f t} \tag{2.14}$$

The spectral correlation characteristics of the cyclostationary signals give us a richer domain signal detection method. We can accomplish the detection task by searching the unique cyclic frequency of the received primary user's signals. Also, information such as the carrier frequency could be calculated according to the unique frequency. Another motivation of using the spectral correlation function for signal detection lies on its robustness to random noise and interference. The spectral correlation of the noise is uniquely large at cyclic frequency equals to zero comparing to that at other cyclic frequencies.

2.5.3.2 Cyclostationarity Feature Detector

Cyclostationary Feature detector is based on the cyclostationarity process in [46] [47] [48] [49].The cyclostationary detection is a statistical test based on the estimated autocorrelation function of one or several known cyclic frequencies.

Cyclostationary detection requires prior knowledge about the process one wishes to detect unlike the energy detection. From here, cyclostationary detection will be able to detect a limited number of systems for which the communication signals processes know cyclostationary properties, but on the other hand, these systems can be explicitly identified by the cyclostationary detection. Some works have been done which apply this type of detector to the problem of spectrum sensing.

- [16] is the first work to suggest using the cyclostationary feature detector for spectrum sensing and it provides a general discussion of underlying theory that makes this detector possible for CR spectrum sensing. In addition, the implementation issue is also discussed.
- [43] and [50] applied cyclostationary features to spectrum sensing of the DVB-T signal which is based on OFDM. A number of algorithms were developed based on the cyclostationarity of OFDM such as pilot and cyclic prefix features. The performance of those algorithms was compared with the energy detector.

2.5.3.3 *Computational Complexity of Cyclostationary Feature*

In addition to Eq.(2.14), the cyclostationary feature can also be obtained equivalently by:

$$S_x^{\alpha}(f) = \lim_{\Delta f \to 0} \lim_{\Delta t \to 0} \int_{-\frac{\Delta t}{2}}^{\frac{\Delta t}{2}} \Delta f \; X_{\frac{1}{\Delta f}}(t, f - \frac{\alpha}{2}).\, X^{*}_{\frac{1}{\Delta f}}(t, f - \frac{\alpha}{2}) dt \tag{2.15}$$

where $X_{T_W}(t,v)$ is a short time Fourier transform (STFT) with a window size of $T_w = \frac{1}{\Delta f}$ and given by:

$$X_{T_w}(t,v) = \int_{-\frac{T_w}{2}} x(u) e^{-j2\pi u} du \tag{2.16}$$

The derivation of Eq.(2.15) from Eq.(2.14) is developed in [46][51]. Put here accurately, Eq. (2.14) is cyclic spectrum density (CSD) and Eq.(2.15) is spectral correlation function (SCF) and the derivation states that, as Δf goes to 0 and observation time Δt goes to infinity; the SCF approaches CSD. In practice, the CSD must be estimated because the signals being considered are defined over a finite time interval (Δt), and therefore the cyclic spectral density cannot be measured exactly. Describing Eq. (2.15) and Eq. (2.16) in discrete form for N observation samples and N' STFT window yields:

$$S_x^{\beta}(k) \cong \frac{1}{N} \sum_{n=0}^{N-1} \left[\frac{1}{N'} X_{N'}\left(n, k + \frac{\beta}{2}\right) X^{*}_{N'}\left(n, k - \frac{\beta}{2}\right) \right] \tag{2.17}$$

$$X_{N'}(k) \stackrel{\Delta}{=} \sum_{n=0}^{N'-1} w(n) x(n) e^{\frac{-j2\pi kn}{N'}} \tag{2.18}$$

where k and β are discrete forms of a spectral frequency (f) and a cyclic frequency (α), respectively; in Eq. (2.18), w[n] is data taper window of size N' used for STFT.

[52] describes a computationally efficient realization structure for Eq.(2.17) which is shown in Figure 2.8.This architecture is based on the Fast Fourier Transform (FFT) and it is known as the FFT Accumulator Method (FAM).

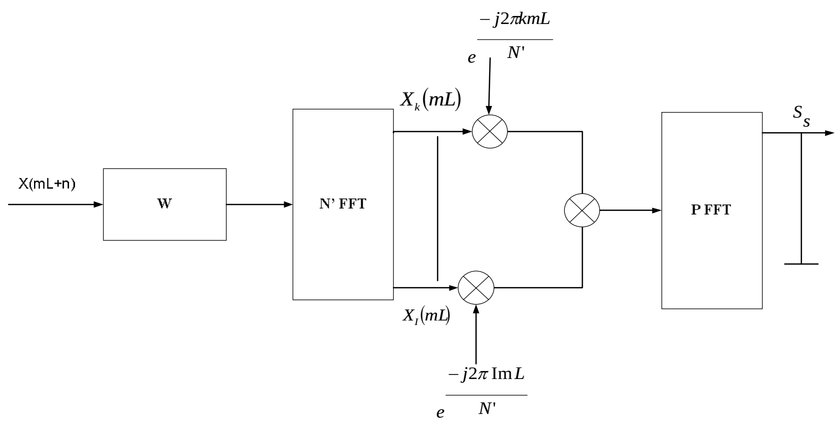


Figure 2.8: FFT accumulator method (FAM) [52]

This architecture consists of three basic stages:

- Computing of the complex demodulates: In this stage, the N input samples are channelized into N' parallel samples (window size of STFT) with overlap factor L of the sliding window. Then N'-point FFT is used to calculate the STFT followed by base band frequency-downshift translation sections.
- Forming the product sequences between each one of the complex demodulates and complex conjugates of the others.
- Smoothing of the product sequences over the total observation samples N using P-point FFT.

The appropriate choice of FFT points depends on the required spectral and cyclic frequency resolutions Δf and $\Delta\alpha$, respectively. The relation between the FFT and the required resolution for the given sampling frequency fs is given by:

$$N^{'} = \frac{f_s}{\Delta f} \tag{2.19}$$

$$P = \frac{f_s}{\Delta\alpha.L} \tag{2.20}$$

The relation between N and P is:

$$N = P.L \tag{2.21}$$

The correspondence between the FFT indices and certain values of f and α in the SCF domains in the output are given as follows [51].

$$S_s \approx S_x^{\alpha_0}\left(f_0\right) \tag{2.22}$$

where

$$f_0 = \frac{k+l}{2N^{'}} \tag{2.23}$$

and

$$\alpha_0 = \frac{k-l}{N^{'}} + \frac{P}{N} \tag{2.24}$$

The complexity of the FAM in terms of the required additions and multiplications of different stages is shown in Table 2.5 [52]. The table shows the complexity in terms of $N^{'}$ and P for each stage. For the first three stages, the complexity depends on $N^{'}$, while the complexity of the last two stages depends on P.

Table 2.5: Complexity summary of FAM

Function / Ops.	Window	*N'* FFT	Down-conversion	Correlation Multiplication	*P* FFT
Real multiplication	$N^{'}$	$2N^{'}\,l\log_2 N^{'}$	$4\ N^{'}$	$4P$	$2P\log_2 P$
Real addition	None	$3N^{'}\,l\log_2 N^{'}$	$2\ N^{'}$	$2P$	$3P\log_2 P$

In this chapter, the implementation complexities of the cyclostationary feature and energy detector are studied as useful tools to compute the complexity of the proposed scheme in chapter 3.

2.5.4 Multi-resolution Spectrum Sensing: Background

There exist several ways to represent a signal and the efficiency of a given representation depends on the required processing. Different representations emphasize different aspects of a signal and therefore, one should look for representations that make relevant information easily accessible.

Non linear approximation (NLA) techniques have played a major role in approximating signal features. In the last two decades, one of the NLA techniques which is called multi-resolution representation occupies an important role and has proven to be a powerful tool both theoretically and practically.

A signal structure depends on the scale at which the signal is being perceived, it should be analyzed at different scales or levels of resolution. This is called multi-resolution representation.

Multi-resolution is actually a biologically inspired technique. Consider for example how our eyes see an object. Let us consider a forest scene at different scales. As we get closer, we can distinguish individual trees, then branches, and finally the leaves. As we go for smaller and smaller scales, we can see details that we did not see before, but at the same time the view field is reduced. Some theories involving the way mammalian brains process auditory and visual information suggest that human perception can be modeled with multi-resolution analysis [53][54].

The following are some of the several reasons why the multi-resolution approach is preferable over other approaches.

1. Most signals exhibit relevant features at many different resolutions.
2. We may have a need for output in different resolution levels.
3. It may also offer a computational advantage.

Recent developments in multi-resolution spectrum sensing representation approaches include wavelet. Most researchers indicate that in order to provide multi-resolution spectrum sensing features, wavelet transform is required. In this section, we will mainly discuss the discrete wavelet transform, energy measurement using wavelet and Parseval's theorem for discrete wavelet transform.

2.5.4.1 Discrete Wavelet Transform (DWT)

The DWT is designed from multi-resolution analysis that decomposes the received signal space into an approximate space V and detail spaces W [57] as shown in Eq. (2.25).

$$V_{j+1} = W_j \oplus W_{j-1} \oplus V_{j-1} \tag{2.25}$$

where W_j is the orthogonal complement of V_j and V_{j+1} and $\oplus$ represents the orthogonal sum of two subspaces. Two spaces, V_j and W_j are constructed by orthonormal scaling function, $\phi_{j,k}$ and an orthonormal wavelet function, $\psi_{j,k}$ respectively. The scaling function $\phi_{j,k}$ and wavelet function, $\psi_{j,k}$ are obtained as

$$\phi_{j,k}(t) = 2^{j/2}\phi\left(2^{j/2}t - k\right) = \sum_l h_{l-2k}\phi_{j+1,k}(t) \tag{2.26}$$

$$\psi_{j,k}(t) = 2^{j/2}\psi\left(2^{j/2}t - k\right) = \sum_l g_{l-2k}\phi_{j+1,k}(t) \tag{2.27}$$

With high pass filter $g_{l-2k} =< \psi_{j,k}, \phi_{j+1,l} >$, and low pass filter, $h_{l-2k} =< \phi_{j,k}, \phi_{j+1,l} >$ where $< >$, means inner product. Using these functions, DWT of the signal, y provides scaling coefficients and wavelet coefficients. The scaling coefficient at J_{th} level and K_{th} time is computed by

$$c_{j,k} = \left\langle f, \phi_{j,k} \right\rangle = \sum_l h^*_{l-2k}\left\langle f, \phi_{j-1,l} \right\rangle = \sum_l h^*_{l-2k} c_{j+1,l} \tag{2.28}$$

The wavelet coefficient at J_{th} level and K_{th} time is

$$d_{j,k} = \left\langle f, \psi_{j,k} \right\rangle = \sum_l g^*_{l-2k}\left\langle f, \phi_{j+1,l} \right\rangle = \sum_l g^*_{l-2k} c_{j+1,l} \tag{2.29}$$

where $c_{j,k}$ and $d_{j,k}$ are scaling coefficients and wavelet coefficients respectively.

Figure 2.9 and Figure 2.10 show three level analysis parts of DWT and its frequency separation theory.

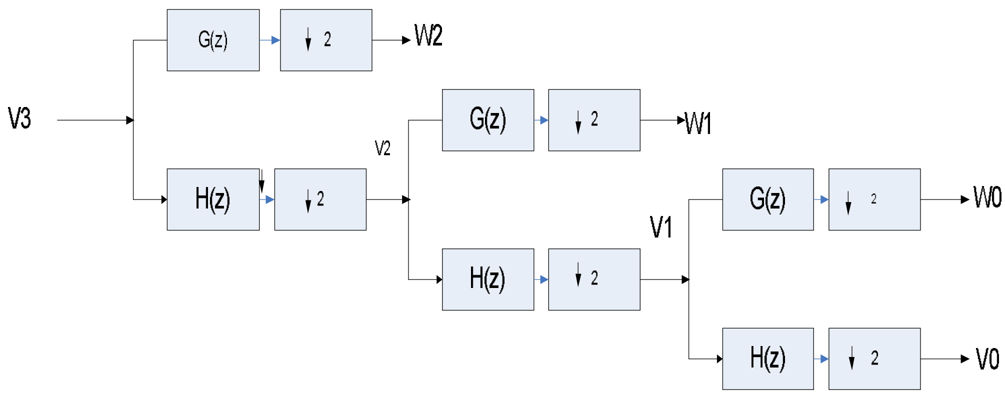


Figure 2.9: Three-level analysis parts of the DWT

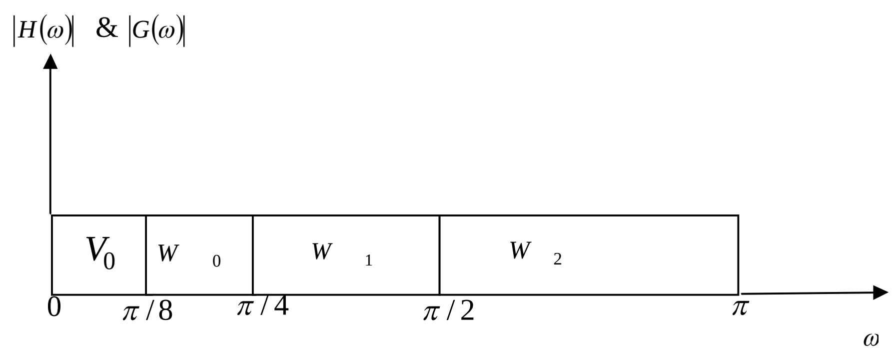


Figure 2.10: Frequency separation of three level analysis parts of DWT

2.5.4.2 Energy Measurements Using Wavelet

Power measurement using wavelets are explained in [55]. If a received signal, r (t) is a periodic signal with period T. Then, the computation of the signal power is illustrated by the Equation (2.30).

$$P = \frac{1}{T}\int_{0}^{t} r^2(t)dt \tag{2.30}$$

and r (t) can be represented as

$$r(t) = \sum_k c_{j_{0,k}} \varphi_{j_{0,k}}(t) + \sum_{j \geq j_0} \sum_k d_{j,k} \varphi_{j_{0,k}}(t) \tag{2.31}$$

where $C_{j0,k}$ and $d_{j,k}$ are scaling coefficients and wavelet coefficients respectively. Therefore, we can easily compute the energy of the signal in the following equation using orthonormal wavelet and scaling function properties.

$$E = \int_0^T r(t)^2 dt \tag{2.32}$$

$$= \int_0^T \left\{ \sum_k c_{j_{0,k}} \phi_{j_{0,k}}(t) + \sum_{j \geq j_0} \sum_k d_{j,k} \varphi_{j_{0,k}}(t) \right\}^2 dt$$

$$= \sum_k c_{j_{0,k}}^2 + \sum_{j \geq j_0} \sum_k d_{j,k}^2$$

It means that the energy of each sub-band can be calculated using the scaling and wavelet coefficients.

DWT is different from continuous wavelet transform (CWT) in mathematical representation. In lieu of presenting a continuous time (t), we can show it in a series of (nT).This is the advantage in technology because digital measurements are equipped with a sampling block and record signal in discrete form.

2.5.4.3 Parseval's Theorem In The Discrete Wavelet Transform

In Parseval's theorem assume a discrete signal $r(n)$ obtained from $r(t)$. So, the energy of this signal is equal to the square sum of the spectrum of the Fourier Transform in the frequency.

$$\frac{1}{N}\sum_{n=\langle N\rangle}\left|r(n)\right|^{2} = \sum_{h=\langle N\rangle}\left|r_h\right|^{2} \tag{2.33}$$

where N is the length of the sample, r_h are the spectrum coefficients of the Fourier transform. Applying the theorem to DWT, we obtain:

$$\frac{1}{N}\sum_{n=\langle N\rangle}\left|r(n)\right|^{2} = \frac{1}{N_j}\sum_{k}\left|c_{a\,j,k}\right|^{2} + \sum_{j=1}^{j}\frac{1}{N_j}\sum_{k}\left|c_{d\,j,k}\right|^{2} \tag{2.34}$$

where c_a, c_d are approximation and details respectively. The first and second terms of the right of equal sign denote the average power of the approximated and detailed version of the decomposed signal, and the terms on the left of the equal sign denote the total energy. The most important parameters in this research work are the approximation c_a and the detail c_d. So, the coefficient of approximated and detailed version c_a and c_d at each resolution level will be used to compute the energy of the signal of interest. The energy of approximated version E_a and detailed version E_d can be computed as follows:

$$E_a = \frac{1}{N_j}\sum_{k}\left|c_{aj,k}\right|^{2} = \frac{\left\|c_a\right\|^{2}}{N_j} \tag{2.35}$$

$$E_d = \frac{1}{N_j}\sum_{k}\left|c_{d\,j,k}\right|^{2} = \frac{\left\|c_d\right\|^{2}}{N_j} \tag{2.36}$$

where $\|c_a\|$ and $\|c_d\|$ are the norm of the expansion coefficients c_a and c_d .

The energy of approximation version E_a and detailed version E_d of the DWT described in this section will be used in the proposed scheme in chapter 3.

2.5.5 Multi-resolution Spectrum Sensing: Related Literature

In this section we review some published multi-resolution spectrum sensing concepts for cognitive radio architecture. The topic of multi-resolution sensing for cognitive radio has been treated in recent literature. Although different methods have been applied in their papers, the basic idea is the same. The total bandwidth is first sensed using coarse resolution. Fine resolution is performed on a portion of the interest bands for the cognitive radio. In such a way cognitive radio avoids sensing the whole band at the maximum frequency resolution. Therefore, the sensing time is reduced and the power has been saved from unnecessary computations. Several methods have been developed and used in the topic of multi-resolution spectrum sensing for cognitive radio experiments. A subset of them will be covered in this section.

2.5.5.1 A Wavelet Based Spectrum Estimation and Spectrum Hole Detection

Tian et al. [56], utilize the wavelet as a powerful tool for analyzing singularity such as band edges. So, the wavelet transform is used to detect the edges in the PSD of the received PU. These edges correspond to transition from occupied band spectrum holes. After identifying the sub-bands within the wideband channel, the average PSD level is estimated in each sub-band which is used to decide if the sub-band can be considered as spectrum hole or not. This approach uses two wavelet solutions: Wavelets modulus maxima and multi-scale wavelet products. The main disadvantage of this approach is requiring high sampling rates in order to characterize the entire wide bandwidth.

Youn et al [57], suggest an alternative approach for wideband spectrum sensing using wavelet. In this paper, a discrete wavelet packet transform based energy detector for performing initial coarse sensing for wide bandwidths is used to decompose the PUs signals into sub-band. The level of decomposition determines the number of required sub-bands. After signal decomposition, the power of each sub-band can be calculated using the scaling and wavelet coefficients. Then, the channel can be sorted in the ascending order based on the calculated power of each sub-band. This technique is proven to be faster and less complex than the one suggested in [56].

Zhi Tian et al. [58], developed the wavelet approach proposed in [56]. The PSD is first estimated for a wide bandwidth using compressive sampling and then the wavelet approach is applied for edge detection to locate the different spectrum areas (black, gray, white spaces) in the estimated PSD. Moreover, in order to reduce the computational complexity, the edge spectrum whose peaks correspond to changes between different spectrum areas may be directly estimated from the compressed measurements without reconstructing the PSD.

Polo, Y.L.et al. [59], proposed another compressive sampling approach for wide bandwidth spectrum estimation and spectrum holes detection. The idea in the proposed algorithm is to directly sample the signal at the information rate of the signal. This can be viewed as an analog-to- digital converter (ADC) operating at the Nyquist rate, followed by compressive sampling. After the compressive sampling based PSD reconstruction is performed using a wavelet edge detector along the approach of [58], the spectrum holes are detected using an energy detector in the frequency domain.

Ying Wang et al. [60], proposed a collaborative detection approach based on the compressive sampling based spectrum sensing method of [59]. The local autocorrelation of the compressed signal is transmitted to the fusion center that then performs spectrum reconstruction followed by energy detection in the frequency domain.

2.5.5.2 Wavelet Based Multi-resolution in Analog Domain.

Chan,S.Y [61], developed another MRSS approach with less hardware efforts to implement (antennas and ADC blocks) relying on an analog wideband spectrum sensing and reconfigurable RF front end. In order to provide the Multi-resolution sensing feature, the wavelet transform was adopted. This type of transformation is applied to the input signal and the resulting coefficient values stand for the representation of the input signal's spectral contents with the given detection resolution. The spectral components are detected by the Fourier transform performed in the analog domain. In this way, bandwidth, resolution and center frequency can be controlled by the wavelet function. A block diagram of this sensing method is presented in Figure 2.11. The building components are an analog wavelet waveform generator where the wavelet pulse is generated and modulated with an I and Q sinusoidal carrier with the given frequency, and a Hann window with 5 MHz bandwidth is selected as the wavelet. The received signal and the wavelet are multiplied using an analog multiplier. The analog integrator computes the correlation of the wavelet waveform with the given spectral width i.e. the resulting sensing resolution and the resulting correlation with I and Q components of the wavelet are inputs to the ADC where the values are digitized and recorded. If the correlation values are greater than a certain threshold level, the sensing scheme determines the reception of an interferer.

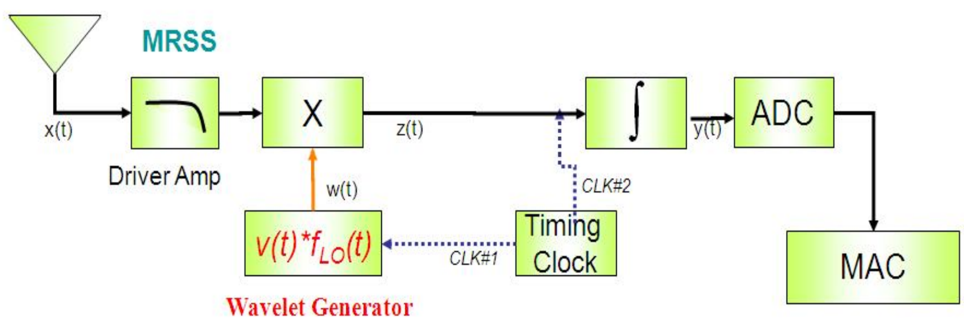


Figure 2.11: MRSS with analog wideband spectrum sensing [61]

Since the analysis is performed in the analog domain, high speed operation and low power consumption can be achieved. Furthermore, by applying the narrow wavelet pulse and a large tuning step size of the frequency of the local oscillator, the MRSS is able to examine a very wide spectrum span in a fast and sparse manner. On the contrary, very precise spectrum searching is achieved with the wide wavelet pulse and the delicate adjusting of the local oscillator frequency. In this manner, by virtue of the scalable feature of the wavelet transform, multi-resolution is achieved without any additional hardware burden.

The disadvantage of this sensing method consists in the difficulty of knowing the frequency information of received signals, which imply relatively complicated hardware compared with the FFT method.

Hur et al [62], proposed a wavelet based multi-resolution sensing technique in the analog domain. A cognitive radio with dual stage spectrum sensing mechanism is proposed. These dual stages provide coarse and fine sensing to meet the sensing speed and accuracy requirements. This technique uses the fact that the wavelet transform has a variety of choices of basis functions. Certain types of those may have a resolution bandwidth as an additional freedom of design. The Wavelet transform coefficient can be obtained by correlating a given signal and the wavelet basis waveform. By adjusting this wavelets pulse width and its carrier frequency, spectral content can be represented with scalable resolution. The spectral content of the received signal presented by the correlation values can be used to identify the presence of the primary user. This technique provides the flexibility to examine a wideband spectrum in a fast coarse manner or in a fine manner and indeed without any hardware burden. The functional block diagram is shown in Figure 2.12. The building blocks consist of a wavelet waveform generator, multipliers and integrators for computing correlation values, and low speed ADCs to digitize the calculated analog correlation value. A similar detector has been proposed in [63], where analog-based multi-resolution spectrum sensing was proposed as a flexible, low-power, high speed spectrum sensing solution.

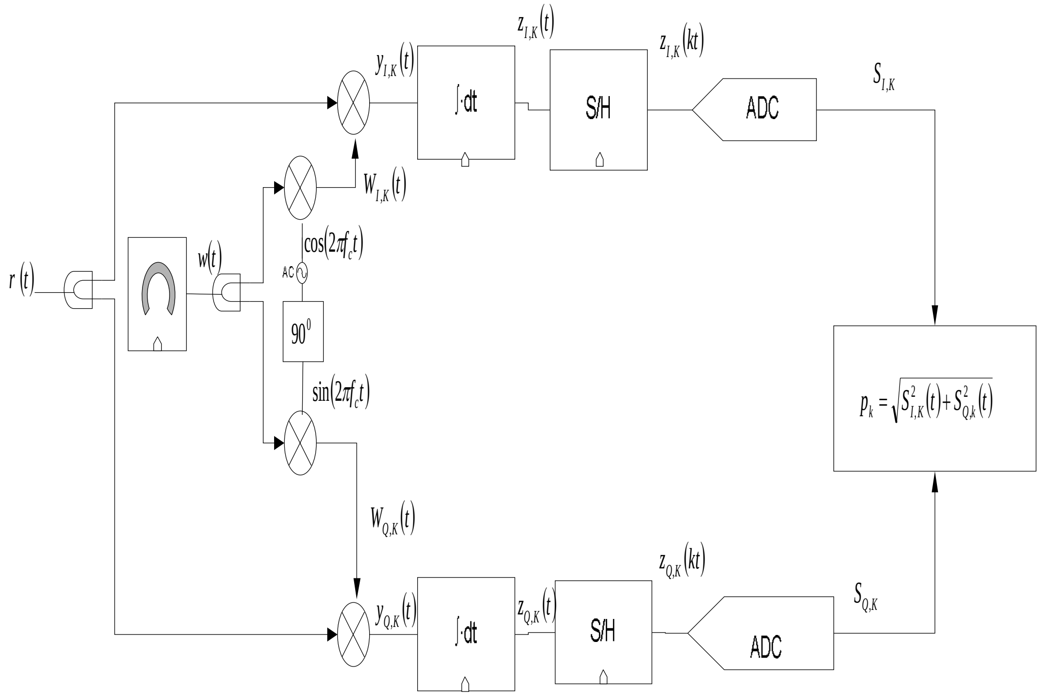
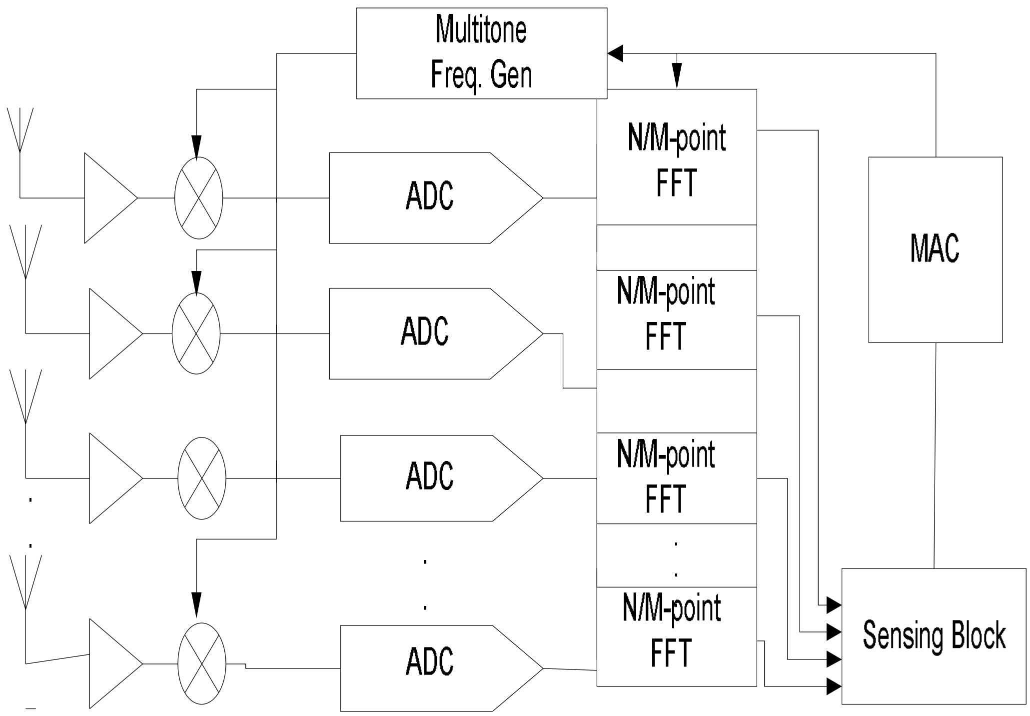


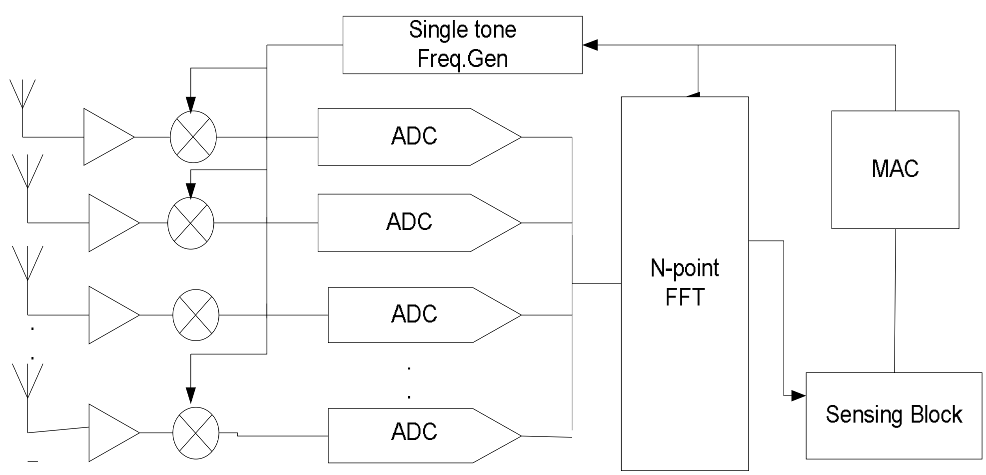
Figure 2.12: Functional block diagram of the MRSS technique [62]

2.5.5.3 Multi-resolution Multiple antenna

Neihart et al [64], discusses an approach using the multi-resolution spectrum sensing that is amenable to multiple antennas cognitive radio. The architecture of the multiple antennas receiver is shown in Figure 2.13. The building block consists of antennas, amplifiers, a multi-tone frequency generator, ADCs, FFT blocks, MAC, and a sensing block. The multi-tone frequency generator outputs four separate center frequencies. The proposed multi-resolution detector performs the sensing first at coarse frequency resolution as shown in Figure 2.13 (a). The fine resolution sensing that follows the coarse sensing is performed only for a small range of frequencies that have the smallest power in the coarse sensing stage as shown in Figure 2.13 (b). Using multiple antennas allows for faster sensing since in the coarse sensing stages all the antennas blocks sense the same frequency bandwidth thus achieving spatial diversity gain. In conclusion, multiple antennas offer benefits through diversity but on the other hand it also requires an expensive structure because of multiple antennas, LNAs, mixers, etc.



a)



b)

Figure 2.13: Block diagram showing a parallel multi-resolution system configured for the a) coarse resolution and b) fine resolution, sensing modes [62]

2.5.5.4 Multi-resolution Spectrum Sensing for single Antenna Cognitive Radio

Qiwei et al. [65], proposed a single antenna Cognitive radio receiver as shown in Figure 2.14. The building block consists of a single antenna, RF front-end, ADC, reconfigurable FFT-based sensing and MAC. The single antenna cognitive radio can digitize the total bandwidth into multiple smaller blocks. A coarse resolution sensing is done by using a smaller K_i size FFT. It was shown that the energy on each FFT bin Ei is compared with a threshold th_i. Per is defined as the percentage of the total number of bins where the energy is larger than th_i. If this percentage is larger than a limit P, Per >P, the total bandwidth is assumed too crowded to accommodate cognitive radio. If no bins have been found with significant energy (no i where $Ei > th_i$), namely $Per = 0$, we think the band is empty. In these two conditions, fine resolution is not needed and cognitive radio will either start communication wait for a licensed user to free the spectrum. Otherwise, the cognitive radio will continue with fine resolution sensing to focus on those high energy bands Ei where licensed users are potentially active. The specific method to select the interested bands is not considered in their discussion. Based on the result of fine resolution sensing, the cognitive radio will determine the transmission scheme and wait for the next sensing cycle. A flowchart describing the multi-resolution sensing scheme is shown in Figure 2.15. The total cost of multi-resolution is obtained by adding the coarse cost and the fine cost when the percentage of total number of bins Per is between 0 and P. However, an important observation is made: only a portion of the larger FFT outputs is needed for fine resolution. In this case the naïve implementation of a larger size FFT is inefficient. Therefore, an efficient algorithm which produces only a part of FFT outputs is desirable. A sparse FFT for OFDM based cognitive radio where a large portion of sub-carriers is switched off to avoid interference to licensed users by loading zeros is proposed in their discussion. A sparse FFT is used in the OFDM receiver to demodulate the data in the nonzero part of the spectrum occupied by cognitive radio. It was shown that the multi-resolution sensing scheme is beneficial in the following aspects:

- it avoids sensing the spectrum with the fixed aspects;

- there is no need to tune the analog front-end to focus on the interesting bands for fine resolution sensing;
- sparse FFT is used for a smart fine resolution sensing which only computes the interested bands in a finer resolution;
- due to the regular computational structure of sparse FFT, it is easy to make a hardware implementation of the reconfigurable FFT module with very small reconfiguration overhead;
- Multi-resolution sensing based on sparse FFT can be easily integrated with the OFDM based cognitive radio.

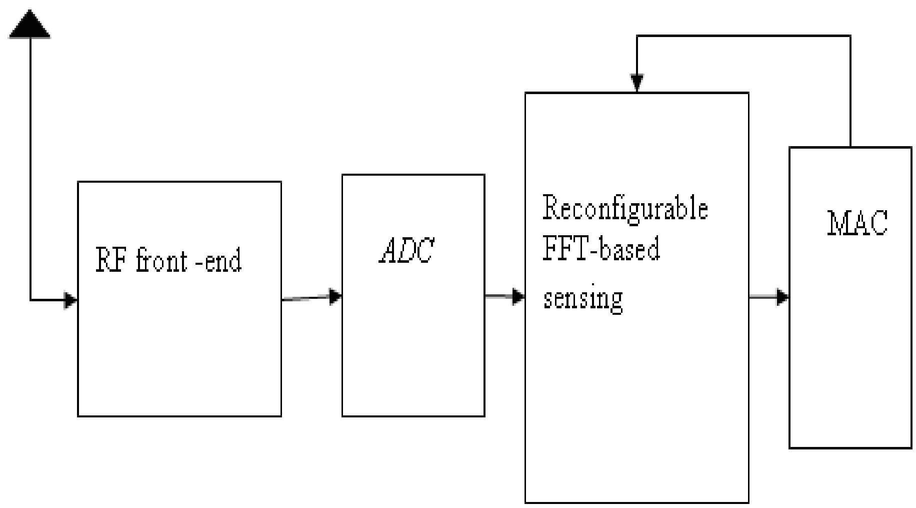


Figure 2.14: Block diagram of reconfigurable FFT based multi-resolution sensing

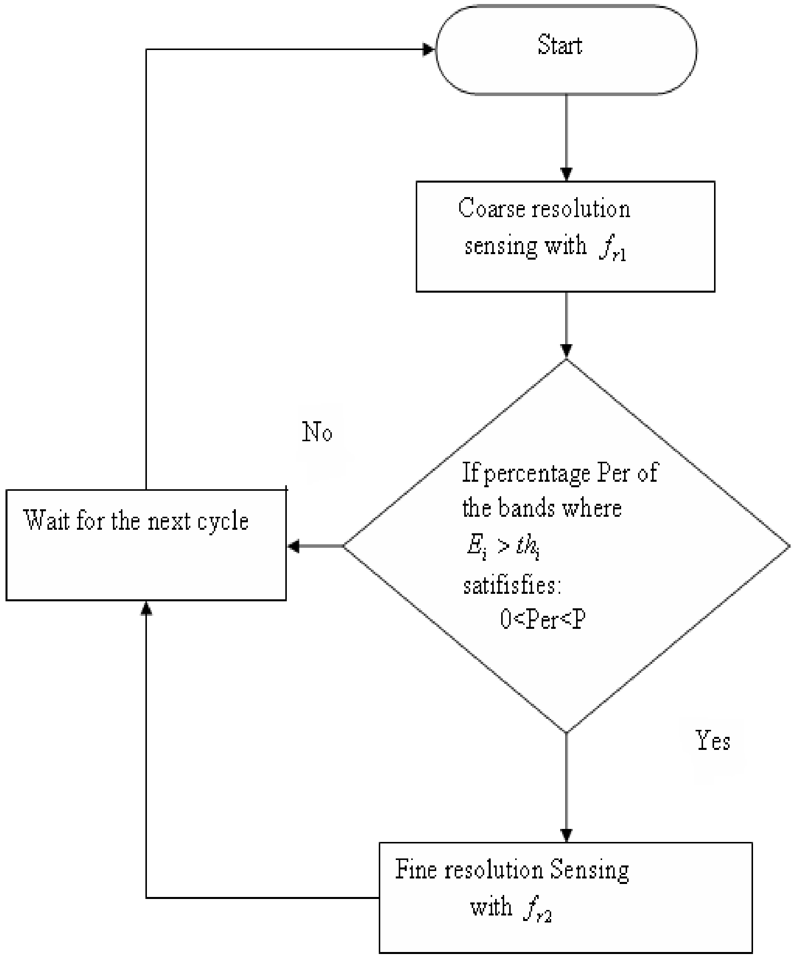


Figure 2.15: Flowchart of multi-resolution sensing

2.5.5.5 Filter Bank-Based Spectrum Sensing

Sheik F. et al [66], proposes instead of using wavelet instead of filter bank for signal decomposition into sub-bands. The power detection is used instead of the PU in each sub-band. In the paper, reduction the complexity of the filter banks architecture by using a poly-phase filter bank.

Smitha, K.G.; Vinod, A.P.[76], proposed a multiresolution filter bank (MRFB) based on the fast filter bank design for variable resolution spectrum sensing in multiple radio receivers. The proposed algorithm overcomes the constraint of fixed sensing resolution in spectrum sensors based on conventional uniform discrete Fourier

Transform filter banks (DFTFB). The results obtained show that the proposed MRFB architecture is 50.5% less complex than that of DFTFBs.

Taejoong Song et al [77], proposed a 122 mW low power multiresolution spectrum sensing IC with self-deactivated partial sensing techniques as an opportunistic spectrum sensing technique for the CR application through the whole white space in ultrahigh frequency bands. The LP-MRSS has shown a successful spectrum sensing functionality of a 24-dB dynamic range with 32% less power than the previous MRSS.

The summary of relevant works in multi-resolution spectrum sensing and cyclostationary feature detector is presented in Table 2.6.

Table 2.6: Summary works in multi-resolution spectrum sensing and cyclostationary feature detector

References		Proposed Technique Contribution	Results	Analysis/ Comments
Ref	**Year**			
[16] D.Cabric et al.	**2004**	Is the first work to suggest using cyclostationary features detector for spectrum sensing	It provides a general discussion of underlying theory of SCF	Robust against noise uncertainty
[61] Chan,S.Y	**Feb.2006**	Developed MRSS approach with less hardware efforts to implement.	Multi-resolution is achieved without any additional hardware burden.	Complicated hardware comparing to FFT
[62] Hur et al.	**May 2006**	Proposed a wavelet based MRSS in the analog domain.	Provides the flexibility to examine a wideband spectrum	provide coarse and fine sensing to meet the sensing speed and accuracy requirements
[63] Park et al.	**Jun 2006**	Proposed another wavelet based MRSS similar to [62].	Flexible, low power, high speed spectrum sensing solution	Analog based spectrum sensing
[56] Tian et al.	**Jun 2006**	Utilizes the wavelet as a powerful mathematical tool for analyzing singularities and edges.	Provides the flexibility to examine a wideband spectrum in fast coarse manner or in fine manner	Requiring high sampling rates.

References		Proposed Technique Contribution	Results	Analysis/Comments
Ref	**Year**			
[57] Tian et al.	**April 2007**	Developed the wavelet approach proposed in [56].	Beneficial to affecting CR agility at affordable cost.	It measures the energy of the signal.
[64] Neihart et al.	**May 2007**	Discuss an approach using the MRSS that is amenable to multiple antenna CR.	Multiple antenna offers benefit through diversity.	It requires an expensive hardware structure because of multiple antennas.
[65] Qiwei et al.	**August 2008**	Proposed a single antenna CR receiver.	It avoids sensing with fixed aspect.	The specific aspect to select the interest frequency band is not considered.
[60] Ying wang et al.	**Feb. 2009**	Proposed a collaborative detection approach based on the compressive sampling based spectrum sensing method of [62].	The spectrum holes are detected using energy detector in frequency domain.	The energy detector is susceptible to interference.
[59] Polo et al.	**April 2009**	Proposed another compressive sampling approach for wide band-width spectrum. Estimation and spectrum holes detection.	The spectrum holes are detected using energy detector in frequency domain.	It can not identify the type of the signal present in the given bandwidth.

In light of this literature review, it can be seen that the spectrum sensing technique is the fundamental requirement for cognitive radio to detect spectral holes. We have explained some of the existing methods of spectrum sensing such as matched filter based spectrum sensing, energy detector based spectrum sensing, cyclostationary feature based spectrum sensing and multi-resolution spectrum sensing. The matched filter is considered an optimal detector but it requires a perfect knowledge of the PU_s signals at the physical and medium access control layers. The energy detector is the simplest and lowest complexity but it cannot recognize signal features, so it cannot be used to distinguish between different signal types. The cyclostationary feature is reliable but it requires extra-computation. The multiresolution spectrum sensing is fast but is not reliable. Among these techniques the multi-resolution spectrum sensing is a popular technique due to its ability to detect quickly the free band. Various signal detection methods have been proposed for multi-resolution. None of these techniques however use multi-resolution sensing with cyclostationary feature for cognitive radio application which is more reliable.

We propose a method of spectrum sensing that combines the quickness of multi-resolution and the reliability of cyclostationary feature detector. We make an important observation: first, a coarse resolution sensing is performed by computing the energy of the lower sub-band and only the sub-band with larger energy is needed for fine resolution. Second, the spectral correlation function is only performed for the channel indexes with small and negligible sub-band energy. The proposed technique for cognitive radio application is a promising spectrum sensing technique due to its ability to perform quick and reliable sensing technique. To the best of our knowledge, there is no work in the literature considering fast and reliable sensing technique for DVB-T and FM wireless microphone signals.

2.6 Summary:

In this chapter, the overview of related research work is given. First of all, the cognitive radio overview is reviewed. Then, the history of software-defined radio (SDR) is reviewed, including the research and applications, and this is followed by the primary users systems. An extensive analysis is presented on spectrum sensing techniques; an important issue for the development of the cognitive radio concept. Different techniques have been applied in their papers to enhance detection. None of these techniques have been used in the proposed scheme for DVB-T and FM wireless microphone signals, which is essential for implementing efficient cognitive radio and their performance, has yet to be characterized.

CHAPTER 3

PROPOSED MULTI-RESOLUTION SPECTRUM SENSING SCHEME

3.1 Introduction

The demand for wireless communication has grown remarkably in the last few years, consequently raising the problem of spectrum scarcity. In this context, cognitive radio (CR) is an emerging technology that aims to overcome spectrum scarcity, one of the most challenging problems in modern wireless communication. The most important requirement of CR is to be aware of spectrum holes in the surrounding RF environment by performing spectrum sensing. This chapter proposes a low-complexity multi-resolution spectrum sensing scheme based on cyclostationarity. It is developed in the context of IEEE 802.22 WRAN as SU and DVB-T single frequency networks and wireless microphones as PUs. The proposed technique is inspired by the quickness of multi-resolution and the reliability of cyclostationary feature detection. In this chapter, first the problem formulation of multi-resolution spectrum sensing is introduced. The RFE architecture is proposed for a WRAN sensing receiver suitable for cognitive radio application. It is followed by the technique itself and then, mainly focus on the methodology for performance evaluation.

3.2 Formulation for Multi-resolution Spectrum Sensing

Assume that there is a specific bandwidth BW MHz in the frequency range of $[f_0\ f_N]$ MHz, and it is available for use in a wideband wireless network. Being cognitive, this network supports different wireless transmission over different bands in the assumed frequency range. A CR at a particular time and place must sense the wireless environment in order to identify spectrum holes for an opportunistic use. Suppose that the radio signal received by the cognitive radio occupies $N = 16$

adjacent spectrum bands, whose frequency locations and energy levels are to be detected and identified. Further assume that DVB-T and wireless microphone signals that are the PUs for UHF and VHF are mainly present in its RF spectrum. The spectrum bands of 8 MHz (DVB-T band) each lie within [f_0 f_N] MHz consecutively, with their frequency boundaries located at $[f_0 + 8(n-1), f_0 + 8n]$ MHz, where $1 \le n \le 16$. The n^{th} band is thus identified by $B_n : \{f\ \varepsilon\ B_{n:} : f_{n-1} < f < f_n\}$, n = 1, 2, 3, ……, N. The PSD structure of a wideband signal is illustrated in Figure 3.1. The following basic assumptions are adopted.

- The frequency boundaries f_0 and $f_N = (f_0 + B)$ MHz are known to cognitive radio. Even though the actual received signal may occupy a larger band, this cognitive radio regards [f_0 f_N] MHz as the wideband of interest and seeks white spaces only within this spectrum range.

- The transmission from wireless microphone is assumed to be in one of the DVB-T band not being used in the area. It is further assumed to be at very low power so as not to disturb DVB-T transmissions in the neighborhood.

It can be recalled that the objectives of this research work are:

- To design an RFE compliant with the MR technique for wideband sensing receivers for cognitive radio application.

- To design and develop a multi-resolution sensing strategy and algorithm for CR application to detect and identify the location of the PUs within the wideband of interest, and thereby, the spectrum holes.

- To identify the unoccupied spectrum within the given DVB-T band when only a wireless microphones with 200 KHz uses that channel. This is with the purpose so the rest of the channel can be used by the cognitive radio.

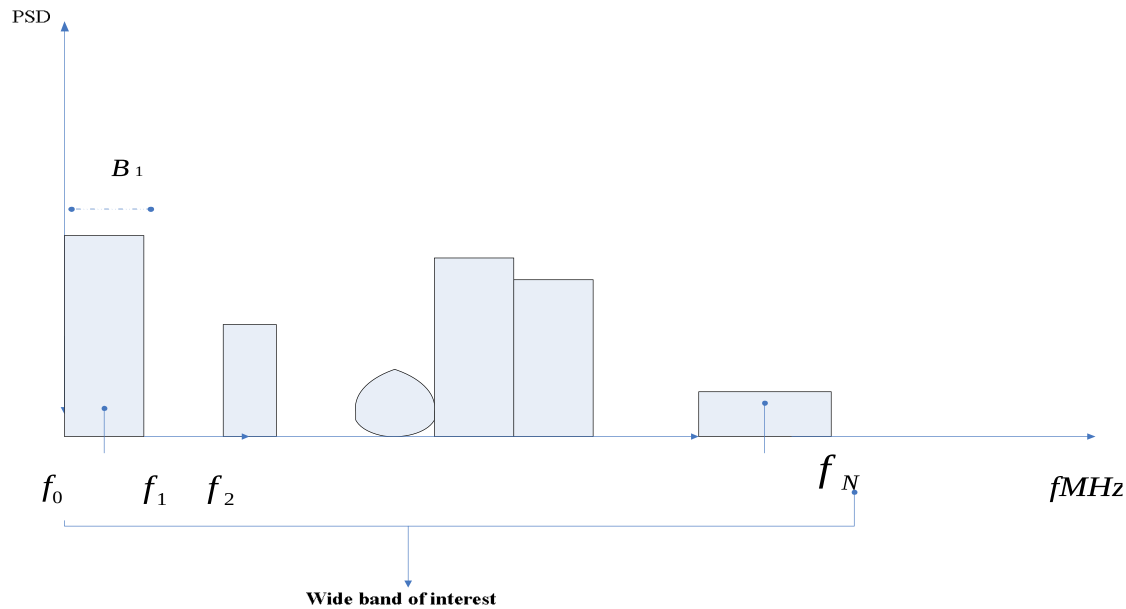


Figure 3.1: N frequency band

This problem formulation is used in this research work in order to satisfy the requirement for the proposed radio front-end (RFE) for a wideband sensing receiver.

3.3 The Proposed RFE For A Wideband Sensing Receiver For Cognitive Radio Application

The proposed radio front-end (RFE) architecture consists of a wideband antenna, an RF band pass filter, low-noise amplifier (LNA), mixer, local oscillator, low-pass filter (LPF), analog-to-digital converter (ADC), and a base-band processing unit as shown in Figure 3.2. After the RFE and base band processing stages, the detection results of spectrum sensing are transferred to a Media Access Control (MAC) layer so the available spectral resources can be identified for the WRAN user's transmission. The spectrum band for sensing is selected by a tunable filter under the control of the MAC layer. The bandwidth of the RF Filter is the same as the bandwidth of the spectrum band which is 128 MHz in this thesis. In this thesis, a DVB-T signal is used whose channel bandwidth is 8 MHz in the UHF. Then, the RF band is down-converted using a local oscillator at frequency of lower edge of the RF band. The resulting base-band extends from 0 MHz to 128 MHz and the band at twice the local oscillator is removed by the low pass filter. An analog to digital converter (ADC) with a sampling frequency of 256 MHz or more, with an appropriate over-sampling factor $\beta = f_s/(2BW)$[67], is used in this architecture. Over-sampling offers more relaxing requirements of the anti-aliasing filters at the cost of a faster sampler. The Texas Instrument (TI) ADC 6129 has been selected, since it provides 256 Mega-samples per second (Msps) sampling rate at a 12 bit-width resolution per sample [78]. It can be implemented for wide band sensing receiver. Finally, spectrum sensing processes the samples using appropriate detection algorithms.

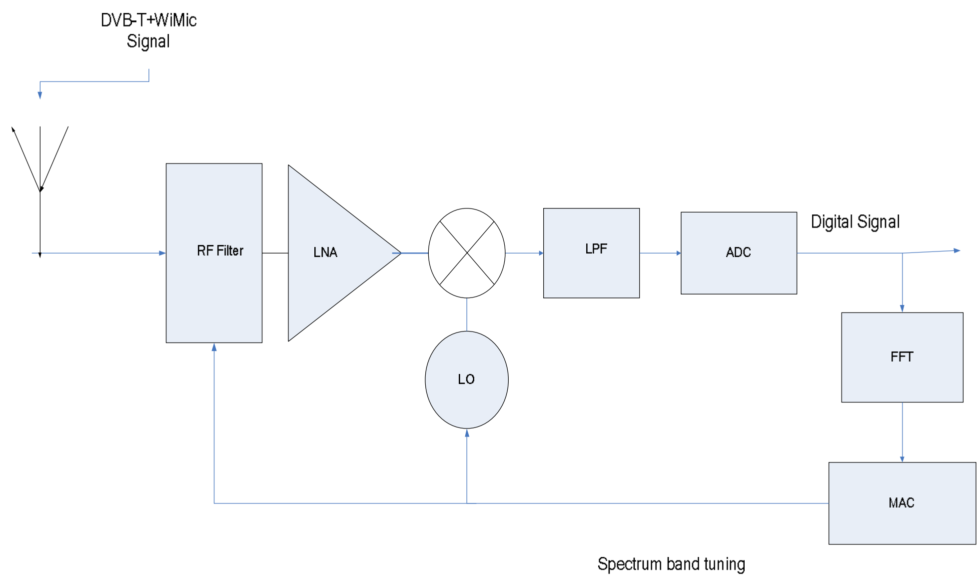


Figure 3.2: Proposed RF front-end

3.4 Proposed Technique

In the Cognitive radio framework, it is assumed that there are multiple primary systems operating in the same frequency bands and in the same area. In such an environment and in order to support adaptability of the CR, classification of primary signals is required. Having the knowledge of which PU is operating, SUs can adapt their parameters to provide the required protection for the primary system.

Classification is also important in the spectrum management function in the CR. For example, if the identified primary signal has a narrow bandwidth in comparison with the channel bandwidth, the CR can optimize the use of the spectrum band by suitably utilizing the fractions of the frequency band available for use. This feature is called bandwidth scalability and can be used to improve spectrum utilization [68]. In the case of IEEE 802.22 WRAN for the CR, we need to classify and identify the DVB-T and wireless microphone signals. The wireless microphones occupy only 200 KHz of an 8 MHz TV channel. However, as of today, no attempt has been made to utilize the rest of the channel by the CR. Without distinction of the wireless microphone from the DVB-T signal, the WRAN CR cannot make good use of bandwidth scalability by using the available bandwidth of the TV channel. The proposed multi-resolution spectrum sensing scheme makes use of the simplicity of energy detector while doing coarse sensing and the robustness of cyclostationary feature while doing fine sensing.

The ability to do coarse sensing as well as fine sensing is in effect multi-resolution sensing. Recent developments in multi-resolution spectrum sensing make use of signal representation techniques that include wavelet. Most researchers indicate that, in order to provide multi-resolution spectrum sensing features, wavelet transform is a useful representation. Therefore, we select the discrete wavelet transform (DWT) as our major signal representation method.

The proposed MR spectrum sensing technique carries out energy based sensing at coarse resolution but cyclostationarity based sensing at fine resolution when the signal strength is perceived weak. For example, assuming that many signals of varying strength occupy the given spectrum, one computes the energy in the entire band. Then one obtains signals at next level finer resolution and computes the energy of each sub-band. If the energy in one sub-band is of the same order as that at the previous level, it implies that the entire signal is present in that sub-band. If, on the other hand, the signal energy is negligible in that sub-band, it may imply the absence of any signal or very weak signal. In such cases, one computes the spectral correlation to locate the presence of the signal. If a wireless microphone signal is present and is weakest of all other PU DVB-T signals, the technique can locate it by using spectral correlation either at highest resolution corresponding to sub-band of 8 MHz or lower resolution corresponding to 16, 32 or 64 MHz sub-bands. The proposed technique can identify the presence of weak wireless microphone or DVB-T signal at any resolution using cyclostationary features while it detects the presence of stronger signals using their signal energy at all resolutions.

The technique is a hybrid technique in that it uses both the energy measurements as in energy based simple techniques and cyclostationary features as in cyclostationary features based complex techniques. However, it uses both in a clever way making use of multi-resolution representation of signals so the technique proves both simple and reliable while retaining the speed advantage of multi-resolution.

3.4.1 Flowchart of the proposed algorithm

The received signal is down-converted and sampled in the RFE of the sensing receiver discussed in Section 3.3, where the total bandwidth is B_{tot} with initial frequency resolution, f_{r0}, is a coarse resolution, $f_{r0} = B_{tot}$. During the sensing, the total bandwidth may have to be divided multiple times into smaller blocks leading to finer resolutions given by $f_{rn} = \frac{B_{tot}}{2^n}$ where n takes the following values 1, 2, 3, and 4 at different levels of decomposition, as shown in Figure 3.3.

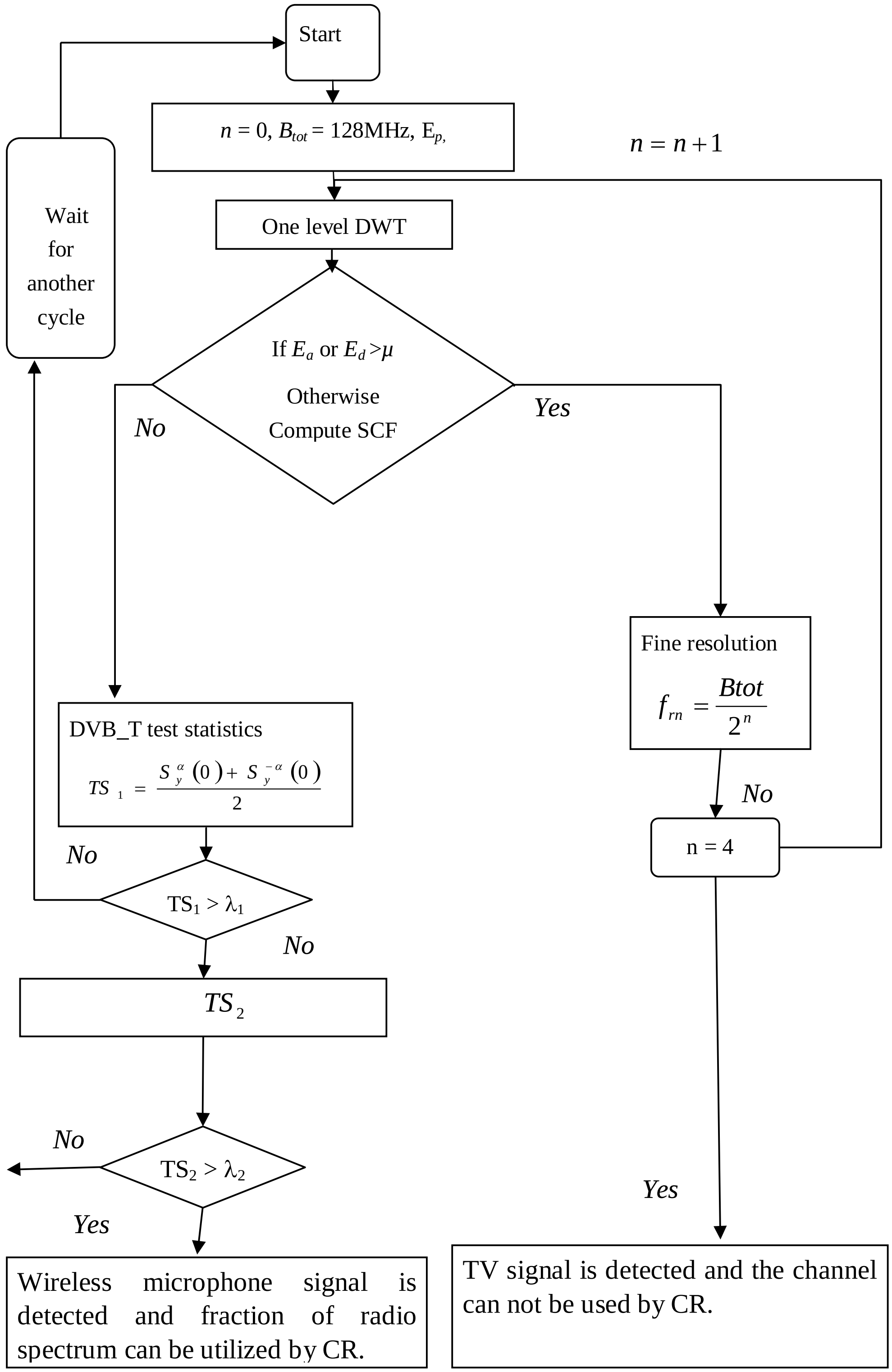


Figure 3.3: Flowchart of the proposed multi-resolution approach

Figure 3.4 below shows four bandwidth resolution levels of the proposed spectrum sensing. The coarsest level is 128 MHz while the finest level is 8 MHz.

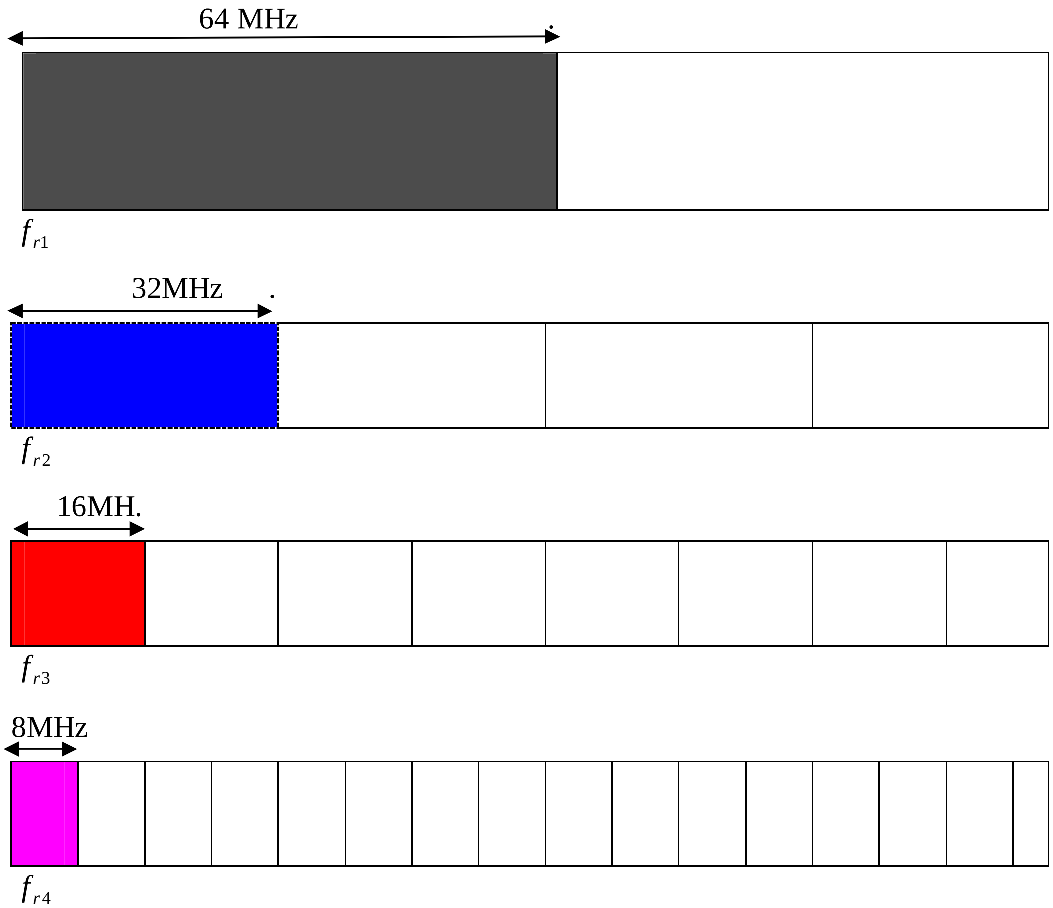


Figure 3.4: Multi-resolution Spectrum Sensing Approach

First, the energy (E_p) in the entire band B_{tot} must be computed. Then, the signals at the next finer resolution must be obtained by using one level discrete wavelet transform (DWT). In this work, Daubechies wavelet of length 11, denoted by symbol, db5, is used for decomposing the signal at finer levels. The choice of db5 is motivated by the requirement that the resulting sub-bands have minimal overlap while adding minimal computational burden. Haar wavelets are known to have minimum computational burden but maximum overlap in frequency. db5 wavelets are optimal in that sense. The 1-level decomposition produces signals with resolution of $f_{r1} = \frac{B_{tot}}{2}$. The energy on each sub-band is calculated using Parseval's theorem for the DWT described in Section 2.5.4.3 as follows:

$$E_a = \frac{1}{N_j}\sum_k \left|c_{aj,k}\right|^2 = \frac{\left\|c_a\right\|^2}{N_j} \tag{3.1}$$

$$E_d = \frac{1}{N_j}\sum_k \left|c_{dj,k}\right| = \frac{\left\|c_d\right\|^2}{N_j} \tag{3.2}$$

where $\left\|c_a\right\|$ and $\left\|c_d\right\|$ are the norm of the expansion coefficients c_a and c_d.

The energy on each sub-band is compared with a threshold, μ. The threshold values are selected by comparing the energy of the previous level (E_p) with the sub-band-energy as follows $\frac{E_a \text{ or } E_d}{E_p} \leq 5\%$, where E_a and E_d are the energy of approximation and detail coefficients respectively. The choice of 5% is arbitrary. It is meant to emphasize that the sub-band energy is nearly same as that at previous level or that the energy is too little. If the energy in one sub-band $(E_a or E_d)$ is of the same order as that at the previous level (E_p), it implies that the entire signal is present in that sub-band. In addition, if the sub-band range is larger than the TV channel which is 8 MHz, fine sensing has to be performed by computing another level of DWT (db5 based wavelet filtering). If the iteration parameter is equal to $n = 4$, at this stage the sub-band range is of the same order as TV bandwidth of 8 MHz, it goes to the MAC layer to look for the available spectral resources for wireless transmission users. If, on the other hand, the signal energy is negligible in that sub-band $(E < \mu)$, it may imply the absence of any signal or very weak signal. In such case, one computes the spectral correlation to locate the presence of signal. To the best of our knowledge, the wireless microphones are considered as low power auxiliary devices and the TV signal also has low power when it is located far from the transmitter. So, the first test statistics has to be calculated to identify a DVB-T signal by averaging the magnitude of the cyclostationary peaks of the signal at one of their cyclic spectrum magnitude as shown in Eq. (3.3). If the computed test statistics are larger than the threshold, λ_1, the decision information of the algorithm is the presence of the DVB-T signal with an 8 MHz bandwidth in the given band. In this case, we examine other TV bands or do sensing again of the same band after a certain period of time *T*, which is derived from the study of spectrum availability in the given area.

$$TS_1 = \frac{S_y^{\alpha}(0) + S_y^{-\alpha}(0)}{2}, \alpha \neq 0 \tag{3.3}$$

The threshold, λ_1, is selected so as to obtain a fixed probability of false alarm of 10% which is required by the IEEE WRAN standard. Thus, the threshold, λ_1, is defined as the value of white Gaussian noise power that causes 10% false alarm, To find the threshold values, the cumulative distribution function (CDF) $F(X)$ of the test statistics TS_1, defined in (3.3), is performed when only noise exists at the input of the proposed scheme under noise uncertainties of 0, 1, and 2dB. If the computed test statistics TS_1 is lower than the threshold, λ_1, then the second test statistics for wireless microphone signal is computed by averaging the magnitude of the cyclostationary peaks as shown in Eq.(3.4). We use the averaging peak at mentioned location because DVB-T signal identification is not considered in this test statistics and the wireless microphone signal at carrier frequency of f_c has four peaks in SCF at $f_0 = \pm f_c, \alpha = 0$ and $f_0 = 0, \alpha = \pm 2 f_c$, the latter two are the cyclostationary feature of the sinusoidal signal.

$$TS_2 = \frac{S_y^0(f_c) + S_y^0(-f_c)}{2} + \frac{S_y^{2f_c}(0) + S_y^{-2f_c}(0)}{2} \tag{3.4}$$

The case when the test statistics TS_2 is greater than the threshold, λ_1, this means the wireless microphone signal with 200 KHz bandwidth is used in the given channel, Since, compared to the TV channel which of 8 MHz bandwidth, it is a narrowband signal, so, the rest of the channel can be utilized by the WRAN CR without causing harmful interference to the wireless microphones receiver. When the test statistics is less than the threshold, λ_1, the whole channel can be used by the cognitive radio. In these two conditions, fine sensing is not needed and the cognitive radio will either start communicating or wait for a licensed user to free the spectrum.

The total computational cost of the proposed scheme is the superposition of the costs involved at both the coarse level and at fine level, as shown below:

$$C = C_{coarse} + C_{fine} \tag{3.5}$$

where C denotes the cost. We make an important observation – fine sensing is performed only for a sub-band with significant energy, while cyclostationary features are used only for subbands with small and negligible energy.

By using the proposed multi-resolution spectrum sensing scheme we benefit from its quickness and reliability. This approach derives its advantages by using the property of multi-resolution and the theory of cyclostationarity features for cognitive radio application that helps it outperform the conventional method of the energy detector. It can be recalled that an energy detector simply measures the energy of the received signal and does not differentiate between the signal type and noise but can only determine the presence of the energy.

3.4.1.1 Use of the Proposed Algorithm in A Typical Detection Scenario

The simulation environment is a DVB-T single frequency network [69], wireless microphone signal and one customer premise equipment (CPE) that can sense the interested frequency band for cognitive radio users.

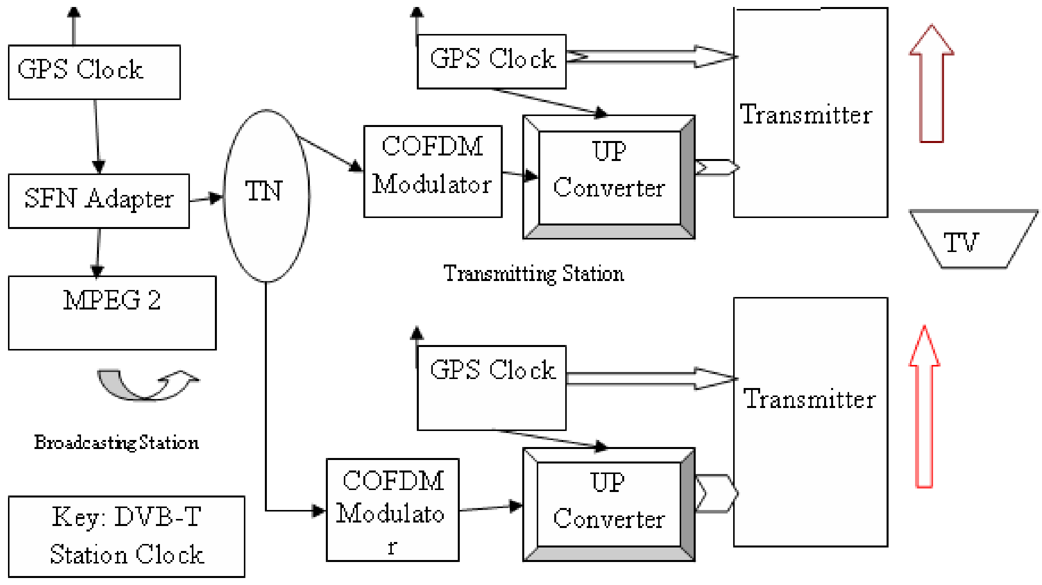


Figure 3.5: Simulation environment scenario

We assume that each DVB-T and wireless microphone signal is a band pass signal with a bandwidth of 8 MHz and 200 KHz respectively. In addition, the channel is an additive white Gaussian noise (AWGN) channel with zero mean and σ^2_w variance. For the purpose of illustration, the radio spectrum is assumed 25% densely populated by the primary users.

The received signal is down-converted and sampled in the RFE of the sensing receiver. Then, the energy (E_p) in the entire band B_{tot} is computed. The primary interested frequency band (or scanning range), B_{tot} is 128 MHz and there are two channels in the frequency band, B_{tot} at the first level of decomposition. The energy on each sub-band is calculated and channel H has been found with negligible energy. It may imply the absence of any signal or the presence of very weak signal. In such case, one computes the spectral correlation of the channel index of negligible energy to locate the presence of signal. The spectral correlation of channel H is performed and noise feature has been found which is uniquely large at cyclic frequency α = 0 axis compared to that at other cyclic frequencies. The first and second test statistics are computed and compared with the thresholds respectively. As the threshold values are set above statistically insignificant peaks, when the noise signal is present at the received side, no candidate primary users are detected. It means, there is no primary user signal only noise exists in channel H. So, this channel can be used by the CR without causing harmful interference to the PUs receivers. On the other hand, the channel L with significant energy was decomposed by computing another level of DWT db5 wavelet filtering with a resolution of f_{r2} to focus on thus a higher sub-band $(32MHZ)$ as shown in Figure 3.6. Channel LL has been found with small sub-band energy and therefore, the spectral correlation of the channel gives us a richer domain signal detection method. The spectral correlation of the channel index with small sub-band energy is computed. A sinusoidal signal at a frequency of f_c was found to have four peaks. The first test statistics is calculated for identifying a DVB-T signal by scanning the maximum cyclostationary peaks of the signals at one of their cyclic spectrum magnitudes. The computed test statistics is lower than the threshold, then the second test statistics for the wireless microphones signal is computed by averaging the magnitude of the peaks at f_0=0, α_0=±56.1MHz and f_0=±28MHz, α_0=0. The test statistics TS_2 is found greater than the threshold λ_1, this means the wireless microphone signal with 200 KHz bandwidth is used in 32 MHz channel bandwidth. Since, compared to the minimum resolution of 32 MHz, the wireless microphone is a narrowband signal, so, the rest of the channel can be utilized by the WRAN CR without causing harmful interference to the wireless microphones receiver. The channel LH with significant energy was decomposed by computing another level of the DWT with a resolution of f_{r3} to focus on thus higher sub-band as shown in Figure 3.6. The channels LHH and LHL have been found with significant energy; in this condition fine resolution is done by computing another level of DWT with a resolution of f_{r4} to focus on this high sub-band energy. The channel LHLL, LHLH and LHHL have been found with significant energy, in this condition fine resolution is not needed because the sub-band range is equal to the TV channel. So, the cognitive radio will either start communicating or wait for the primary users to free the spectrum. Channel LHHH has been found with negligible sub-band energy. The spectral correlation of channel LHHH is performed. The spectral correlation of the noise has been found which is uniquely large at cyclic frequency α equal to zero comparing to that at other cyclic frequencies. The first and second test statistics of the proposed scheme have been calculated and compared with the thresholds. As the thresholds values are set above statistically insignificant peaks and the noise signal is present at the received side, no candidate primary users are detected.

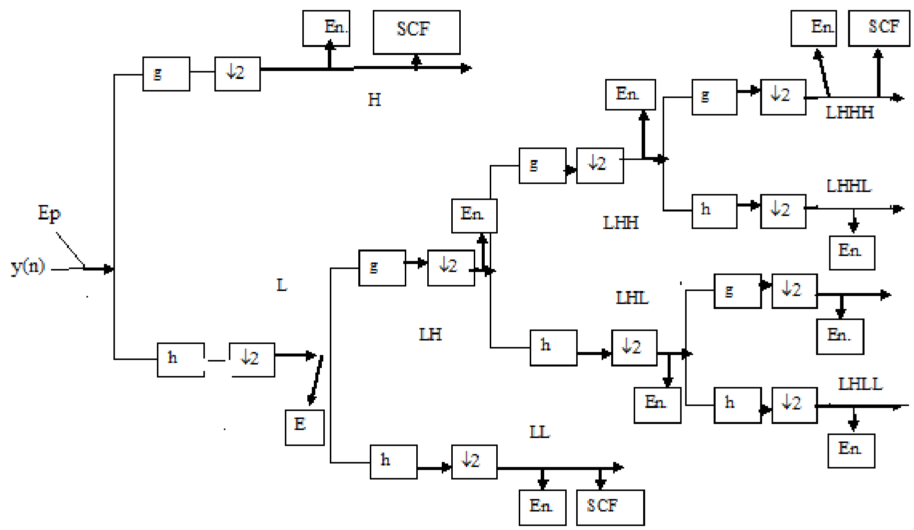


Figure 3.6: The multi-resolution based cyclostationary feature algorithm

in this Figure 3.6 g, h, ↓2, En, and SCF represent the high pass filter, low pass filter, down-sampling by 2, energy of the channel and cyclostationary feature detection respectively.

3.4.2 Methodology of Performance Evaluation of The Proposed Technique

The following six cases are selected to study that the proposed multi-resolution spectrum sensing scheme and are compared to the fixed energy detector and brute force SCF. The six cases are analyzed to determine the range and scenarios of occupancy over which the proposed scheme proves superior. These cases are able to capture performance related information within the wideband of interest.

- Case 1: 25% of the radio spectrum is densely populated by the primary users.
- Case 2: 25% of the radio spectrum is populated by the primary users in distributive manner.
- Case 3: 50% of the radio spectrum is densely populated by the primary users.

- Case 4: 50% of the radio spectrum is populated by the primary users in a distributive manner.
- Case 5: 80% of the radio spectrum is densely populated by the primary users.
- Case 6: 80% of the radio spectrum is populated by the primary users in distributive manner.

Before the performance evaluation can be discussed under these scenarios, it is necessary to define what performance is. The performance is defined as the accomplishment of a given task measured against preset standards of accuracy, completeness, and cost. So, the following performance metrics are considered for the assessment of the proposed multi-resolution spectrum sensing scheme:

- Probability of correct classification
- Complexity of the system

3.4.2.1 Probability of Correct Classification

The performance of this approach is evaluated using the probability of correct classification P_c. Within the context of cognitive radio, P_c evaluates the ability of the classification approach to identify the type of PU which occupies the channel. In this research, the performance of the proposed multi-resolution scheme is computed assuming DVB-T or wireless microphone signal as the weakest signal. The probability of correct classification used as a performance measure is estimated from 300 trials. It gives lowest SNR for 90% classification at a given noise uncertainty. In addition to evaluating the proposed approach over AWGN, certain parameters are also considered: Noise floor, Noise uncertainty, and the thresholds used in the algorithm to compare the test statistics.

3.4.2.1.1 Noise Floor Calculation

To be able to evaluate the performance of spectrum sensing techniques, noise power captured by the omni-directional antenna from the surrounding environment as well as the noise introduced by RFE circuitry should be estimated. An estimation of noise power is given by [70].

$$N(dBmW) = -174 + NF + 10\log(BW) \tag{3.6}$$

where -174 $(dBmW/Hz)$ is power spectrum density of thermal noise , NF is the noise figure of low noise amplifier (dB) and (BW) is the range of spectrum band to be sensed. Using the value of noise $NF = 11\,dB$ [70] and the radio signal received by the cognitive radio occupies $N = 16$ spectrum bands, whose frequency locations and energy levels are to be detected and identified. The spectrum bands of 8MHz each lie within [f_0 f_N] consecutively is used, the noise power will be -94 dBm. This value is used as noise floor in performance evaluation of sensing algorithms.

3.4.2.1.2 Noise Uncertainty

It is well known that noise in communication systems is not only thermal noise introduced by the receiver but also an aggregation of various nearby unintended sources. Although the noise floor in the detector input has been calculated, the exact noise power is not known. This lack of knowledge of the noise floor is called “noise uncertainty” [44]. There are many reasons for noise uncertainty [71]:

- Thermal noise variation because of temperature change.
- Low noise amplifier (*LNA*) gain variation according to temperature change.
- Calibration error.
- Error in estimate due to interference.

The first factor of thermal variation due to temperature changes affects the value of noise power spectrum density (*PSD*).Thermal noise *PSD* could be described by,

$$N_0 = K_b T \tag{3.7}$$

where K_b is Boltzman constant and T is the temperature degree in Kelvin. According to [44], to explain how the change in the temperature affects the N_0, let the temperature change from T_1 to T_2 .So, the changes in N_0 is given by,

$$\Delta N_0 = 10\log(K_b T_2) - 10\log(K_b T_1) = 10\log\left(\frac{T_2}{T_1}\right) \tag{3.8}$$

If it is assumed that the room temperature raised from *300 ^{0}K to 320 ^{0}K*, then the change in thermal noise PSD is,

$$\Delta N_0 = 10\log\left(\frac{320}{300}\right) = 0.28dB \tag{3.9}$$

The second factor of variation in LNA gain (G_{LNA}) due to change in temperature can be illustrated for GaAs LNA operating at a UHF band of TV broadcast that has changed in gain about 0.01 dB/^{0}C[71]. To find LNA gain for 20 ^{0}C temperature change,

$$\Delta G_{LNA} = 20 * (0.01) = 0.2dB \tag{3.10}$$

The third factor of calibration error is the error during the initial calibration. For 1 ms samples used for calibrating power estimator, the standard deviation of the initial calibration is about 0.22 dB [72].

By combining these errors, we have noise uncertainty of ± 0.7 dB which can be rounded up to ± 1 dB. However, it must be noted that this noise uncertainty may be much worse if the forth factor of interference from the other SUs is also considered. In this thesis, noise uncertainty of 0, 1, 2 dB are used for performance evaluation.

In this thesis, we use robust statistics [38] to model the effects of noise uncertainty in a spectrum sensing technique. This model could be considered as the worst case approach. The PSD of the noise is given by,

$$N(dB/Hz) = N_0 + NF \pm \Delta \tag{3.11}$$

where Δ noise uncertainty in dB and NF =11 dB is the noise figure of a low noise amplifier and N_0 is the Gaussian noise. Robust statistics models use the upper limit of noise PSD which is,

$$N(dB/Hz) = N_0 + NF + \Delta \tag{3.12}$$

to calculate the probability of a false alarm (P_{fa})The lower limit of noise *PSD* which is,

$$N(dB/Hz) = N_0 + NF - \Delta \tag{3.13}$$

Equation (3.13) is used to calculate the probability of the correct classification, P_c. Noise uncertainty is an important factor to evaluate the performance of any spectrum sensing technique.

3.4.2.1.3 Deriving the Threshold

The threshold λ_1, is defined as the value of white Gaussian noise power that causes 10% false alarm. Accordingly, threshold is set for $P_{fa} = 0.1$. The Cumulative distribution function (*CDF*) of the test statistics when only noise signal exists at the input of the detector is used to set the threshold. Figure 3-7 shows the thresholds for the proposed algorithm for 0, 1 and 2 dB noise uncertainties. From the obtained *CDF*, the thresholds values are obtained where $F(\lambda) = 0.9$. The values of thresholds are indicated by yellow points in the Figure 3.7.

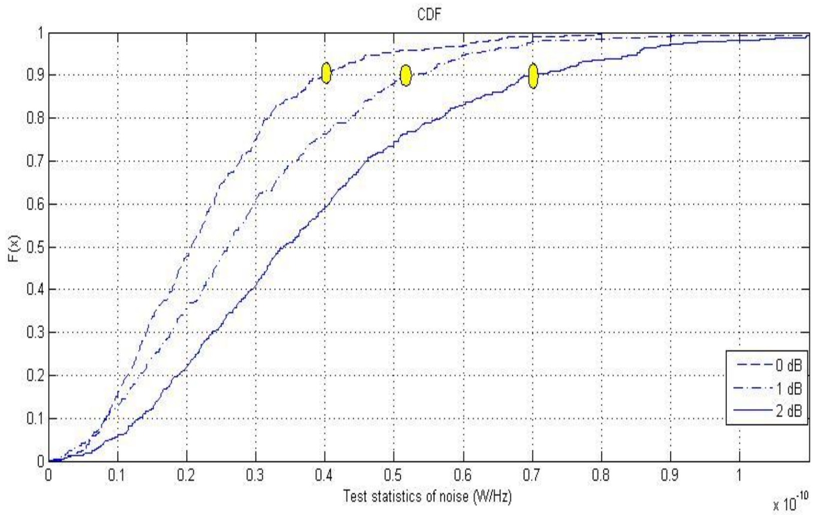


Figure 3.7: Determining the thresholds for the proposed algorithm for 0, 1, 2 dB noise uncertainties.

3.4.2.2 Complexity of the system

In this thesis, complexity refers to time complexity of performing computations on the proposed multi-resolution spectrum sensing scheme. It can be recalled that the proposed scheme is the combination of the simplicity of energy detection and the robustness of cyclostationary features. So, the computational complexity of energy and cyclostationary features detectors described in Section 2.5.2.1 and Section 2.5.3.3; respectively are used to evaluate stage by stage the overall complexity of the proposed multi-resolution spectrum sensing approach.

3.4.2.3 Experiment Methodology

In this research, we demonstrate for each scenario the following parameters:

- Cyclostationnary feature based sensing of weak signal
- Power spectrum and detection of the simulated primary user's signals.
- The number and block sizes required for each scenario.
- The computational complexity of the proposed scheme.
- The performance evaluation for each scenario.

- Computational complexity analyses and comparison of the proposed scheme of that of fixed energy detector, multi-resolution spectrum sensing energy detector, and the brute force SCF.

For the sensing scheme, the performance is evaluated by computing the probability of the correct classification versus the SNR under noise uncertainties of 0, 1, and 2 dB.

The methodology of performance evaluation is as follows:

- The received signal is down-converted and sampled in the RFE of the sensing receiver.
- The thresholds values are set for fixed $P_{fa} = 10\%$ by applying the test statistics of the algorithm to WGN for different values of noise uncertainties.
- The cumulative distribution function (*CDF*) of the test statistics is used to set the threshold values for $P_{fa} = 10\%$.
- The flowchart of the proposed multi-resolution spectrum sensing approach is applied to the received signal with AWGN for different values of noise uncertainties.
- The complexity of the system is analyzed in comparison with fixed energy detector, brute force cyclostationary feature detector and MRSS energy detector.
- To create a graph of probability of correct classification versus SNR, plot a series of points. Each of these points required to run a simulation at specific value of SNR averaged over 300 trials.

3.4.3 Validation

Our technique is compared with the fixed energy detector, MRSS - energy detector and brute force SCF in terms of complexity and performance evaluation using same parameters and methodology.

3.5 Summary:

In this chapter, the problem statement for multi-resolution spectrum sensing was described for RFE wideband sensing receiver. The proposed RF front-end for a wideband sensing receiver was described. Then, the proposed technique was introduced. Finally, the methodology for the performance evaluation of the proposed algorithms was presented.

CHAPTER 4

SIMULATION RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, the algorithm proposed in the previous chapter is evaluated under AWGN noise uncertainties. As mentioned earlier, the proposed technique detects the weakest signal using cyclostationary features while stronger signals are detected using energy based detection. First, the probability of correct classification is obtained assuming DVB-T as the weakest signal in different scenarios. Next, the same is obtained assuming wireless microphone to be the weakest signal. Then, various scenarios mentioned in the methodology described in Section 3.4.2 are analyzed individually. For each of these scenarios, the power spectrum of the simulated PUs signals is presented. At a fixed SNR, the spectrum sensing using the proposed technique is presented step by step for the first scenario, and summarily repeated for other scenarios. Then, the complexity of the proposed scheme for each scenario is analyzed. The performance of the proposed multi-resolution approach for each scenario is evaluated using the probability of the correct classification under noise uncertainties of 0, 1, and 2 dB. Finally, the performance of the technique is evaluated in comparison to those of fixed energy detector, MRSS energy detector and brute force SCF.

4.2 Cyclostationary Features Based Sensing of Weakest Signal

In this section, the performance of the proposed multi-resolution scheme is computed assuming DVB-T or wireless microphone signal as the weakest signal. Since the weakest signal is analyzed using cyclostationary features, the following sections present the probability of correct classification of DVB-T or wireless microphone in different scenarios under noise uncertainties of 0, 1 and 2 dB.

4.2.1 The Performance of the Proposed DVB-T Sensing Algorithm

It is assumed that, under various scenarios, the proposed technique may seek to classify the weakest DVB-T signal either in 8 MHz band or 16 or 32 or 64 MHz band. Therefore, the performance of the proposed technique is evaluated over AWGN under noise uncertainty scenario when DVB-T signal is present in 8, 16 and 32 MHz channel bandwidth.

Figure 4.1 shows the evaluation results for a classification approach to distinguish a DVB-T signal over an AWGN in the case of 0, 1, and 2 dB noise uncertainties. The result clearly indicates that above 90% of the received signals are correctly classified at $SNR = -8$ dB and above. Without noise uncertainty DVB-T user is identified with 90% and 100% probability of the correct classification at -8 dB and -7 dB respectively. In the case of 1 dB noise uncertainty 90% and 100% probability of correct classification are achieved at SNR of -5.8 dB and -5 dB respectively. For 2 dB noise uncertainty 100 % probability of correct classification is achieved at the SNR of -2 dB. The DVB-T signal is detected and located at $\alpha = \pm 44\, MHz, f = 0$. The performance of the system degrades by nearly 2.2 dB SNR when the DVB-T signal is present in 32 MHz bandwidth.

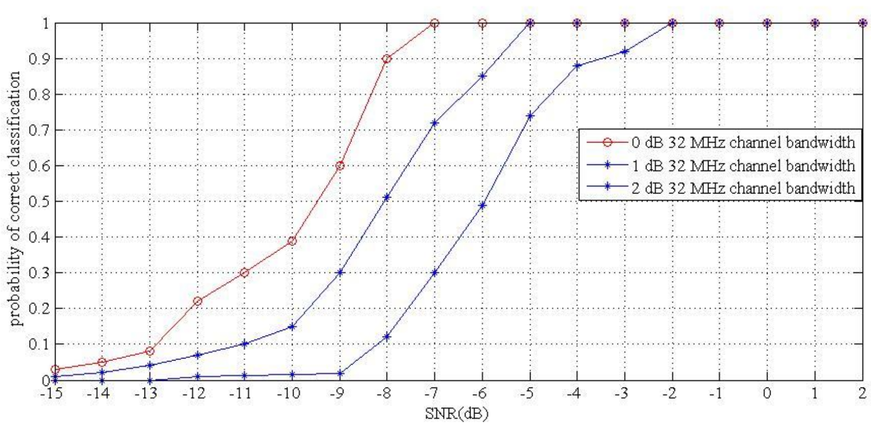


Figure 4.1: Classification approach performance for DVB-T signal at 32MHz channel under noise uncertainties of 0, 1 and 2dB.

Figure 4.2 shows the evaluation results for a classification approach when the DVB-T signal is present in 16 MHz channel bandwidth. The result clearly indicates that above 90% of the received signals are correctly classified at $SNR = -11$ dB and above. Without noise uncertainty a DVB-T user is identified with the probability of 90% and 100% probability of the correct classification are achieved at $SNR = -11$ dB and $SNR = -10$ dB, respectively. In the case of 1 dB noise uncertainty 90% and 100% probability of correct classification are achieved at SNR of -9 dB and -8 dB respectively. For 2 dB noise uncertainty, 100 % probability of correct classification is achieved at the SNR of -6 dB. The DVB-T signal is detected and located at $\alpha = \pm 60MHz, f = 0$. The performance of the system degrades by nearly 2 dB.

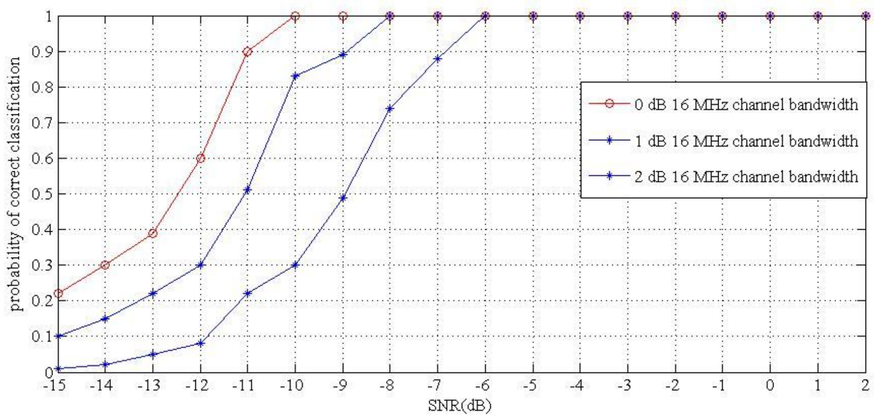


Figure 4.2: Classification approach performance for DVB-T signal at 16MHz channel under noise uncertainties of 0, 1 and 2dB.

Figure 4.3 shows the evaluation results for a classification approach when the DVB-T signal is present in 8 MHz channel bandwidth. The result clearly indicates that above 90% of the received signals are correctly classified at $SNR = -13$ dB and above. Without noise uncertainty a DVB-T user is identified with the probability of 90% and 100% probability of the correct classification are achieved at $SNR = -13$ dB and $SNR = -12$ dB respectively. In the case of 1dB noise uncertainty 90% and 100% probability of correct classification are achieved at SNR of -12 dB and -11 dB respectively. For 2 dB noise uncertainty 100 % probability of correct classification is achieved at the SNR of -10 dB. The DVB-T signal is detected and located at $\alpha = \pm 84\, MHz, f = 0$. The SNR performance of the proposed algorithm degrades by nearly $1\, dB$.

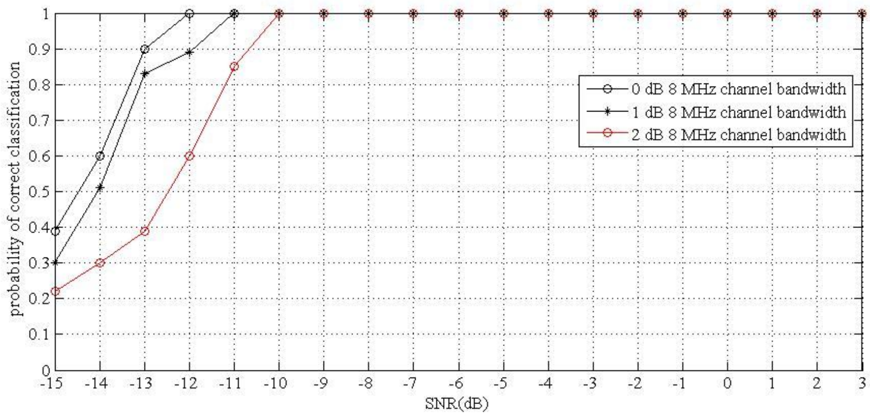


Figure 4.3: Classification approach performance for DVB-T signal at 8MHz channel under noise uncertainties of 0, 1 and 2dB.

4.2.2 The Performance of the Proposed Wireless Microphone Sensing Algorithm

Similarly, under the assumption that the wireless microphone signal is the weakest signal, the present evaluation results of the proposed technique are obtained in 8, 16 and 32 MHz band over an AWGN assuming of 0, 1, and 2 dB noise uncertainties.

Figure 4.4 shows the results of classifying wireless microphone at 32 MHz band. The result clearly indicates that above 90% of the received signals are correctly classified at $SNR = -8$ dB and above. Without noise uncertainty a wireless microphone user is identified with the probability of 90% and 100% probability of the correct classification are achieved at -8 dB and -7 dB, respectively. In the case of 1 dB noise uncertainty 90% and 100% probability of correct classification are achieved at SNR of -6.5 dB and -5 dB respectively. For 2 dB noise uncertainty 100 % probability of correct classification is achieved at the SNR of -3 dB. The wireless microphone signal is detected and located at $f_0 = 0, \alpha_0 = \pm 56.1\, MHz$ and $f_0 = \pm 28\, MHz, \alpha_0 = 0$. The performance of the system degrades by nearly 2.5 dB SNR in this scenario.

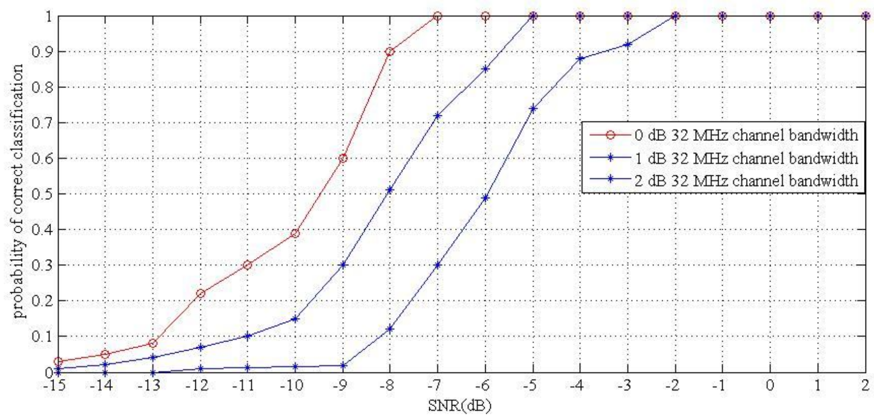


Figure 4.4: Classification approach performance for wireless microphone at 32 MHz channel under noise uncertainties of 0, 1 and 2 dB.

Figure 4.5 shows the evaluation results for a classification approach when a wireless microphone signal is present in 16MHz channel bandwidth. The result clearly indicates that above 90% of the received signals are correctly classified at $SNR = -10.8$ dB and above. Without noise uncertainty a wireless microphone user is identified with the probability of 90% and 100% probability of the correct classification are achieved at -10.8dB and -9dB respectively. In the case of 1dB noise uncertainty 90% and 100% probability of correct classification are achieved at SNR of -9.5dB and -8dB respectively. For 2dB noise uncertainty 100 % probability of correct classification is achieved at the SNR of -7dB. The wireless microphone signal is detected and located at and $f_0 = \pm 12$MHz, $\alpha_0 = 0$. The performance of the system degrades by nearly 1.2dB SNR in this scenario.

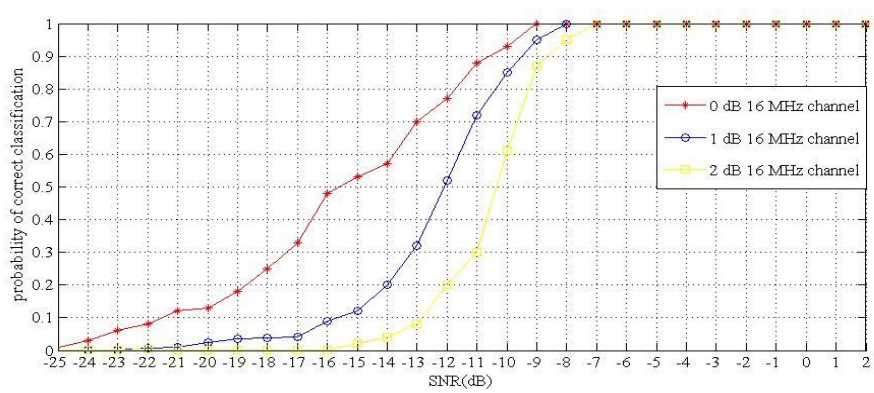


Figure 4.5: Classification approach performance for wireless microphone signal at 16MHz channel under noise uncertainties of 0, 1 and 2dB.

Figure 4.6 shows the evaluation results for a classification approach when a wireless microphone signal is present in 16 MHz channel bandwidth. The result clearly indicates that above 90% of the received signals are correctly classified at $SNR = -14$ dB and above. Without noise uncertainty a wireless microphone user is identified with the probability of 90% and 100% probability of the correct classification are achieved at -14dB and -12dB respectively. In the case of 1 dB noise uncertainty 90% and 100% probability of correct classification are achieved at SNR of -13dB and -9dB respectively. For 2dB noise uncertainty 100 % probability of correct classification is achieved at the SNR of -10dB. The wireless microphone signal is detected and located at $f_0 = 0, \alpha_0 = \pm 72.1\,MHz$ and $f_0 = \pm 36\,MHz, \alpha_0 = 0$. The *SNR* performance of the system degrades by nearly 2 dB in this scenario.

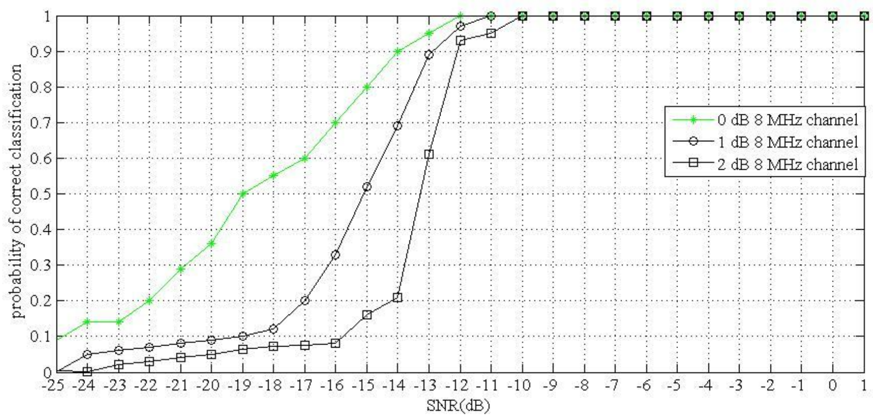


Figure 4.6: Classification approach performance for wireless microphone at 8MHz channel under noise uncertainties of 0, 1 and 2dB.

4.3 Power Spectrum and detection of simulated Primary Signals

In this section, the multiresolution sensing scheme as mentioned in Section 3.4.2 is demonstrated; six cases with different channel occupancy are assumed. First the time response of the received signal is plotted. Then, the power spectra of those cases are depicted and the performance of the proposed algorithm is tested. In all the six cases, one wireless microphone signal is assumed to be present. It is also assumed to have the weakest signal level.

4.3.1 Case1: When 25% of the Radio Spectrum is densely populated By the Primary

The received signal $r(t)$ contains a wireless microphone signal $x_{FM}(t)$described in Section 2.4.2, DVB-T signal $s(t)$ described in Section 2.4.4.1 and additive white Gaussian noise $w(t)$, we have

$$r(t) = s(t) + x_{FM}(t) + w(t) \tag{4.1}$$

In this case 25% of the radio spectrum is densely occupied by the primary users. The location of the primary user's signals are fixed as f = 28, 36, 44, 52 MHz. Figure 4.7a shows the time response using a direct simulation of Eq.(5.1) and Figure 4.7b shows the received signal at the CPE using the FFT scheme. Since center frequencies are 28, 36, 44 and 52 MHz, we anticipate the energy of channel 4, 5, 6, and 7 to be more than other channels.

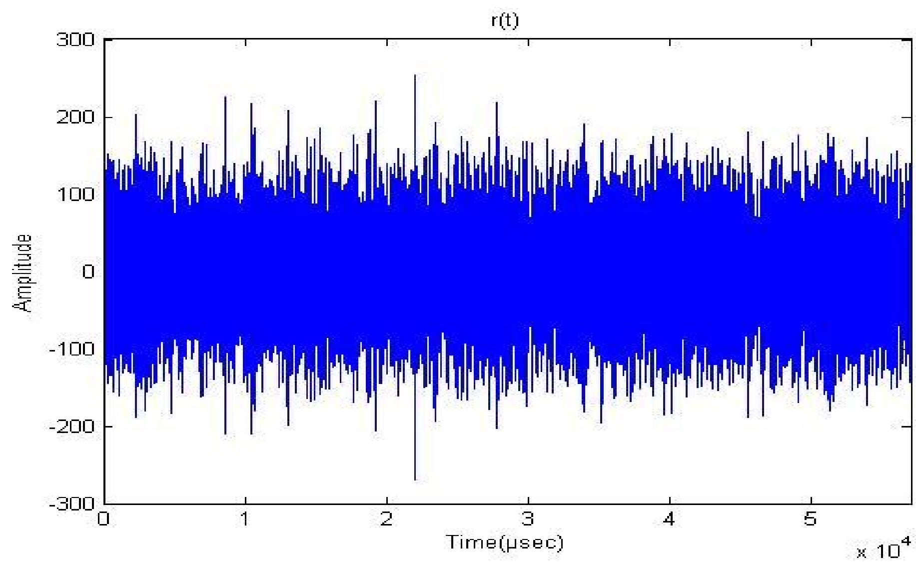


Figure 4.7a: Time response of the received signal over AWGN and SNR = 1dB

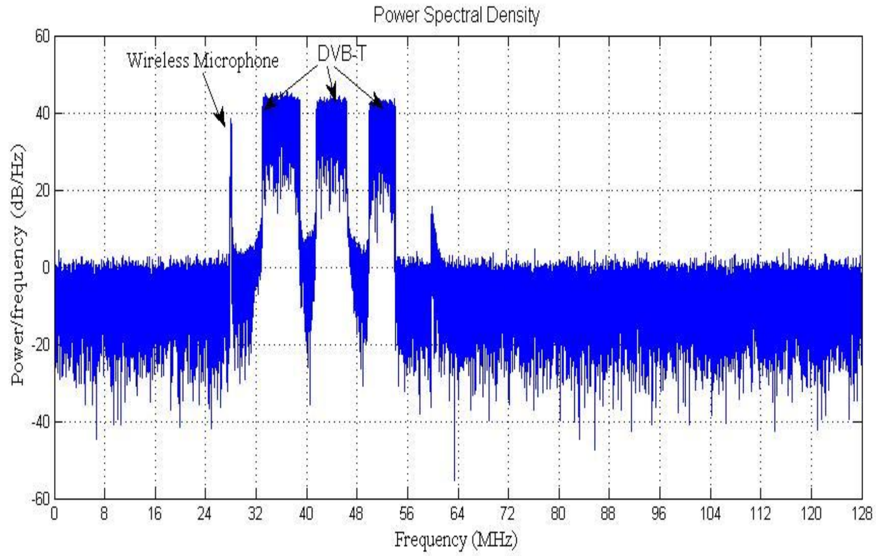


Figure 4.7b: Received signal at CPE

The energy of the received signal at the input of the detector is calculated and Figure 4.8 shows the energy of the received signal at the input of the proposed technique.

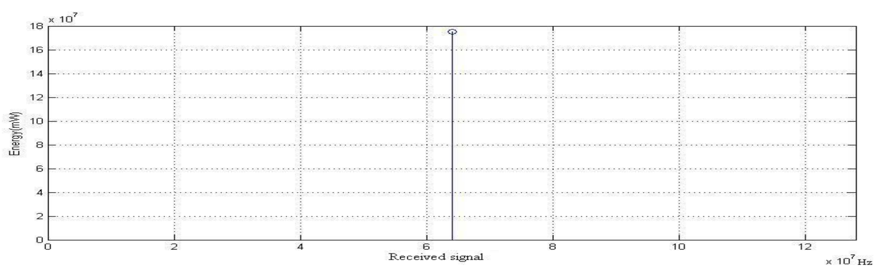


Figure 4.8: The energy of the channel at the input of the proposed technique

The received signal is decomposed using DWT and the energy of each channel is calculated and Figure 4.9 shows the energy of the channel at the first level of decomposition.

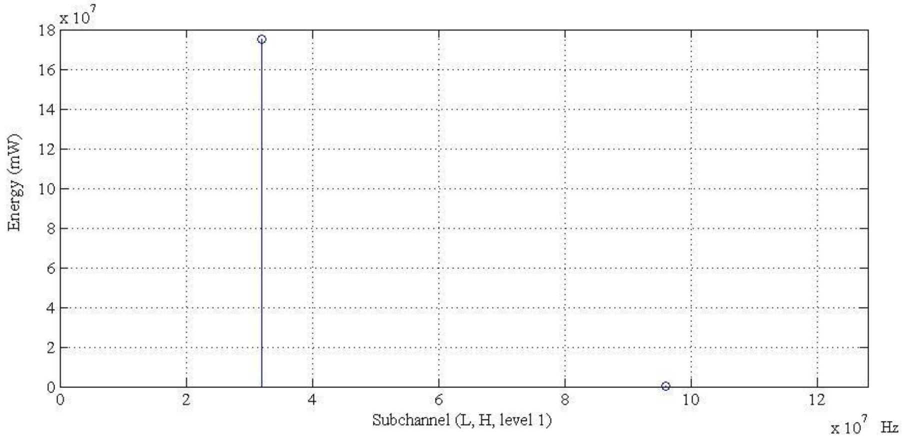


Figure 4.9: The energy of the channel at the first level of decomposition

Channel H has been found with negligible sub-band energy. The spectral correlation of the channels indexes with negligible sub-band energy is computed. At channel H, the spectral correlation of the noise is found which is uniquely large at cyclic frequency equals to zero compared to that at other cyclic frequencies as shown in Figure 4.10. In addition, channel L with large sub-band energy is decomposed again using DWT and Figure 4.11 shows the energy of the channel at the second level of decomposition.

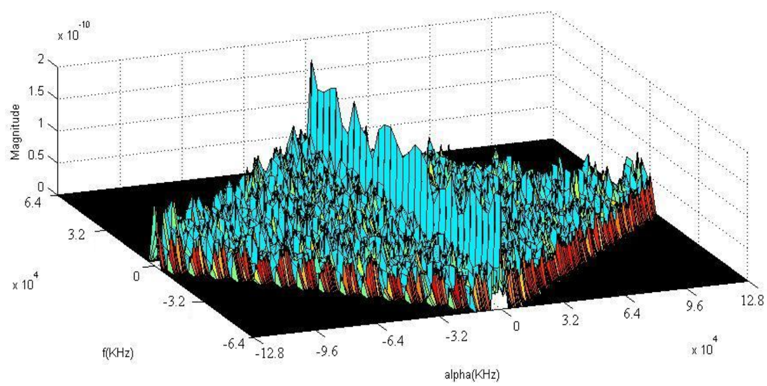


Figure 4.10: Surface plot of the SCF estimate for noise signal, channel H

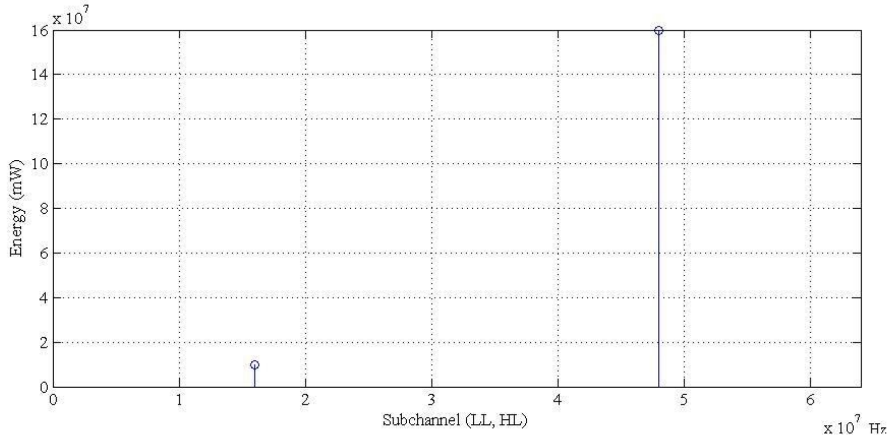


Figure 4.11: The energy of the channel at the second level of decomposition of channel L

Channel LL has been found with small sub-band energy. The spectral correlation of the channel index with small sub-band energy is computed. A sinusoidal signal at the frequency of f_c is found to have four peaks in the SCF as shown in Figure 4.12.

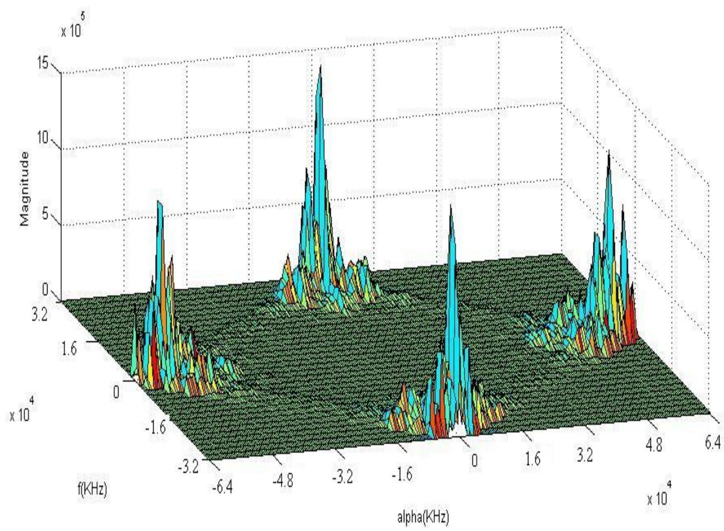


Figure 4.12: Surface plot of the SCF estimate for wireless microphone signal, channel LL

The channel LH with large sub-band energy is decomposed and the energy in each sub-band is calculated. Figure 4.13 and Figure 4.14 show the energy of channel at the third and fourth level of decomposition.

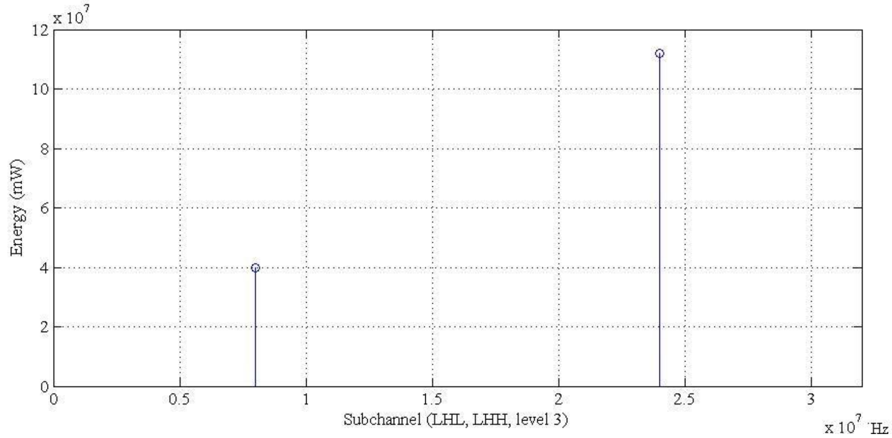


Figure 4.13: The energy of the channels at the third level of decomposition

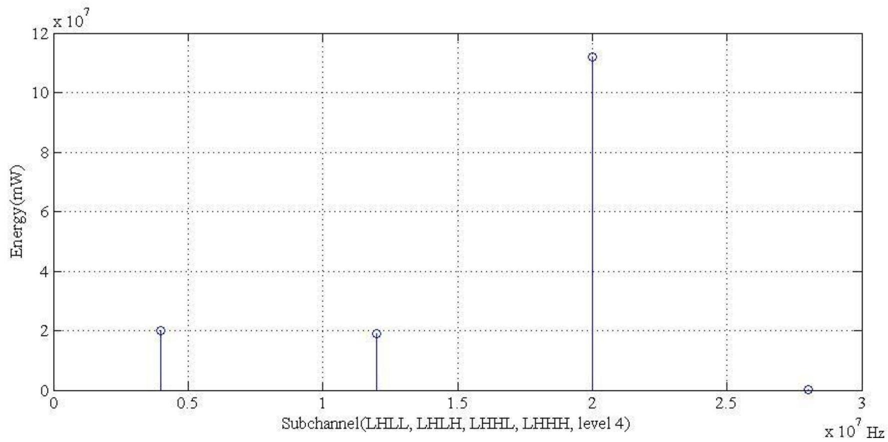


Figure 4.14: The energy of the channels at the fourth level of decomposition

Channel LHHH has been found with negligible sub-band energy. The spectral correlation of the channels index with negligible sub-band energy is computed. At channel LHHH, the spectral correlation of the noise is found which is uniquely large at a cyclic frequency α equals to zero compared to that at other cyclic frequencies as shown in Figure 4.15.

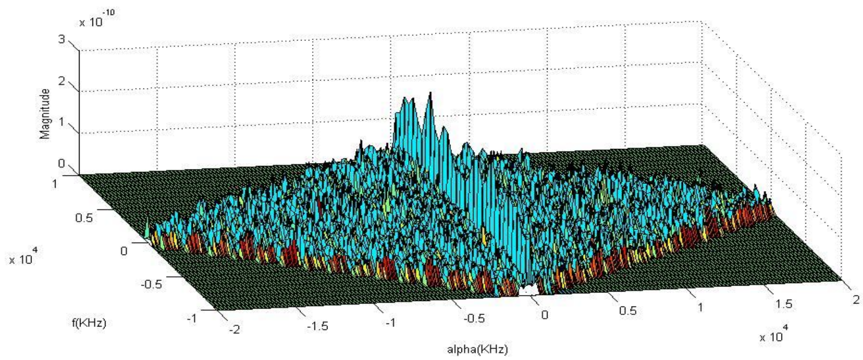


Figure 4.15: Surface plot of the SCF estimate for noise signal, channel LHHH

From the obtained result, the number and the block sizes of data where cyclostationary features are computed and similarly those that are used in energy detectors are summarized in Table 4.1.

Table 4.1: Number and block sizes required when 25% of the radio spectrum is densely populated by the primary users

25% of the radio spectrum is densely populated by the primary users					
Funct. Operation	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Total**
Energy	2	2	2	4	10
SCF	1	1	0	1	3

4.3.1.1 Computational Complexity of spectral correlation at each level of decomposition of the proposed scheme

The computational complexity of the spectral correlation at each level of decomposition in the proposed scheme can be calculated as follows:

For example, assuming the number of data to be computed is N= 2048, and for fs =65536 Hz, $\Delta f = 256$ Hz, $\Delta\alpha = 64$Hz and L=16, using Eq.(2.19) and Eq.(2.20), N' and P can be calculated and they are N'=256 and P=64 (both are approximated to be power of two) using Table 2.5 for these calculated values, the real multiplication required for the five stages of each detector at the first level of decomposition is 6400 and real addition is 7936. The complete results are summarized in the Table 4.2

Table 4.2: Complexity analysis of the Cyclostationary Feature detector per block at each level of decomposition

Complexity of SCF detector per block				
Function / Operation	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Real multiplication	6400	3456	2112	1504
Real addition	7936	4224	2560	1824

It can be seen that the computational complexity of cyclostationary feature detector per block at coarse resolution is much higher than that of finer resolution.

4.3.1.2 Computational Complexity of the energy detector successive level of decomposition

Similarly, the computational complexity of the energy detector at each level of decomposition of the proposed scheme is calculated and summarized in Table 4.3 using the equation of energy detector in Section 2.5.2.1.

Table 4.3: Computational Complexity of energy detector per block at different levels of decomposition of the proposed scheme

Complexity of energy detector per block, N = 2048				
Function / Operation	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Real multiplication	4096	2048	1024	512
Real addition	4094	2046	1022	510

4.3.1.3 Complexity of the proposed scheme when 25 % of the radio spectrum is densely populated by the primary users

The results in Table 4.1, Table 4.2 and Table 4.3 are used to compute the over all complexity of the proposed multi-resolution spectrum sensing scheme when 25% of the radio spectrum is densely populated by the primary users and the result is summarized in Table 4.4.

Table 4.4: Computational complexity of the proposed scheme when 25 % of the radio spectrum is densely populated by the primary users

Operation / Function	**Real multiplication**	**Real addition**
25% Densely populated	26240	28524

The performance of the proposed scheme using the present scenario will be discussed in the next section.

4.3.1.4 Lowest SNR for 90% classification at given noise uncertainty when 25% of the radio spectrum is densely populated by the primary user

The wireless microphone signal is detected at 32 MHz bandwidth as shown in Figure 4.12. The results of classifying wireless microphone signal at lowest SNR for 90% classification at given noise uncertainty gave similar result to the result obtained in Section 4.2.2 when the wireless microphone signal was present in 32 MHZ band. The result obtained for minimum SNR_{min} = - 8 dB can be adopted from Section 4.2.2 when the wireless microphone signal was present at 32 MHz bandwidth.

As the threshold value is set above a statistically insignificant peak, when noise signals are present at the received side, no candidate primary users are detected. As a result, the probability of a correct classification for the overall channels with a noise signature equal to zero, $P_c = 0$. It means that, there is no signal, only noise exists in channels H and LHHH. These channels can be used by a cognitive radio without causing harmful interference to the primary users. The proposed algorithm detects and locates the unoccupied band in one step, so 50% of the radio spectrum is saved from unnecessary computation.

Here are some conclusions that can be drawn about the behavior of the proposed multi-resolution spectrum sensing scheme when 25 % of the radio spectrum is densely populated by the primary users.

- It detects and locates the wireless microphone signal within the wideband of interest.
- It locates the unused spectrum in one step of decomposition, so 50% of the radio spectrum is saved from the unnecessary computation, while the fixed energy detector requires four levels of decomposition to detect and locate the unused spectrum.
- It requires 10 and 2 blocks of different size of energy and cyclostationary features detector respectively.
- It requires 26240 real multiplications and 28524 real additions.
- It classifies 90% of the received signals at the $SNR = -8\,\text{dB}$ and above when the primary user signal is present in 32 MHz channel bandwidth.

4.3.2 Case 2: When 25% of the Radio Spectrum is populated By the Primary Users in Distributed Manner

In this case 25 % of the radio spectrum is occupied by the primary users in a distributive manner. The location of the primary user's signals are fixed as *f*=4, 36, 52, 68 MHz. Figure 4.16 shows the received signal at the CPE using the FFT scheme. Since center frequencies are 4, 36, 52 and 68 MHz, we anticipate the energy of channel 1, 5, 7, and 9 is more than that of other channels.

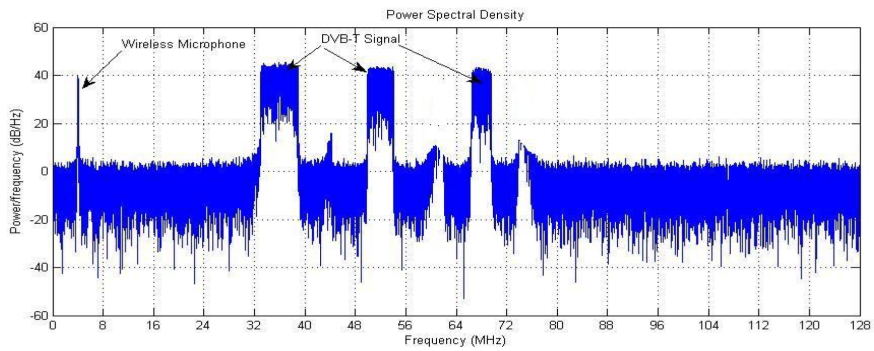


Figure 4.16: Received signal at CPE

From the result obtained the number of block size of cyclostationary features and energy detectors required in the proposed scenario is summarized in Table 4.5.

Table 4.5: Number of block size required when 25% of the radio spectrum is populated in a distributed manner

25% of the radio spectrum is populated in distributed manner					
	Level 1	**Level 2**	**Level 3**	**Level 4**	**Total**
Energy	2	4	4	6	16
SCF	0	2	1	3	6

The computational complexity of the cyclostationary feature and energy detector block size at each level of decomposition will be calculated in the next section.

4.3.2.1 Complexity of the proposed scheme when 25% of the radio spectrum is populated in distributed manner

The results shown in Table 4.2, Table 4.3 and Table 4.5 are used to compute the overall complexity of the proposed multi-resolution spectrum sensing scheme when 25% of the radio spectrum is populated by the primary users in a distributed manner and the result is summarized in Table 4.6.

Table 4.6: Computation complexity of the proposed scheme when 25 % of the radio spectrum is populated in distributed manner

Operation / Function	Real multiplication	Real addition
25% Distributed primary user's	37088	40000

4.3.2.2 Lowest SNR for 90% classification at given noise uncertainty when 25% of the radio spectrum is occupied by the primary users in distributed manner

In this scenario, the wireless microphone signal is detected at 32 MHZ bandwidth. The results of classifying wireless microphone signal gave similar result to the result obtained in Section 4.2.2 when the wireless microphone signal was present at 32 MHz bandwidth. The result obtained a minimum SNR_{min} = - 8 dB can thus be adopted from Section 4.2.2 in a manner similar to the last example.

4.3.3 Case 3: when 50% of the radio spectrum is densely populated by the primary users

In this case 50 % of the radio spectrum is densely populated the primary users. The location of the primary user's signals are fixed as f = 36, 44, 52, 60, 68, 76, 84, 92 MHz. Figure 4.17 shows the received signal at the CPE using the FFT scheme. Since center frequencies are 36, 44, 52, 60, 68, 76, 84, 92 MHz, we anticipate the energy of channels 5, 6, 7, 8, 9, 10, 11, and 12 to be more than other channels.

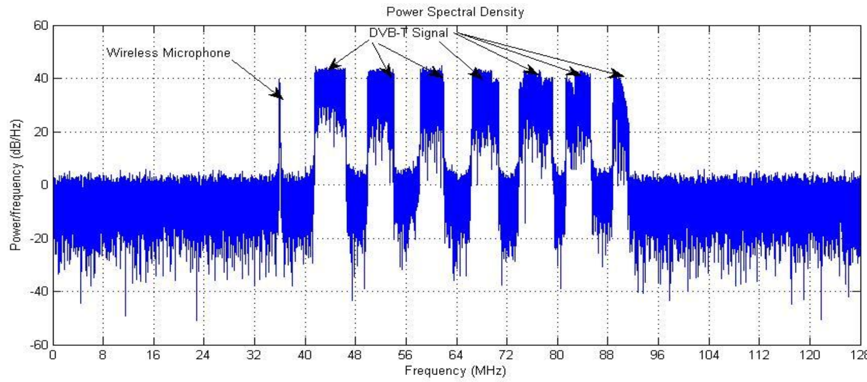


Figure 4.17: Received signal at CPE

From the result obtained the number of block size of energy and cyclostationary features detectors required in the proposed scheme are summarized in the Table 4-7.

Table 4.7: Number of block size when 50% of the radio spectrum is densely populated by the primary users

50% of the radio spectrum is densely populated by the primary users					
Funct. / operation	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Total**
Energy	2	4	6	10	22
SCF	0	1	1	1	3

4.3.3.1 Complexity of the proposed scheme when 50 % of the radio spectrum is densely populated by the primary users

The results in Table 4.2, Table 4.3 and Table 4.7 are used to compute the overall complexity of the proposed multi-resolution spectrum sensing scheme for the case when 50% of the radio spectrum is densely populated by the primary users and the result is summarized in Table 4.8.

Table 4.8: Computation complexity of the proposed scheme when 50 % of the radio spectrum is densely populated by the primary users

Operation / Function	Real multiplication	Real addition
50% Densely populated	34720	36216

4.3.3.2 Lowest SNR for 90% classification at given noise uncertainty when 50% of the radio spectrum is densely populated by the primary user

In this scenario, the wireless microphone signal is detected at 8 MHZ bandwidth. The results of classifying wireless microphone signal gave similar result to the result obtained in Section 4.2.2. The obtained result of minimum SNR_{min} = - 14 dB can be borrowed from Section 4.2.2 when the wireless microphone signal was present in 8 MHz bandwidth.

4.3.4 Case 4: when 50% of the radio spectrum is populated in a distributed manner

In this case 50 % of the radio spectrum is occupied by the primary users in distributive manner. The location of the primary user's signals are fixed as f =20, 36, 44, 60, 76, 92, 100, 116 MHz and. Figure 4.18 shows the received signal at the CPE using the FFT scheme. Since center frequencies are 20, 36, 44, 60, 76, 92, 100, 116 MHz, we anticipate the energy of channels 3, 5, 6, 8, 10, 12, 13, and 15 is more than that of other channels.

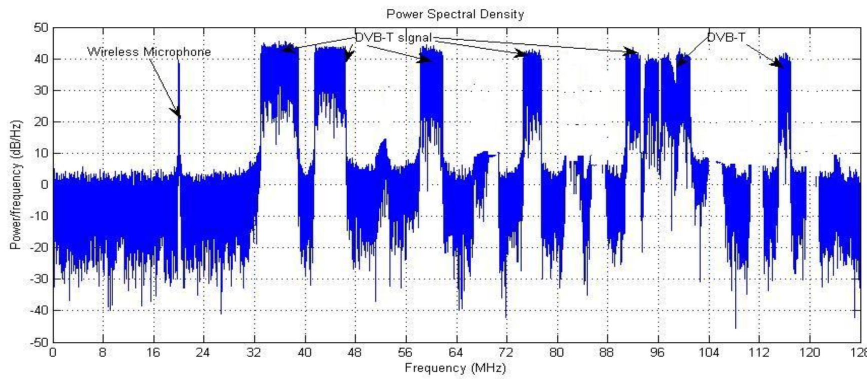


Figure 4.18: Received signal at CPE

From the result obtained the number of block size of energy and cyclostationary features detectors required in the proposed scheme are summarized in the Table 4-9.

Table 4.9: Number of block size when 50% of the radio spectrum is populated in a distributed manner

50% of the radio spectrum is populated in distributed manner					
Funct. / Operation	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Total**
Energy	2	4	6	12	24
SCF	0	1	0	5	6

4.3.4.1 *Complexity of the proposed scheme when 50% of the radio spectrum is populated in a distributed manner*

The results in Table 4.2, Table 4.3 and Table 4.9 are used to compute the overall complexity of the proposed multi-resolution spectrum sensing scheme when 50% of the radio spectrum is populated in distributed manner and the obtained result is summarized in Table 4.10.

Table 4.10: Computation complexity of the proposed scheme when 50 % of the radio spectrum is populated in a distributed manner

Function \ Operation	Real multiplication	Real addition
50 % Distributed primary user's	39648	41968

4.3.4.2 *Lowest SNR for 90% classification at given noise uncertainty when 50% of the radio spectrum is occupied by the primary user in distributed manner*

In this scenario the wireless microphone signal is detected at 32 MHZ bandwidth. The results of classifying wireless microphone signal gave similar result to the obtained result in section 4.2.2. The obtained result of minimum SNR_{min} = - 8 dB can be adopted from Section 4.2.2 when the wireless microphone signal was present in 32 MHz bandwidth.

4.3.5 Case 5: when 80% of the radio spectrum is densely populated by the primary users

In this case 80 % of the radio spectrum is densely populated by the primary users and the location of the primary users' signals are fixed as f=28, 36, 44, 52, 60, 68,76, 84, 92, 100, 108 MHz. Figure 4.19 shows the received signal at the CPE using the FFT scheme. Since center frequencies are 28, 36, 44, 52, 60, 68, 76, 84, 96, 100, and 108 MHz, we anticipate the energy of channels 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, and 14 to be more than that of other channels'

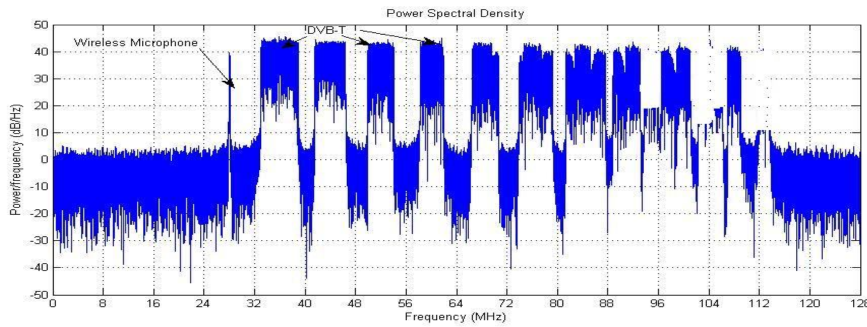


Figure 4.19: Received signal at CPE

From the result obtained the number of block size of energy and cyclostationary feature detector required in the proposed scenario is summarized in the Table 4.11.

Table 4.11: Number of block size when 80% of the radio spectrum is densely populated by the primary users

80% of the radio spectrum is densely populated by the primary users					
Funct. / Operation	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Total**
Energy	2	4	6	10	22
SCF	0	1	1	0	2

4.3.5.1 Complexity of the proposed scheme when 80% of the radio spectrum is densely populated by the primary users

The results shown in Table 4.2, Table 4.3 and Table 4.11 are used to compute the overall complexity of the proposed multi-resolution spectrum sensing scheme when 80% of the radio spectrum is densely populated by the primary users and the obtained result is summarized in Table 4.12.

Table 4.12: Computation complexity of the proposed scheme when 80 % of the radio spectrum is densely populated by the primary users

Operation / Function	Real multiplication	Real addition
80 % Densely populated	39648	41968

4.3.5.2 Lowest SNR for 90% classification at given noise uncertainty when 80% of the radio spectrum is densely populated by the primary user

In this scenario, the wireless microphone signal is detected at 32 MHZ bandwidth. The results of classifying wireless microphone signal gave similar result as in Section 4.2.2. The obtained result of minimum SNR_{min} = - 8 dB can be adopted from Section 4.2.2 when the wireless microphone signal was present in 32 MHz bandwidth.

4.3.6 Case 6: when 80% of the radio spectrum is populated by the primary users in distributed manner

In this case 80 % of the radio spectrum is occupied by the primary users in distributive manner and the location of the primary user's signals are fixed as f =12, 36, 44, 52, 60, 76, 84, 92, 100, 108, 124 MHz. Figure 4.20 shows the received signal at the CPE using the FFT scheme. Since center frequencies are 12, 36, 44, 52, 60, 76, 84, 92, 100, 108, and 124 MHz, we anticipate the energy of channels 2, 5, 6, 7, 8, 10, 11, 12, 13, 14, and 16 to be more than that of other channels.

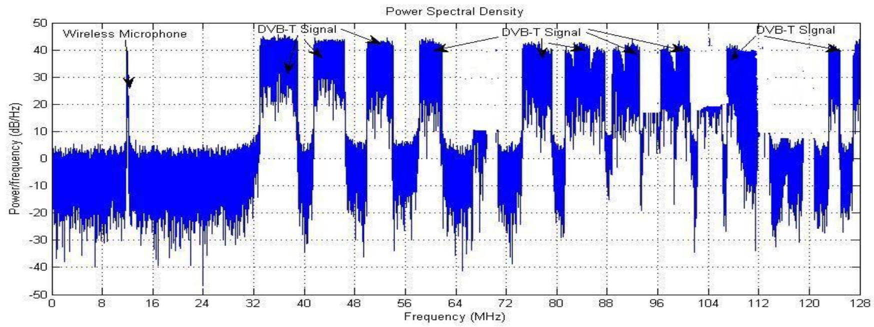


Figure 4.20: Received signal at CPE

From the result obtained the number of block size of energy detector and cyclostationary feature detector required in the proposed scenario is summarized in the Table 4.13.

Table 4.13: Number of block size when 80% of the radio spectrum is populated in a distributed manner

80% of the radio spectrum is populated in a distributed manner					
Funct. / **Operation**	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Total**
Energy	2	4	8	12	24
SCF	0	0	2	2	4

4.3.6.1 Complexity of the proposed scheme when 80% of the radio spectrum is populated in a distributed manner

The results in Table 4.2, Table 4.3 and Table 4.13 are used to compute the overall complexity of the proposed multi-resolution spectrum sensing scheme when 80% of the radio spectrum is populated in a distributed manner and the obtained result is summarized in Table 4.1.

Table 4.14: Computation complexity of the proposed scheme when 80 % of the radio spectrum is populated in distributed manner

Operation / Function	Real multiplication	Real addition
80 % Distributed primary user's	37952	39440

4.3.6.2 Lowest SNR for 90% classification at given noise uncertainty when 80% of the radio spectrum is occupied by the primary user in distributed manner

In this scenario, the wireless microphone signal is detected at 16 MHZ bandwidth. The results of classifying wireless microphone signal gave similar result as in Section 4.2.2. The obtained result of minimum SNR_{min} = - 10.8 dB can be adopted from Section 4.2.2 when the wireless microphone signal was present at 16 MHz bandwidth.

4.3.7 Summary Analysis of the Complexity of proposed MR algorithm

An analysis of the number of mathematical operations (considers only real multiplication) needed in the proposed technique shows the complexity analysis of the proposed scheme and is compared with those of the fixed energy detector, multi-resolution energy detector and brute force cyclostationary feature detector. For the six cases mentioned before, the results are summarized in the Table 4.15.

Table 4.15: Complexity analysis of the result

	Proposed technique		Fixed energy detector		MRSS-energy detector		Brute force SCF	
	Real Mult	**Minimum SNR 90%**	**Real mult**	**Min SNR 90%**	**Real mult.**	**Min SNR 90%**	**Real mult.**	**Minimum SNR 90%**
25% densely populated	26240	-8dB and above	32768	NA	16384	NA	408640	-14dB and above
50% densely populated	34720	-14dB and above	32768	NA	27648	NA	408640	-14dB and above
80% densely populated	33216	-8dB and above	32768	NA	27648	NA	408640	-14 dB and above
25% distributed	37088	-8dB and above	32768	NA	23552	NA	408640	-14dB and above
50% distributed	39648	-8dB and above	32768	NA	28672	NA	408640	-14dB and above
80% distributed	37952	-10.8dB and above	32768	NA	30720	NA	408640	-14 dB and above

The results obtained shows that the proposed MRSS scheme when 25% of the radio spectrum is densely populated by the primary users achieves lowest SNR for 90% classification at -8 dB while the brute-force with the same condition achieves it at -14 dB and it is not applicable (NA) for the fixed energy detector and the MRSS based energy detector. However, the computational complexity of the brute force SCF is sixteen times the proposed MRSS scheme. When 25% of the radio spectrum is populated in distributed manner the proposed MRSS scheme achieves lowest SNR for 90% classification approach at -10.8 dB while the brute-force SCF achieves it at -14 dB. However, the computational complexity of brute force is about thirteen times the proposed MRSS scheme. The results clearly indicate that the proposed MRSS scheme has poorest minimum SNR at -8 dB and the best minimum SNR at -14 dB. More general information will be shown below.

Furthermore, the results of Table 4.15 are also plotted in a graph. Additionally, the graph contains a more complete study where the spectral occupancy of both distributed and dense manner is varied every 5% and the computational complexity of the proposed MR algorithm is obtained. Figure 4.21 shows the graph containing the comparative results of computational complexity as a function of fractional occupancy comparison between the proposed MRSS scheme, the MRSS energy detector, the fixed energy detector, and the brute force SCF.

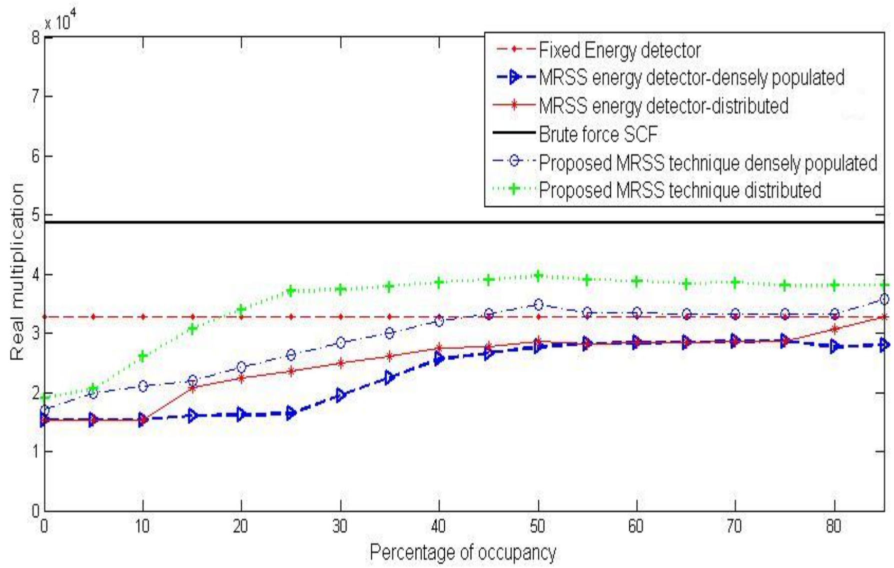


Figure 4.21: Computational complexity

From the above results, the total number of real multiplications of the proposed MRSS scheme is less than the fixed energy detector and brute force SCF when 25% of the radio spectrum is densely populated by the primary users' and 15% in the case of a distributed scenario but greater than the MRSS energy detector over the all range of occupancy. It is shown that the savings can be considerable when the number of primary users' is small and not distributed. For example, when only 4 out of 16 are present in the wideband of interest in densely manner the total cost of the proposed

MRSS scheme is the complexity of coarse plus the complexity of the fine, totally about 26240 real number of multiplication. Comparing this with the fixed energy detector, it offers above 19% saving. However, this savings will diminish with the increasing number of primary users in the wideband of interest. The breakeven point is when 42 % of the total bandwidth is densely populated by the primary users. Beyond this the complexity of the proposed scheme will exceed the fixed energy and the MRSS energy detector but outperform the brute force SCF. For example, when 50% of the radio spectrum is populated by the primary users the complexity of the proposed scheme is greater than the MRSS energy detector and falls in between the fixed energy detector and the brute force SCF. When 80% of the radio spectrum is densely populated by the primary users, the proposed MRSS scheme has almost the same complexity with the fixed energy detection and fall in between the MRSS energy detector and the brute force SCF. When 80% of the radio spectrum is populated by the primary users in distributed manner the total real multiplication of the proposed MRSS scheme is greater than the MRSS energy detector and the fixed energy detector but less than the brute force SCF. The proposed algorithm reduces the complexity and makes the spectrum sensing faster and more reliable using the property of multi-resolution and the theory of cyclostationary feature for cognitive radio application.

4.3.7.1 Over all Analysis of the proposed scheme

Here are some conclusions that can be drawn about the behavior of the proposed multi-resolution spectrum sensing scheme.

The results clearly show that the proposed scheme is beneficial in the following aspect:

- It avoids sensing the band with fixed aspect.
- It identifies and locates the channels in which primary users exist in and also it can easily select the unoccupied candidate channels with one step when 25% of the radio spectrum is densely populated by primary users and requires two to four steps when 25% (distributive), 50%, and 80 % of the radio spectrum is populated by primary users while, on the other hand, the energy detector

cannot identify the type of primary users which is present in the given channel and require four steps to detect primary users which are present on the given channel.

- It works faster and is more reliable than the fixed energy detector because it is dependent on the quickness of multi-resolution and the reliability of cyclostationary feature.
- It increases the performance in the low *SNR* environment and above 90% signals are correctly classified as SNR= -8 dB and above when the primary user signal is present in 32 MHz. In addition, above 90% of the signals are correctly classified at SNR= -14 dB and above when the primary users signal is present 8 MHz Channels.
- Reducing the complexity is another improvement. Specifically the proposed MRSS scheme performs the decomposition of the received signal not only to the final level but to the $n = 4$ level.

It is also seen that, as compared to energy based MRSS technique, the proposed technique is computationally more expensive. This however is offset by the advantage of better classification of the proposed technique.

4.4 Summary

In this chapter, the proposed algorithm described in Chapter 3 is evaluated over an AWGN with fixed noise uncertainties. DVB-T and wireless microphone signals are simulated using Matlab®. The performance of the proposed scheme has been evaluated by probability of correct classification under noise uncertainties of 0, 1, 2 dB and the computational complexity. The evaluation results clearly show that the performance can be achieved by the application of the proposed scheme especially in a low SNR environment. It detects and locates the primary signals of interest and the unused radio spectrum within the bandwidth of interest. It works faster and is more reliable than the fixed energy detector as it is dependent on the property of multi-resolution and the robustness of cyclostationary features detector. Finally, this work has demonstrated that, by combining the simplicity of the energy detector and the robustness of the cyclostationary feature detector within the multiresolution format, it can offer improvement in the radio spectrum sensing for cognitive radio application.

In the next chapter, we will conclude the entire work of this thesis and recommend future work that can be carried out.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Introduction

In the previous chapters, the proposed multi-resolution spectrum sensing scheme has been described and the performance results thereof presented. This technique is inspired by the quickness of the multi-resolution and the reliability of cyclostationary features detector. In this chapter, we conclude the entire work of this thesis and suggest future work for further research.

5.2 Conclusion

The demand of wireless communication has grown remarkably in the last thirty years, consequently causing an acute problem of spectrum scarcity. Today, it is one of the most challenging problems in modern wireless communication. To overcome this, the concept of cognitive radio has been proposed and this technology is fast maturing. It is shown that the first and foremost function a cognitive radio must do is to sense the spectrum as accurately as possible and do it with lowest complexity. Since the spectrum sensing is the fundamental requirement for CR, we have explained some of the existing methods of spectrum sensing such as matched filter based spectrum sensing, energy detector based spectrum sensing, cyclostationary feature based spectrum sensing and multi-resolution spectrum sensing. It has been shown that multi-resolution sensing is a popular technique in the recent literature. It is also shown that various signal detection techniques have been proposed for multi-resolution spectrum sensing technique. None of these techniques, however, use multi-resolution using cyclostationary feature for CR application which is more reliable.

In this thesis, the cyclostationary feature based low complexity multi-resolution spectrum sensing technique for cognitive radio application is proposed. The main focus is on developing quick and reliable algorithms for spectrum sensing. It is shown that the technique proposed is inspired by the quickness of multi-resolution and the reliability of the cyclostationary features detector. An important observation is made: first, a coarse resolution sensing is done by computing the energy of each sub-band and only the sub-band with larger energy is needed for fine resolution. Second, the cyclostationary feature detection is only performed for the channel indexes with small and negligible sub-band energy to identify the type of signal used in the given band. In order to make better spectrum sensing and utilization, a suitable RFE for the proposed sensing technique is provided to give a complete understanding of the CR spectrum sensing problem. RFE architecture is also a critical design issue in the CR and the work will not be complete without proposing an appropriate architecture for CR application. For any detection problem, noise is usually the main impairment, therefore the impact of noise and also the noise uncertainty considered. The flowchart and the experiment methodology for the proposed technique are also explained. The following experiment methodology was adopted for this work:

- The received signal is down-converted and sampled in the RFE of the sensing receiver.
- The thresholds values are set for fixed $P_{fa} = 10\%$ by applying the test statistics of the algorithm to WGN for different values of noise uncertainties.
- The cumulative distribution function (*CDF*) of the test statistics is used to set the threshold values for $P_{fa} = 10\%$.
- The flowchart of the proposed multi-resolution spectrum sensing approach is applied to the received signal with AWGN for different values of noise uncertainties.
- The complexity of the system is analyzed in comparison with fixed energy detector, brute force cyclostationary feature detector and MRSS energy detector.
- To create a graph of probability of correct classification versus SNR, we plotted a series of points. Each of these points required us to run a simulation at specific value of SNR averaged over 300 trials.

MATLAB® simulation is used to simulate the PUs signals and also used to evaluate the overall performance of the system. The results obtained clearly indicate that better performance can be achieved by the proposed scheme in even in lowest SNR environment under noise uncertainties. In addition, the proposed technique is the only technique which is able to detect the empty band when only a wireless microphone is present in the given band. It works faster and is more reliable than fixed energy detector and brute force cyclostationary because it is dependent on the quickness of the multi-resolution and the reliability of cyclostationary features. The results clearly indicate that the proposed scheme is beneficial in the following aspect:

- It avoids sensing the band with fixed aspect.
- It identifies and locates the channels in which primary users exist in and also it easily selects the unoccupied candidate channels with one step when 25% of the radio spectrum is densely populated by primary users and requires two to four steps when 25% (distributive), 50%, and 80 % of the radio spectrum is populated by primary users. The energy detector however cannot identify the type of primary users which is present in the given channel and requires four steps to detect primary users which are present on the given channel.
- The computational complexity for densely populated scenario in all cases is lower than for the distributed scenario.
- It works faster and is more reliable than the fixed energy detector because it is dependent on the quickness of multi-resolution and the reliability of cyclostationary feature.
- It increases the performance in the low *SNR* environment and above 90% signals are correctly classified as $SNR = -8\,\text{dB}$ and above when the primary user signal is present in 32 MHz. In addition, above 90% of the signals are correctly classified at $SNR = -14\,\text{dB}$ and above when the primary users signal is present 8 MHz Channels.
- Reducing the complexity is another improvement. Specifically the proposed MRSS scheme performs the decomposition of the received signal not only to the final level but to the $n = 4$ level.

The major contributions of this thesis and some future research directions are presented in the following Sections.

5.3 Contribution

Some contributions of this research work are listed below:

- An appropriate RFE compliant with the proposed MR technique for wideband sensing receivers for cognitive radio application is designed.
- A novel multi-resolution sensing strategy and algorithm for CR application to detect and identify the locations of the PUs within the wideband of interest is designed and developed with the following attributes:
    - ✓ Coarse resolution sensing is performed by computing the energy of the lower sub-band and only the sub-band with larger energy is needed for fine sensing.
    - ✓ The spectral correlation function is performed only on the channel indexes with small and negligible sub-band energy.
- A novel strategy is proposed to identify the unoccupied spectrum within the given DVB-T band when only a wireless microphone with 200 KHz bandwidth uses that channel. This is with the purpose that, when wireless microphone, though a primary user, is operating, the remaining spectrum in the band can still be used by the cognitive radio.
- In turn, the proposed technique identifies and locates the unused spectrum within the wideband of interest where primary users are absent.

5.4 Suggested future work

Cognitive radio is an emerging wireless technology that aims to produce a way to utilize the radio spectrum and there are many aspects regarding spectrum sensing that need further research work. Although we have focused on the WRAN standard for CR in this thesis, the proposed method of spectrum sensing can be used for any application in future and can also be applied to any PUs. Public safety communication systems and military systems are other example of the targeted CR based application where spectrum sensing is critical.

In another context of IEEE 802.22 WRAN for CR, we have considered only wireless microphone as the most common part 74 devices in the TV bands. But for real systems, all part 74 devices should be considered.

Accordingly a possible extension of this work is to develop appropriate spectrum sensing algorithms and classification approach for these devices. Examples of Part 74 devices include: professional wireless intercom systems, wireless video assist system and wireless IFB (Interrupted Feedback).

Finally, the proposed multi-resolution spectrum sensing algorithm for cognitive radio applications is to be implemented and tested in real environment. The implementation can both be on an field-programmable gate array (FPGA)-based hardware platform or programmable digital signal processing (DSP) platform. Alternatively, it can also be on an application-specific integrated circuit (ASIC).

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