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## DECLARATION

I, Raveendranadh Anagani here by declare that the work embodied in this dissertation entitled "**FPGA implementation of Cooperative Spectrum Sensing based on Cyclostationary features for Cognitive Radio**" submitted to the University Of Hyderabad, Hyderabad, for partial fulfillment of the degree of M.Tech in Integrated Circuit Technology has been carried out by me under the supervision of Dr.Samrat L. Sabat, School of Physics, University Of Hyderabad. To the best of my knowledge, this work has not been submitted for any other degree in any University.

Raveendranadh Anagani
M.Tech (Integrated Circuit Technology)
Reg.No: 09PIMT04

# FPGA implementation of Cooperative Spectrum Sensing based on Cyclostationary features for Cognitive Radio

A Thesis submitted in the partial fulfillment of the requirements for the award of degree of

Master of Technology
in
Integrated Circuit Technology

by

**Raveendranadh Anagani**
**09PIMT04**

School of Physics
University of Hyderabad
Hyderabad, India

June, 2011

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Hyderabad, India

# CERTIFICATE

This is to certify that the project work "**FPGA implementation of Cooperative Spectrum Sensing based on Cyclostationary features for Cognitive Radio**" carried out by **Mr. Raveendranadh Anagani** bearing the Reg.No. 09PIMT04 under my guidance in partial fulfillment of the requirements for the award of Master of Technology in Integrated Circuit Technology in University of Hyderabad. The matter embodied in this dissertation has not been submitted in any other University for the award of any other degree.

**Dr. Samrat L. Sabat**
Project Supervisor,
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**Prof. C. Bansal**
Dean,
School of Physics,
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*To*

*My Parents*

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**Raveendranadh Anagani**

# Abstract

The Radio spectrum is an indispensable natural resource for evolution of future generation wireless systems. The recent statistical studies on radio spectrum usage have shown that the pre-allocation of spectrum bands to specific wireless communication applications lead to poor utilization of spectrum in terms of different dimensions such as frequency, time and geographical space. Cognitive radio (CR) is an innovative technology to resolve the impending spectral scarcity and under utilization of spectrum. The Main functions of CR are spectrum sensing, spectrum management, spectrum sharing and spectrum mobility. Spectrum sensing is the essential component in the CR functions. The primary objective of spectrum sensing is to detect the presence of signal in a particular band of frequency. This provides more spectrum access opportunities to CR users without interference to the licensed user (Primary user (PU)) networks. The main challenge for spectrum sensing technique is to detect the signal in low signal to noise ratio and fading environment. Several signal processing techniques are being used for spectrum sensing. Each technique has their own merits and demerits.

In this work, spectrum sensing is performed based on Spectral Coherence Function (SCF) and Entropy estimation using cyclostationary features of the received signal. Cyclostationary feature detection technique is studied because of its better sensing ability for low signal to noise ratio (SNR) signals. In addition, recently Entropy based detection is shown as robust method of detection and it is based on the concept that the entropy or uncertainty of the received signal reduces if the received signal is a modulated signal. So we have proposed entropy based detection using cyclostationary properties for spectrum sensing. In this work two different kind of modulated signals are considered such as QPSK, DVB-T under additive white Gaussian noise (AWGN) and Rayleigh fading channel environment as specified in IEEE 802.22 standard for validating the algorithm. Sensing performance of both algorithms are analyzed using Monte-Carlo methods. In practice, sensing performance is often compromised with multipath fading, shadowing and receiver uncertainty issues. To mitigate the impact of these issues, the proposed approach (entropy + cyclostationary) is extended for cooperative sensing using different fusion rules (Hard and Soft decision rules). The performance of proposed entropy detection is compared with SCF detection technique. Simulation result discloses that, Entropy detection algorithm detect signals of signal-to-noise ratio upto -26dB using seven nodes in cooperation for detection probability $P_d \geq 0.9$ and false alarm probability $P_{fa} \leq 0.1$. Whereas, SCF method detects upto -23dB. Sensing algorithm of single node is implemented in Xilinx Virtex4 (XC4VSX35-10FF668) Field Programmable Gate Arrays (FPGA).

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# Abbrevations

ASIC - Application Specific Integrated Circuit
AWGN - Additive White Gaussian Noise
BS - Base Station
CAF - Cyclic Autocorrelation Function
CLB - Configurable Logic Block
CPE - Customer Premises Equipment
CR - Cognitive Radio
CRN - Cognitive Radio Network
DSP - Digital Signal Processing
DVB-T - Digital Video Broadcast for Terrestrial
FCC - Federal Communications Commission
FFT - Fast Fourier Transform
FPGA - Field Programmable Gate Array
HIL - Hardware in the Loop
IOB - Input/Output Block
ISE - Integrated Simulation Environment
Pd - Probability of detection
Pfa - Probability of False Alarm
PU - Primary User
QPSK - Quadrature Phase Shift keying
ROC - Receiver Operating Characteristic
SCF - Spectral Coherence function
SNR - Signal to Noise Ratio
SPTF - Spectrum Policy Task Force
SU - Secondary user
WRAN - Wireless Regional Area Network

## About the CD:

The CD-ROM provided at the end of this dissertation includes all the models of the system generator used in this dissertion, the complete thesis in pdf form, and also includes the MATLAB code used in this work. For details see the related documentation in the CD.

# Chapter 1

# Introduction

## 1.1 Problem definition

In cognitive radio (CR) network, the cognitive users need to sense the spectrum usage by the primary users to dynamically access the unused spectrum. But, in practice the strength of the signal in the channel is very low. Thus, the fundamental problem of spectrum sensing in CR is to discriminate between following binary Hypothesis test.

$H_0 : x(t) = w(t)$

$H_1 : x(t) = hs(t) + w(t)$

Where $H_0$ stands for the absence of the signal, $H_1$ is the presence of signal. $x(t)$ is the received signal by the secondary user. $s(t)$ is the primary users transmitted signal, $w(t)$ is the additive white Gaussian noise (AWGN), and $h$ is the channel gain. This hypothesis is valid if one node is being used for sensing the sectrum.

However due to different effect of channels like fading, shadowing the single node sensing is not reliable. This can be solved by using more than one node in cooperation for sensing the spectrum. Precisely this is known as cooperative spectrum sensing. For this, the above hypothesis can be defined as

$H_0 : x_i(t) = w_i(t), i = 0, 1, \ldots M - 1$

$H_1 : x_i(t) = s_i(t) + w_i(t)$

where, $M$ is the number of nodes in cooperation.

In this work we propose an entropy based cooperative spectrum sensing algorithm using cyclostationary features for detecting the presence of signal in the scanned spectrum. Moreover implementing the algorithm in Field Programmable Gate Array (FPGA) for signal detection for faster and real time detection is one of the challenge for cognitive radio. So the proposed sensing algorithm is also implemented in Xilinx Virtex4 (XC4VSX35-10FF668) FPGA.

## 1.2 Motivation

Wireless communication and its high data rate applications have found an explosive growth in recent years. It has been predicted that in the next five years, about 55% of all users will access wireless internet. Hence the demand of more spectrum resources will increase significantly and it is especially important to manage spectrum resources efficiently. Spectrum is a very costly and limited resource, which has to be used intelligently to meet the requirements. However, according to the recent studies and reports published by Federal Communications Commission (FCC), the pre-allocation of spectrum bands to specific wireless communication applications lead to poor utilization of spectrum interms of different dimensions such as frequency, time, and geographical space [1,2]. It indicates that scarcity of spectrum resources is not due to fundamental lack of spectrum resources, but due to inefficient spectrum allocation. In this situation, the cognitive radio (CR) technology has been proposed as a candidate for improving the efficiency of radio spectrum. To improve the spectrum utilization efficiency, CR system essentially requires dynamic spectrum sensing technique. It can exploit the vacant space (spectrum hole). CR unit should be able to scan the primary user frequency band as quickly as possible with desired accuracy. This requires efficient spectrum sensing techniques. Once a spectrum hole is detected the secondary user can avail that spectrum for communication. During the secondary user in use, if a primary user commences the transmission suddenly, the secondary user has to hop from that band to another empty band. This process is called spectrum hopping (mobility) in CRN. Spectrum hopping and spectrum allocations are out of scope of this thesis [3].

Various spectrum sensing techniques are reported in literature which can be classified basically into energy detection, cyclostationary feature detection and matched filter based detection. Energy detection is based on measuring the energy of the received signal in the desired frequency band and comparing it with a threshold value. It is easy to implement and does not require knowledge about the primary user signal properties. However, it is extremely vulnerable to noise and interference level. Moreover, the energy detection does not differentiate between modulated signals, noise and interference. As an alternative, cyclostationary feature based detection is proposed to exploit the built-in periodicity of modulated signal for primary user detection. The sensing performance of cyclostationary feature detection has been found to be superior as compared to the energy detection technique. Matched filtering is an optimal way for signal detection in communication systems. However, it requires prior knowledge of the licensed user signal which may not be available [4].

The objective of this work is to i) study and implement an efficient spectrum sensing techniques using cyclostationary feature detection algorithm with spectral cohrence method (SCF) method and Entropy method in both non cooperative and cooperative ways ii) compare the perfromance of above algorithms in terms of the minimum SNR that an algorithm can detect with desired level of probability of detection, and maximum frequency of operation. Henceforth to provide the scope for efficient utilization of available spectrum for wireless communication systems.

## 1.3 Technical Approach

The goal of cyclostationary based spectrum sensing is to detect the presence of primary user reliably and find the availability of spectrum hole by using the inbuilt cyclic property of the DVB-T signal. This can be carried out by using either SCF detection or by Entropy detection.

In SCF based cyclostationary spectrum sensing, by deciding a suitable threshold and comparing it with the estimated SCF, and averaging over number of cyclic frequencies, the presence of primary user can be decided. This method requires (i) computation of Autocorrelation function (ii) multiplying it with an exponential signal in order to make it cyclic, (iii) computation of FFT of the cyclic signal for calculating spectral correlation for estimating SCF. Whereas in Entropy based cyclostationary spectrum sensing, the presence of primary user is decided by comparing the threshold with the estimated Entropy based on spectral correlation values. To eliminate the problems due to shadowing and fading, both the techniques are extended for cooperative scheme. The implementation of these techniques in FPGA and validation of cyclostationary detector performance are studied in non cooperative methods. The results obtained in HIL simulation are compared with results obtained from MATLAB.

## 1.4 Field Programmable Gate Array (FPGA)

Field-programmable gate arrays are chips that can be programmed to perform virtually any logic operation. They can be used in place of multiple smaller components such as glue logic, or they can contain large designs such as processors or graphics controllers. Many FPGAs can be reconfigured any number of times making them ideal for design prototyping, and they have recently been replacing ASICs and MPGAs in low-volume productions due to the high initial cost and long turnaround time of these custom manufactured chips. Their high logic capacity and abundance of flip-flops distinguish FPGAs from other kinds of programmable logic devices [5].

### 1.4.1 Internal architecture

FPGA is a two-dimensional array of configurable (programmable) logic blocks along with configurable interconnects between these blocks. Design engineers can configure (program) such devices to perform a variety of tasks. The internal architecture of FPGA is shown in figure 1.1. FPGAs are composed of an array of Configurable Logic Blocks (CLBs) surrounded by a ring of Input/Outputs Blocks (IOBs). The CLBs are the primary building blocks that contain elements for implementing customizable gates, flip flops and wiring for connectivity. The IOBs provide circuitry for communicating signals with external devices.

### 1.4.2 Merits and Demerits

FPGAs have historically been used for a wide variety of signal-processing applications. Many of the reasons for this are quite general, and are advantages that the devices bring to many disciplines, not just signal-processing. FPGAs have a highly adaptable architecture that allows for much different computational architecture. Reconfiguration of the devices permits rapid prototyping and design changes. This in turn can lead to a faster product time-to-market. FPGAs are relatively low-cost, compared to many fixed- architecture alternatives, and allow designs to be created which utilize parallel processing for increased data throughput.

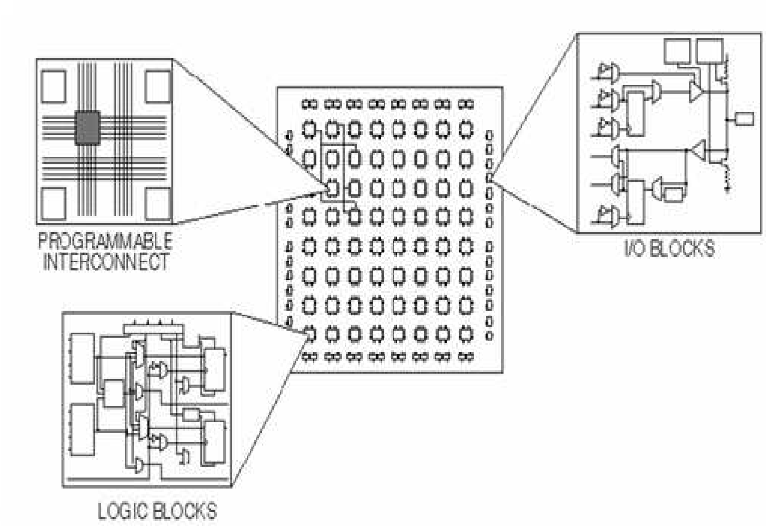


Figure 1.1: Internal Architecture of FPGA [6]

Some of the disadvantages of FPGAs are least efficient use of silicon/wiring resources, Limited size options, Limited performance, Not good for high volume applications, If used for prototyping, still may have significant changes, when migrate to higher performance design and package solution.

### 1.4.3 Virtex4 FPGA

Hardware implementation of spectrum sensing algorithms is performed in virtex4 FPGA board with device XC4VSX35, package: FF668, speed: -10. The resources available in this type FPGA are [7] Number of slices: 15360, Number of slice flip-flops: 30720, Number of 4input LUTs: 30720, Number of bonded IOBs: 448, Number of FIFO16s: 192, Number of GCLKs: 32, Number of DSP48s: 12.

## 1.5 Tools Used

### 1.5.1 MATLAB

MATLAB(matrix laboratory) is a numerical computing environment and fourth-generation programming language. Developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and Fortran.

### 1.5.2 Xilinx ISE

ISE (Integrated Software Environment) design suite is the conjugation of various Xilinxs design tools (software) for logic embedded and DSP applications. It is a powerful yet flexible integrated design environment that allows us to design Xilinx FPGA and CPLD devices from design entry to implementation. It includes a user interface called as project navigator that helps us to manage the entire design process including design entry, simulation, synthesis, implementation, and finally download the configuration into FPGA device [7].

### 1.5.3 Xilinx System Generator (Sysgen)

The Xilinx System Generator for DSP bridges the gap between the high-level abstract version of a design and its actual implementation in a Xilinx FPGA. The System Generator for DSP developed in partnership with Math Works Inc. enables designers to develop high-performance DSP systems for Xilinx FPGAs using the popular MATLAB/Simulink. New capabilities include estimation of FPGA resources from within Simulink, HDL Co-Simulation, Hardware in the loop simulation and real time debugging using chip scope pro as shown in figure 1.2.


Figure 1.2: Performing FPGA Hardware Inloop simulation with Simulink [7]

## 1.6 Hardware in the Loop (HIL) Simulation

Traditionally functional testing of a design is done by giving a set of known inputs and measuring the response of the system to these inputs. Now a days there is more pressure to get products to market faster and reduce design cycle times. This has led to a need for dynamic testing, where designs are tested while in use with the entire system. Because of the cost and safety concerns, simulating the rest of the system with real-time hardware is preferred for testing individual components of in the actual system. Dynamic testing also encompasses a larger range of test conditions compared to static testing. Hardware-in-the-Loop (HIL) verification is one of the dynamic testing strategies used in this work [7].

Advantages of HIL simulation: A hardware subsystem can be tested using HIL simulation without having the entire system ready, thus making testing an effective part of the development process, from design to deployment. Real-time HIL simulations not only enable shorter time to complete the design by reducing the development period, but also reduce cost of testing the design.

## 1.7 Thesis Scope

This thesis is restricted to define SCF and Entropy based cyclostationary algorithms for spectrum sensing in both non-cooperative and cooperative modes and implementation of non-cooperative algorithms in FPGA. The performance of the design is tested for the case of additive white Gaussian noise channel. Algorithmic verification is carried out by MATLAB and HIL simulation in FPGA.

## 1.8 Thesis Structure

This section briefly outlines the contents of each chapter. The dissertation is organized into six chapters. A list of all reference sources consulted is given chapter wise.

**Chapter 1** is an introductory chapter describing technical approach for the need for spectrum sensing and the motivation behind solving this problem. Thesis scope is also included in this chapter. It gives the brief introduction to HIL simulation, FPGAs and the tools used for the work.

**Chapter 2** presents an introduction to cognitive radio standard IEEE 802.22 in the TV band spectrum and different spectrum sensing techniques proposed in literature and compare them.

**Chapter 3** presents an introduction to the SCF based cyclostationary spectrum sensing algorithm in both non-cooperative and cooperative mode. The detection algorithm applied to QPSK and DVB-T signal is discussed.

**Chapter 4** presents an introduction to the Entropy based Cyclostationary spectrum sensing algorithm in both non-cooperative and cooperative mode. The detection algorithm applied to DVB-T signal is discussed.

**Chapter 5** presents the implementation of both SCF based and Entropy based cyclostationary spectrum sensing algorithms in non cooperative mode on FPGA, HIL simulation using system generator and validation of detector performance. The resources utilized/ consumed by this design are also included along with the timing reports and frequency of operation.

**Chapter 6** Conclusions and future efforts needed for this work are presented in this chapter.

## 1.9 References

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# Chapter 2

# Spectrum sensing

## 2.1 Introduction

The recent developments in wireless communication system, demands more radio frequency channels for accomodating new wireless services. But the radio spectrum is a limited resource and has already been allocated to the existing wireless communications; therefore the current radio spectrum is being scarce. The scarcity of radio spectrum is a significant problem for enabling the development of broadband wireless access. The studies [1] found significant available spectrum in most of the bands as shown in figure 2.1 and figure 2.2.

However, the studies of the Federal Communications Commission (FCC) Spectrum Policy Task Force has illustrated that in certain licensed bands below 3 GHz, the usage of spectrum is sparcely used at any given location and time as show in figure 2.3.

On the other hand, the present Wireless systems are characterized by static spectrum allocations, fixed radio functions and limited network coordination. They do not allow different wireless services to share the same radio spectrum even though it is not being used. Thus spectrum access is more significant problem than physical scarcity of spectrum.

The underutilization of some frequency bands opens up the opportunity to identify and exploit spectrum holes. A spectrum hole is defined as a band of frequencies assigned to a primary user, but at a particular time and specific geographic location, the band is not being utilized by that user [3]. If a secondary user

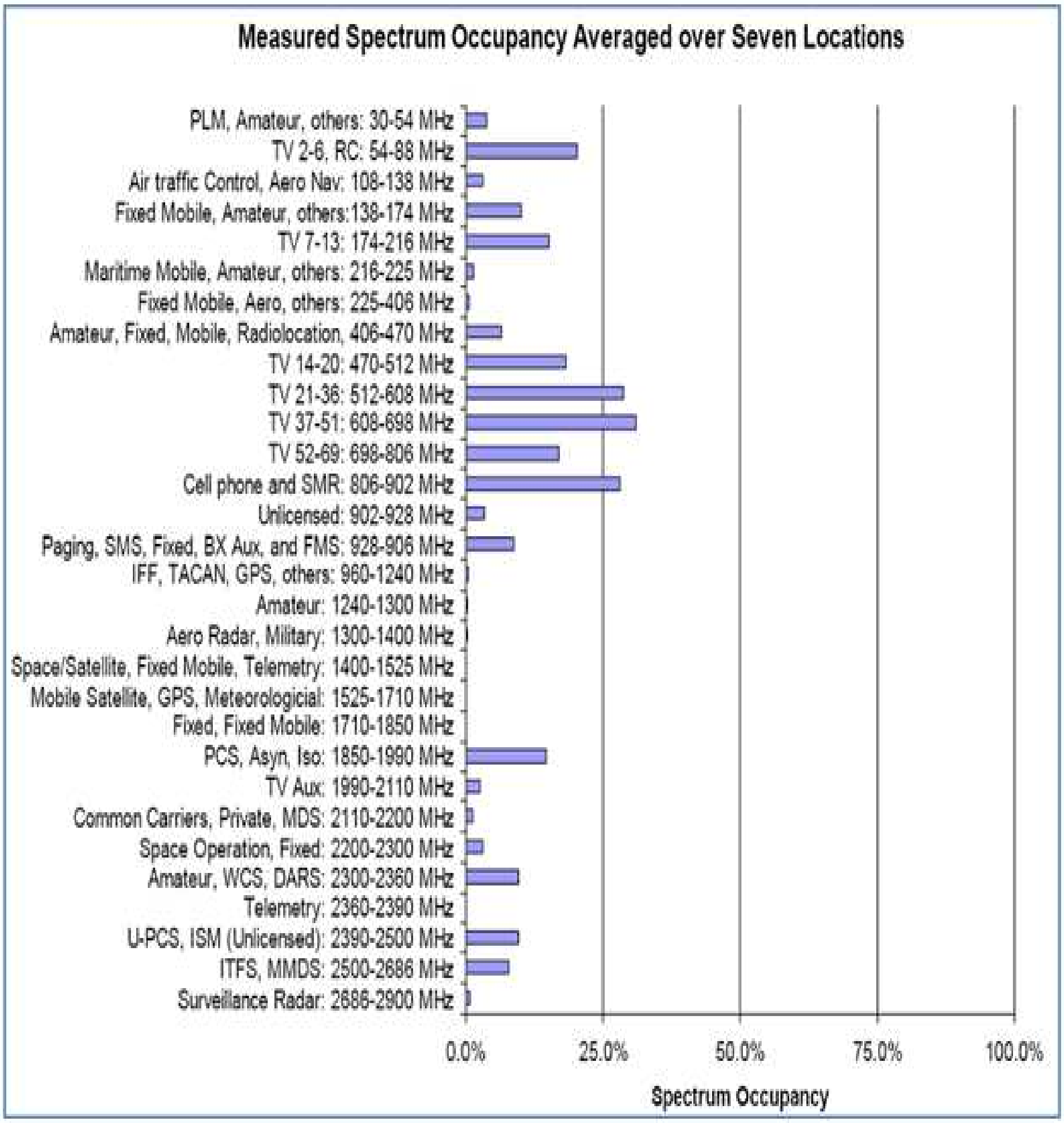



Figure 2.1: Spectrum occupancy in each band averaged over seven locations [1]

can access a spectrum hole, the spectrum utilization is improved significantly. A promising mechanism to improve the spectrum utilization by exploiting the spectrum holes is based on the cognitive radio concept.

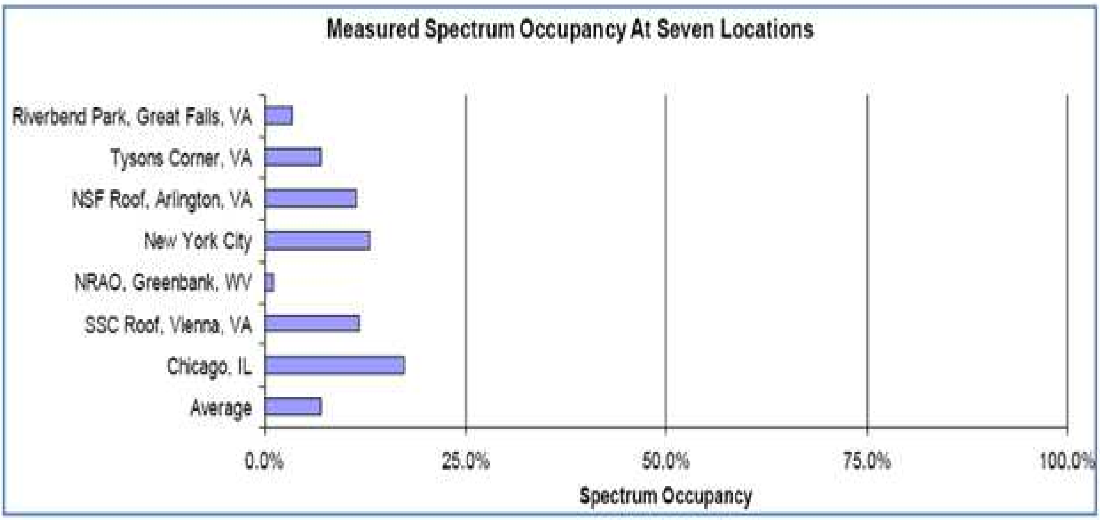
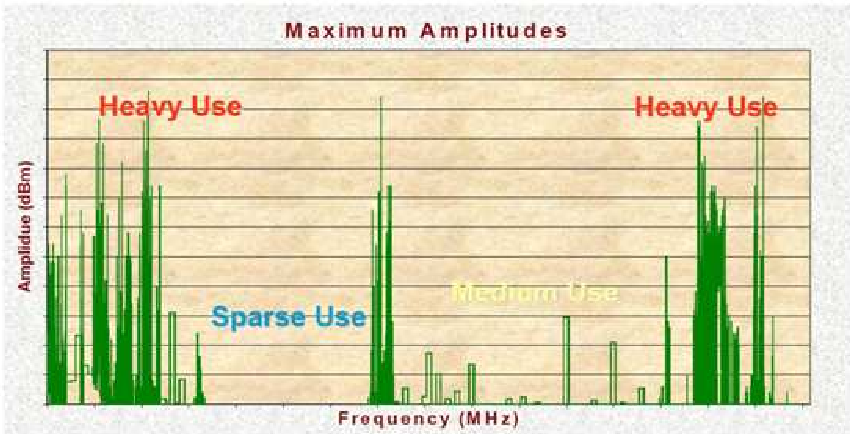



Figure 2.2: Spectrum occupancy at each location [1]




Source: FCC, Spectrum Policy Task Force, Technology Advisory Council (TAC) Briefing (December 2002).

Figure 2.3: Spectrum Utilization [2]

## 2.2 Cognitive Radio

The aim of cognitive radio is to use the natural resources efficiently in all the domains like frequency, time and transmitted energy. Spectral efficiency is playing an increasingly important role as future wireless communication systems will accommodate more and more users and high performance (e.g. broadband) services. Cognitive radio technologies can be used in lower priority secondary systems that improve spectral efficiency by sensing the environment and then filling the discovered gaps of unused licensed spectrum with their own transmissions [4].

Cognitive radio interacts with real time environment to dynamically alter its operating parameters such as transmition power, carrier frequency, modulation types to acclimate itself with the environment. Cognitive Radio takes advantage of the available spectrum without causing interference to primary users. Thus it intends to fulfill the requirement of efficient radio spectrum utilization [5, 6]. Figure 2.4 shows the basic cognitive functions of cognitive radio.

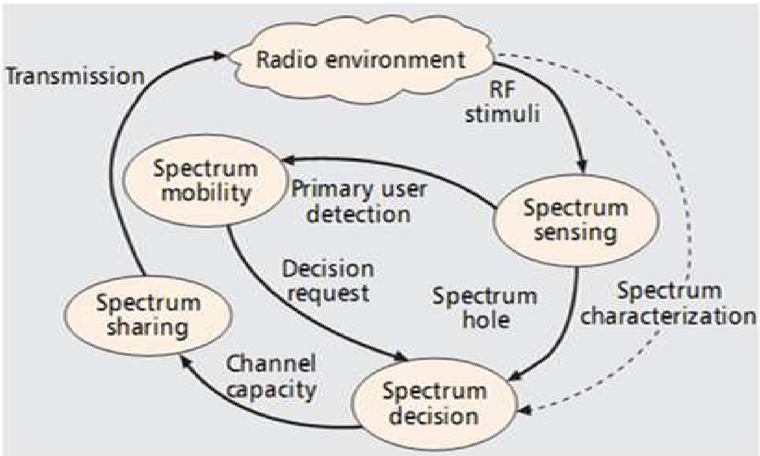



Figure 2.4: Cognition Cycle [7]

The major function of cognitive radio is spectrum sensing which scans and detects unused spectrum for their use without causing harmful interference with licensed users.

## 2.3 Cognitive Radio Standard

Since a cognitive radio operates as a secondary user which does not have primary rights to any pre assigned frequency bands, it is necessary for it to dynamically detect the presence of primary users. In December 2003, the FCC issued a Notice of Proposed Rule Making that identies cognitive radio as the candidate for implementing opportunistic spectrum sharing. In response to this, in 2004, the IEEE formed the 802.22 Working Group to develop a standard for wireless regional area networks (WRAN) based on cognitive radio technology [8]. WRAN systems will operate on unused VHF/UHF bands that are originally allocated for TV broadcasting services and other services such as wireless microphone, which are called primary users [9].

### 2.3.1 Dynamic spectrum access

There are several methods that can be used by a cognitive radio network for dynamically access the spectrum. The two methods used with IEEE 802.22 for spectral awareness are Geo-location/database, Spectrum Sensing. In the first method, knowledge of the location of the cognitive radio devices combined with a database of licensed transmitters can be used to determine which channels are locally available for reuse by the cognitive radio network. Spectrum sensing consists of observing the spectrum and identifying which channels are occupied by licensed transmission. The IEEE 802.22 network quickly modifies its operating frequency so as to only operate on channels unused by licensed transmissions. Thus, the IEEE 802.22 network must both quickly identify which channels are allowed for use and move to a new unused channel, if the current operating channel becomes occupied by a licensed transmission [10].

### 2.3.2 Topology

The 802.22 system specifies a fixed point-to-multipoint (P-MP) wireless air interface whereby a base station (BS) manages its own cell and all associated Consumer Premise Equipments (CPEs), as depicted in Figure 2.5

The BS controls the medium access in its cell and transmits in the downstream direction to the various CPEs, which respond back to the BS in the upstream direction. In addition it also manages a unique feature of distributed sensing [11]. Spectrum sensing involves observing the radio frequency spectrum and processing the observations to determine if a channel is occupied by a licensed transmission. Spectrum sensing is included as a mandatory feature within IEEE 802.22. IEEE 802.22 maintains a chart during sensing to classify channels as per availability occupied, available and prohibited according to the requirements in the table 2.1. This table is updated either by system operator or by the 802.22 sensing mechanism itself [11].

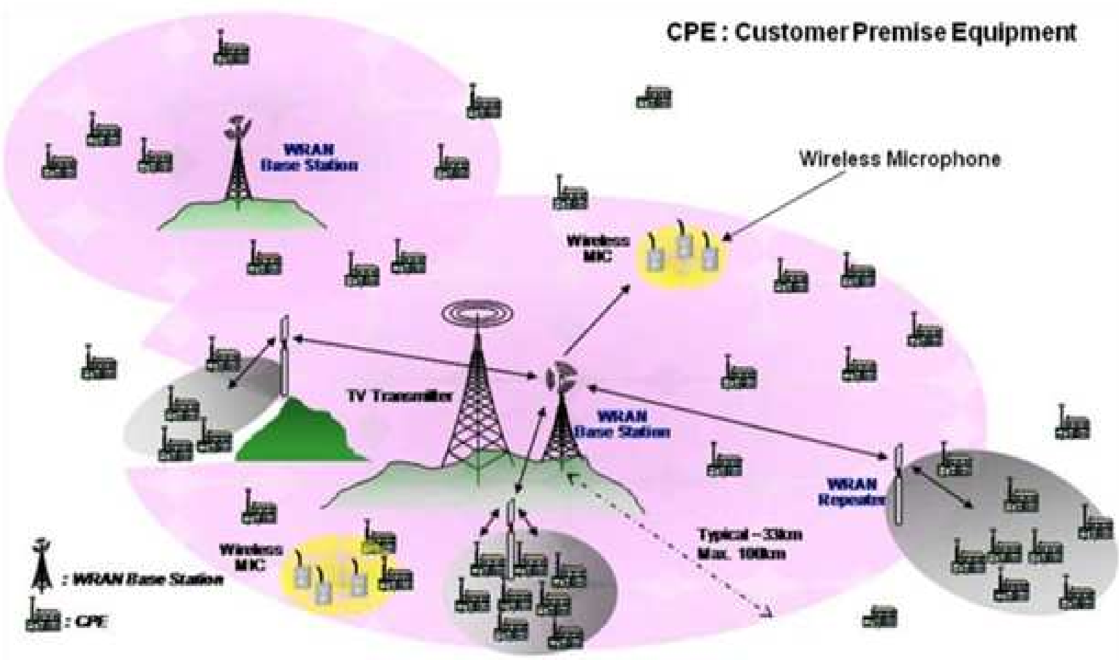



Figure 2.5: Deployment Scenario of IEEE 802.22 [11]

| Parameter | Value for Wireless Microphone | Value for TV Broadcasting |
|---|---|---|
| Channel Detection Time | $\leq 2sec$ | $\leq 2sec$ |
| Channel Setup Time | 2 sec | 2 sec |
| Channel Opening Transmission Time | 100 msec | 100 msec |
| Channel Move Time | 2 sec | 2 sec |
| Interference Detection Threshold | -107 dBm | -116 dBm |

Table 2.1: Sensing Requirements of IEEE 802.2

## 2.4 Spectrum sensing methods for cognitive radio

Spectrum sensing in CR system is the process of sensing the spectrum to locate unoccupied/underutilized spectrum segments/channels (spectrum holes) or white spaces. These are called white spaces because of their lack of activity and could be accessed and utilized through dynamic spectrum access techniques [12]. Most widely used spectrum sensing techniques are shown in figure 2.6. Apart from this we have waveform basted detection, radio identification method and many more.

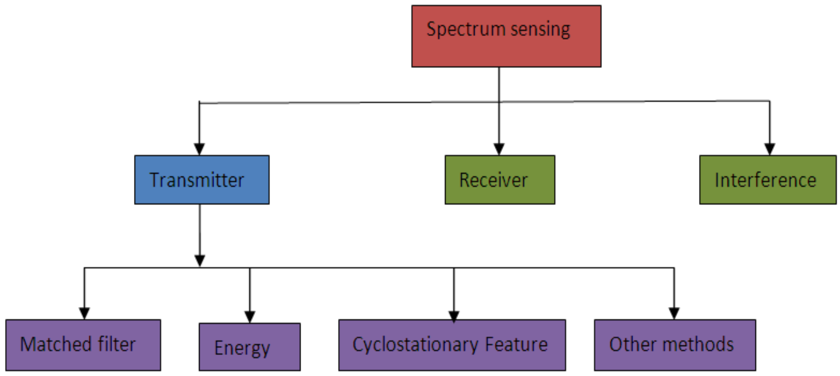



Figure 2.6: spectrum sensing techniques [8]

### 2.4.1 Matched filter based sensing

Matched filtering is known as the optimum sensing method for detection of primary users when the footprints of transmitted signal is known. The main advantage of matched ltering is the short time to achieve a certain probability of false alarm or probability of miss detection as compared to other methods. However, matched filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation type, pulse shaping and frame format. Moreover, since cognitive radio needs receivers for all signal types, the complexity for implementation of sensing unit is impractically large. Another disadvantage of matched filtering is large power consumption as various receiver algorithms need to be executed for detection [12].

### 2.4.2 Energy detector based sensing

Energy detector based approach [13], also known as radiometry or periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexities. In addition, it is more generic as receivers do not need any prior knowledge on the primary users signal. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noiseoor. Some of the challenges with energy detector based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low signal-to-noise ratio (SNR) values. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals [7].

### 2.4.3 Cyclostationary based sensing

Cyclostationarity feature detection is a method for detecting Primary user transmissions by exploiting the cyclostationarity features of the received signals. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing. Instead of power spectral density (PSD), cyclic correlation function is used for detecting signals of a scanned spectrum. The cyclostationary based detection algorithms can differentiate noise from primary users signals. This is a result of the fact that noise is wide-sense stationary (WSS) with no correlation while modulated signals are cycloStationary with spectral correlation due to the redundancy of Signal periodicities. Furthermore, cyclostationarity can be used for distinguishing among different types of transmissions and primary users [12].

### 2.4.4 Waveform based sensing

Known patterns are usually utilized in wireless systems to assist synchronization or for other purposes. Such patterns Include preambles, midambles, regularly transmitted pilot patterns, spreading sequences etc. A preamble is a known sequence transmitted before each burst and a midamble is transmitted in the middle of a burst or slot. In the presence of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself. This method is only applicable to systems with known signal patterns, and it is termed as waveform-based sensing or coherent sensing [12].

### 2.4.5 Radio identification based sensing

A complete knowledge about the spectrum characteristics can be obtained by identifying the transmission technologies used by primary users. The goal is to identify the presence of some known transmission technologies and achieve communication through them. The two main tasks are initial mode identification (IMI) and alternative mode monitoring (AMM). In IMI, the cognitive device searches for a possible transmission mode (network) following the power on. AMM is the task of monitoring other modes while the cognitive device is communicating in a certain mode. In radio identification based sensing, several features are extracted from the received signal and they are used for selecting the most probable primary user technology by employing various classification methods [5].

### 2.4.6 Other sensing methods

Other alternative spectrum sensing methods include multitaper spectral estimation, wavelet transform based estimation, Hough transform, and time-frequency analysis [12].

## 2.5 Comparison of Various Sensing Methods

A basic comparison of the sensing methods is shown in figure 2.7 interms of their complexity and accuracy.

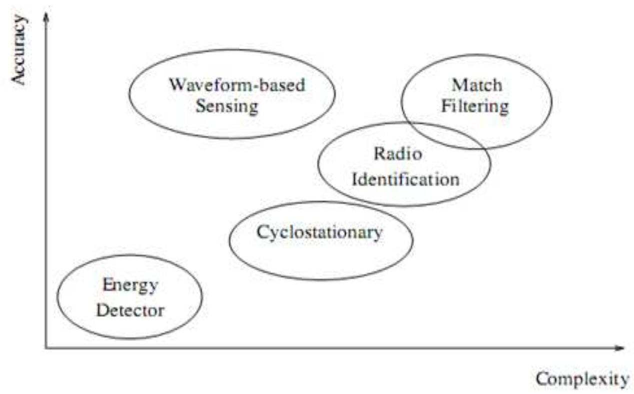



Figure 2.7: Comparison of various spectrum sensing techniques [12]

Further the advantages and disadvantages of different sensing techniques are shown in table 2.2.

| Spectrum sensing technique | Advantages | Disadvantages |
|---|---|---|
| Energy detection | 1.No prior information about Signal is required. 2. Low computational cost. | 1. Does not work in low SNR. 2. Con not distinguish between Signal and noise. 3. Does not work for spread spectrum signals |
| Cyclostationary Feature Detection | 1. Robust in low SNR. 2. Robust to interference | 1. Requires partial information about primary user signal. 2. High computational cost |
| Matched filter | 1. Optimal performance. 2. Low computational cost | 1. Requires prior information about primary user signal. |
| Wavelet Detection | 1. Effective for wideband signal | 1. Does not work for spread spectrum signals. |

Table 2.2: Comparison of various spectrum sensing techniques

## 2.6 Spectrum sensing challenges

Spectrum sensing in cognitive radio networks is challenged by several sources of uncertainty ranging from channel randomness to device level and network-level uncertainties. Since spectrum sensing should perform robustly even under worst case conditions, such uncertainties usually have implications in terms of the required detection sensitivity [14].

### 2.6.1 Hardware Requirements

Spectrum sensing for cognitive radio applications requires high sampling rate, high resolution analog to digital converters (ADCs) with large dynamic range, and high speed signal processors. Also in cognitive radio, terminals are required to process transmission over a much wider band for utilizing any opportunity. Hence, cognitive radio should be able to capture and analyze a relatively larger band for identifying spectrum opportunities. These impose additional requirements on the radio frequencies (RF) components such as antennas and power amplifiers as well forcing them to operate over a range of wide operating frequencies. Furthermore, high speed processing units (DSPs or FPGAs) are needed for performing computationally demanding signal processing tasks with relatively low delay.

### 2.6.2 Hidden Primary User Problem

The hidden primary user problem is similar to the hidden Node problem in Carrier Sense Multiple Accessing (CSMA). It can be caused by many factors including severe multipath fading or shadowing observed by secondary users while scanning for primary users transmissions. Figure 2.8 shows an illustration of a hidden node problem where the dashed circles show The operating ranges of the primary user and the cognitive Radio device. Here, cognitive radio device causes unwanted Interference to the primary user (receiver) as the primary transmitters signal could not be detected because of the locations of devices.

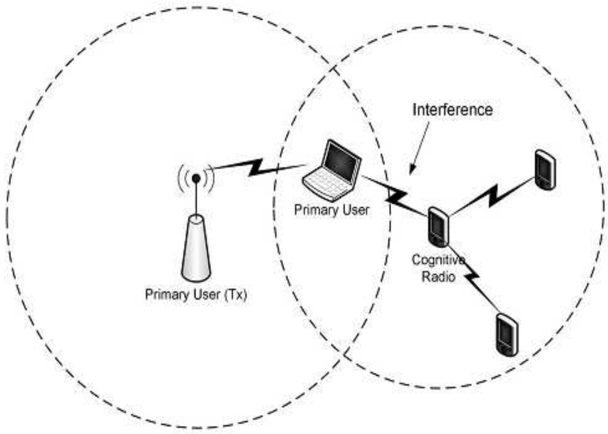



Figure 2.8: illustration Of a hidden node problem [14]

### 2.6.3 Detecting spread spectrum primary users

For commercially available devices, there are two main types of technologies: xed frequency and spread spectrum. The two major spread spectrum technologies are frequency- Hoping spread-spectrum (FHSS) and direct-sequence spread- spectrum(DSSS). Fixed frequency devices operate at a single frequency or channel. An example to such systems is IEEE802.11a/g based WLAN. FHSS devices change their Operational frequencies dynamically to multiple narrowband channels. This is known as hopping and performed according to a sequence that is known by both transmitter and receiver. DSSS devices are similar to FHSS devices, however, they use A single band to spread their energy. Primary users that use spreads spectrum signaling are difficult to detect as the power of the primary user is distributed over a wide frequency range even thoughthe actual information band width is much narrower.

### 2.6.4 Security

In cognitive radio, a selsh or malicious user can modify its air interface to mimic a primary user. Hence, it can mislead the Spectrum sensing performed by legitimate primary users.

### 2.6.5 Sensing time and frequency

Primary users can claim their frequency bands anytime while cognitive radio is operating on their bands. In order to prevent interference to and from primary license owners, cognitive radio should be able to identify the presence of primary users as quickly as possible and should vacate the band immediately. Hence, sensing methods should be able to identify the presence of primary users within certain duration. This requirement poses a limit on the performance. In addition to sensing frequency, the channel detection time, channel move time and some other timing related parameters are also defined.

## 2.7 Cooperative spectrum sensing

One of the most challenging issues of spectrum sensing is the hidden terminal problem, which happens when the cognitive radio is shadowed or in deep fade. To address this issue, multiple cognitive radios can be coordinated to perform spectrum sensing. This type of technique is known as cooperative spectrum sensing. To facilitate the analysis of cooperative sensing ,it is classified into three categories based on how cooperating CR users share the sensing data in the network [13]: centralized, distributed, and relay-assisted. These three types of cooperative sensing are illustrated in figure 2.9.

### 2.7.1 Decision fusion in cooperative sensing

In the case of cooperative sensing, sharing information among cognitive radios and combining results from various measurements is a challenging task. The shared information can be soft or hard decisions made by each cognitive device. The literture results show that soft information-combining outperforms hard information-combining method in terms of the probability of missed opportunity. On the other hand, hard-decisions (AND, OR or M-out-of-N) are found to perform as good as soft decisions when the number of cooperating users is high in. When hard decisions are used; methods can be used for combining information from different cognitive radios. The reliability of spectrum sensing at each secondary user also has to be taken into account [7].

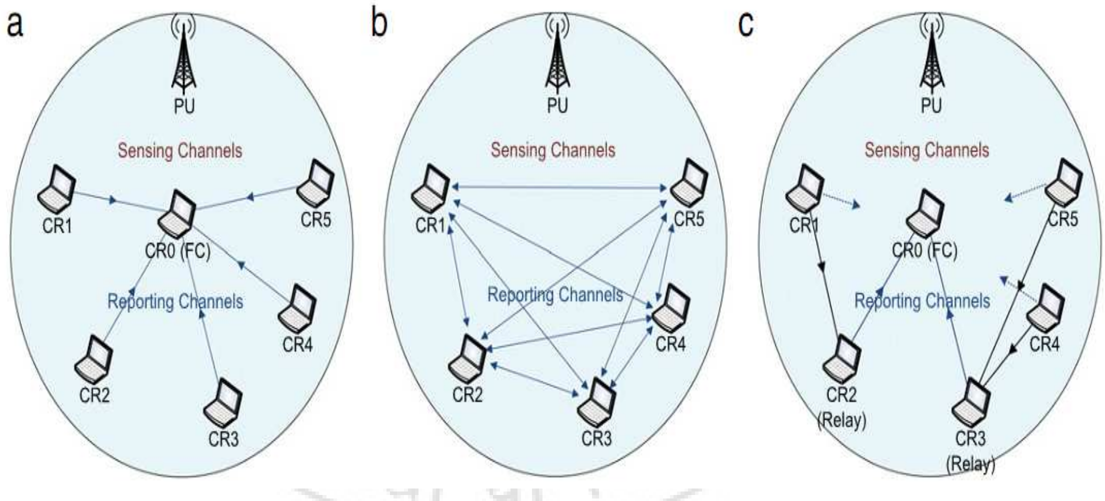



Figure 2.9: Classification of cooperative spectrum sensing [13]

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# Chapter 3

# Spectral Coherence Method

## 3.1 Objective

Cooperative spectrum sensing technique avoids fading and shadowing issues which are predominant in non cooperative sensing. The aim of this chapter is to develop a cyclostationary spectrum sensing technique using spectral coherence method for cognitive radio networks. The main objectives achieved in this chapter are:

1. Spectrum Sensing based on Spectral Coherence Method (SCF) is able to detect weak licensed user signals and shows superiority compared to energy detection.

2. Cooperative detection enhances the performance of the system compared to single node detection.

## 3.2 Work done in this chapter

The cyclostationary based spectrum sensing using spectral coherence method is studied and the algorithm performance is verified using QPSK and DVB-T signals. Cooperative cyclostationary technique is developed to improve the performance of sensing technique. All the simulations are perfromed in MATLAB tool.

## 3.3 Sensing algorithm

The complete block diagram of both SCF based and Entropy based cyclostationary spectrum sensing techniques is shown in figure 3.1. In SCF detection method the estimated SCF over number of cyclic frequencies is compared with pre calculated threshold $Thc$. In Entropy detection method the estimated Entropy is compared with pre calculated threshold $The$.

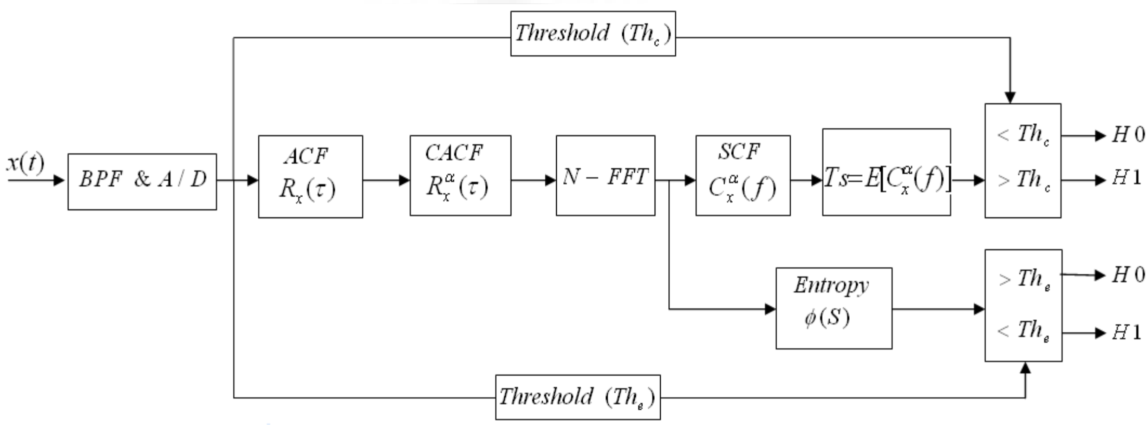


Figure 3.1: Spectrum occupancy in each band averaged over seven locations

### 3.3.1 Hypothesis testing

A hypothesis test is a rule that, given a set of recieved signal samples $x$, makes a decision as to which hypothesis best explains the presence of signal or only noise in the recieved samples.

The spectrum sensing problem can be modeled into a binary Hypothesis test as follows [1]

$$\begin{aligned} H_0 &: x(t) = w(t) \\ H_1 &: x(t) = hs(t) + w(t) \end{aligned} \tag{3.1}$$

Where $H_0$ stands for the absence of the signal in the channel, $H_1$ is the presence of a primary signal in the band. $x(t)$ is the received signal by the secondary user. $s(t)$ is the primary users transmitted signal, $w(t)$ is the additive white Gaussian noise (AWGN) and $h$ is the channel gain.

### 3.3.2 SCF detection method

A process $x(t)$ is second-order cyclostationary if its mean and autocorrelation are periodic in time with some period $T$ [2].

$$m_x(t+T) = m_x(t) \tag{3.2}$$

$$R_x(t+T+\frac{\tau}{2}, t+T-\frac{\tau}{2}) = R_x(t+\frac{\tau}{2}, t-\frac{\tau}{2}) \tag{3.3}$$

In the case of cyclostationary process, the cyclic autocorrelation function (CAF) is non zero for a set of cyclic frequencies $\alpha$=0. The cyclic autocorrelation function at cyclic frequency $\alpha$ can be estimated as

$$R_x^{\alpha}(\tau) = \frac{1}{T}\int_{-T/2}^{T/2} R_x(\tau)e^{-j2\pi\alpha t}dt \tag{3.4}$$

Where $\alpha$=$(m/T)$; $m$=0,1,2,3.................
And $R_x(\tau) = \int_{-\infty}^{\infty} x(t)x^*(t-\tau)dt$.

In discrete domain the cyclic autocorrelation is

$$R_x^{\alpha}[k] = \frac{1}{N}\sum_{n=-N/2}^{N/2} R_x[k]e^{-j2\pi\alpha n} \tag{3.5}$$

In our work, the autocorrelation is computed in a particular time interval with $N$= 512 samples, and $k = 0, 1, \ldots N-1$.

Where $R_x[k]$ the autocorrelation function for $k-1$ delays of the signal

$$R_x[k] = \sum_{n=1}^{N-k+1} x[n]x^*[n+k-1]$$

And $x[n]$ is the discrete form of received signal.

The spectral correlation (SC) of the received signal $x(t)$ can be obtained from the Fourier transform of cyclic autocorrelation as

$$S_x^{\alpha}(f) \cong \int_{-\infty}^{\infty} R_x^{\alpha}(\tau)e^{-j2\pi f\tau}d\tau \tag{3.6}$$

In descrite domain with FFT length of 512, the above equation becomes

$$S_x^\alpha(\Omega) \cong FFT(R_x^\alpha[k]) \tag{3.7}$$

From this the spectral coherence function (SCF) can be calculated as

$$C_x^\alpha(\Omega) \cong \frac{S_x^\alpha(\Omega)}{[S_x(\Omega+\alpha/2)S_x(\Omega-\alpha/2)]^{1/2}} \tag{3.8}$$

It allows us to measure the strength of second-order periodicity contained within a time series signal in an unified way.

For a signal which does not exhibit cyclostationary $\mathrm{R}_x^\alpha(\tau) = 0(\alpha \# 0)$. The values of $\alpha$, with which this function is nonzero are determined by the hidden periodicities observed in $x(t)$. For communication signals, $\alpha$ is typically related to the symbol rate, chip rate and carrier frequency.

In this algorithm the test statistic we considered is based on spectral average over number of $\alpha's$.

$$Ts = \left| \frac{1}{n} \sum_{\alpha} C_x^\alpha(\Omega) \right| \tag{3.9}$$

Where $n$ is number of cyclic frequencies.

Test statistic is a numerical summary of a set of data that reduces the data to one or a small number of values that can be used to perform the hypothesis test.

### 3.3.3 Threshold calculation

The threshold is calculated using the equation 3.10. It depends on the received signal variance $\sigma_x^2$, number of samples taken for detection $(N)$ and probability of false alarm $(P_{fa})$ [3].

$$Thc = \sqrt{\sigma_x^2(1/N)\log(P_{fa})} \tag{3.10}$$

If $Ts$ is above $Thc$, we decide that the sensed spectrum is occupied otherwise it is vacant.

## 3.4 Detector performance metric

Some important terms to evaluate the detector performance are described as follows [8]

Probability of false alarm ($P_{fa}$): It is the probability that the test incorrectly decides that the considered frequency is occupied when it actually is not, and it can be written as

$$Pfa = \Pr(Ts > {}^{Thc}/_{H_0})$$

Probability of detection ($P_d$): It is the probability of detecting a signal on the considered frequency when it truly is present. Thus, a large detection probability is desired. It can be formulated as

$\mathrm{P}_d$=Pr($Ts > {}^{Thc}/_{H_1}$)

Probability of mis-detection ($P_m$): It is the probability of mis-detecting a signal on the considered frequency when the signal truly present.
$Pm = 1 - P_d$

Detector ROC: we can describe the full range of the detector decisions in a single curve, called receiver operating characteristic (ROC) curve. It is plotted by taking Pfa on x-axis and $P_d$ on y-axis.

When the signal is stronger there is less overlap in the probability of occurrence curves, and the ROC curve becomes more bowed. The detector ROC is shown in figure 3.2. The slope of the curve at any instant gives the value of threshold used for decision for those values of $P_d$, Pfa. If only noise is present, the curve looks like a straight line as shown in figure 3.2. Any signal curve that crosses this line will not be detected by detector and puts a constraint on minimum detectable SNR required.

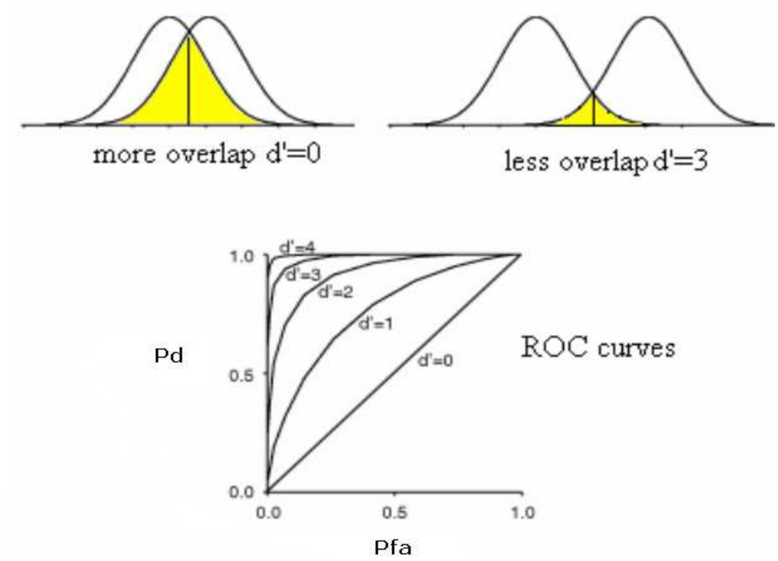


Figure 3.2: Probability of occurrence curves ROC curves for different signal strengths [9]

## 3.5 Cooperative algorithm

In centralised cooperative spectrum sensing a central identity called fusion center ($FC$) controls the three-step process of cooperative sensing. First, the $FC$ selects a channel or a frequency band of interest for sensing and instructs all cooperating CR users to individually perform local sensing. Second, all cooperating CR users report their sensing results via the control channel. Then the FC combines the received local sensing information, determines the presence of PUs, and diffuses the decision back to all the CR users in the cooperative network.

### 3.5.1 Hypothesis testing

For a cognitive radio network with $M$ secondary users. The binary hypothesis test for spectrum sensing at the $i^{th}$ time instant is formulated as [4]:

$$\begin{aligned} H_0 &: x_i(t) = w_i(t), i = 0, 1, \dots M-1 \\ H_1 &: x_i(t) = s_i(t) + w_i(t) \end{aligned} \tag{3.11}$$

Where $s(t)$ denotes the signal transmitted by the primary user and $x_i(t)$ is the received signal by the $i^{th}$ secondary user. The signal is distorted by the channel gain $h_i$, which is assumed to be constant during the detection interval, and is further corrupted by the zero-mean additive white Gaussian noise $w_i$(t).

### 3.5.2 Cooperative decision methods

All $M$ secondary users will take their local decision based on the cyclostationary technique. In cooperation all the decisions are combined at a common node called fusion center (FC) in a centralized way. The local sensed data by secondary users are combined using different decision logics. The decision logics are broadly classified into i) Hard decision and ii) Soft decision:

#### 3.5.2.1 Hard decision

In hard decision fusion [5], each CR makes a local decision about the presence of primary users and then sends the binary decision (i.e., a single bit) to the fusion center for decision fusion. The OR logic operation can be used to combine decisions from several secondary users, where the fusion center decides H1 if any one of the users claims that H1 is true. Likewise, an AND logic operation can be used, which decides H1 if and only if all the nodes claim that H1 is true.

Detection probability ($P_d$) of OR is [6]

$$C_{d-OR} = 1 - \prod_{i=1}^{M}(1 - P_{d,i}) \tag{3.12}$$

Where $P_{d,i}$ is the detection probability of the $i^{th}$ CR user (or $i^{th}$ node).
Detection probability ($P_d$) of AND is

$$C_{d-AND} = \prod_{i=1}^{M} P_{d,i} \tag{3.13}$$

#### 3.5.2.2 Soft decision

In soft combination, all the CR users in cooperation send their original sensing information to the base station without any local processing and the decision is made at the base station by combining them appropriately. Some of the soft decision logics are Equal Gain Combing (EGC), Waighted Gain Combing (WGC), and Log Likelihood Ratio Test (LLRT).

The Soft decision technique used in this work is based on EGC. The fusion center combines all the detection gains together. The global decision is evaluated by comparing the combined gain with a predened threshold at the fusion center. Detection probability ($P_d$) of EGC can be written as [7],

$$Pd - EGC = Q_{mu}(\sqrt{2\gamma_e}, \sqrt{Th}) \tag{3.14}$$

Where $\gamma_e$ is the combined SNR of all nodes, $Q_{mu}$ is the $Q$ function. $Th$ is the threshold of the detector.

## 3.6 Simulation results

### 3.6.1 Non cooperative detection

The simulation of algorithm is carried out for signals of primary users of different modulations such as QPSK and DVB-T. The received signal is filtered by a band-pass filter and the time of observation $T = N * ts$, where $ts = (1/fs)$, $fs$ is the sampling frequency. DVB-T specification is given in Table 3.1. In this algorithm, the autocorrelation is computed in a particular time interval with 512 samples and $\alpha = 0$ to 1 in the steps of 0.1. ($\alpha$=($m/T$); $m$=0,1,2,3. . . . . . . . . . . . . . . . .)

| | |
|---|---|
| Transmission Mode | 2K |
| Number of Carriers | 1705 |
| Carrier Frequency | 4.8MHz |
| Modulation | 64 QAM |
| Channel Band Width | 6MHz |
| Code Rate | 2/3 |
| Guard Interval Ratio | 1/4 |
| Data Rate | 3.732-23.751Mbps |
| Observed Time | 43.2 $\mu sec$ |

Table 3.1: Sensing Requirements of IEEE 802.2

The detector computed the average spectral coherence over number of cyclic frequencies of the received signal in the observed time period and compares it with a precomputed threshold (Thc) as equation 3.10. Threshold is determined by the desired value of probability of false alarm ($P_{fa}$). Noise is assumed to be independent and identically distributed (iid) with zero-mean and circularly symmetric complex Gaussian with variance one. But in practice it is random. The algorithm is simulated for SNR range between -24dB to -10dB in steps of 2dB. We computed the detection probability using test statistic by 300 iterations. The detection probability is computed for different probability of false alarms. More approximation of the ROC curve is possible with increasing the number of iterations.

The spectral coherence at different cyclic frequencies for received signal with noise and without noise is shown in figure 3.3 and in figure 3.4 respectively. From these figures it is clear that noise is a random signal so its SCF over different cyclic frequencies is very low. But, if the received signal contains primary modulated signal then its SCF has significant values due to periodic nature.

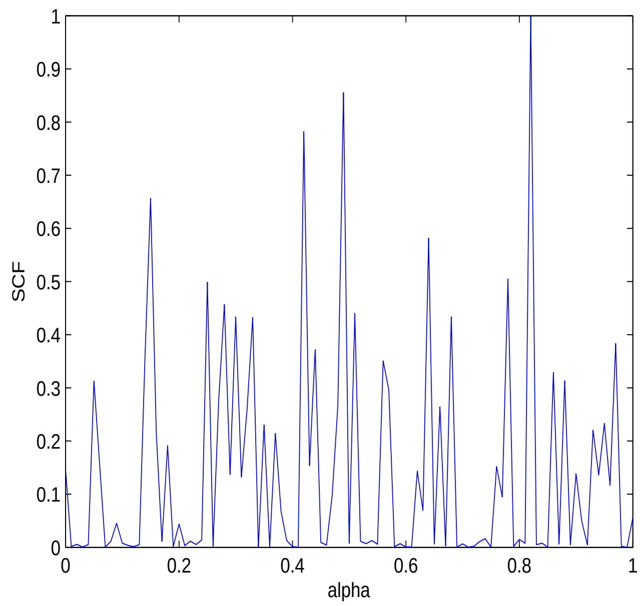


Figure 3.3: spectral coherence Vs alpha for the received signal

The performance of detector is measured from ROC curve which is the plot between probability of detection $P_d$ and probability of false alarm ($P_{fa}$). Figure 3.5 and figure 3.6 are the ROC curves for QPSK and DVB-T signal respectively. From these figures it is clear that the detection probability ($P_d$) increases as we increase $P_{fa}$ as well as SNR.

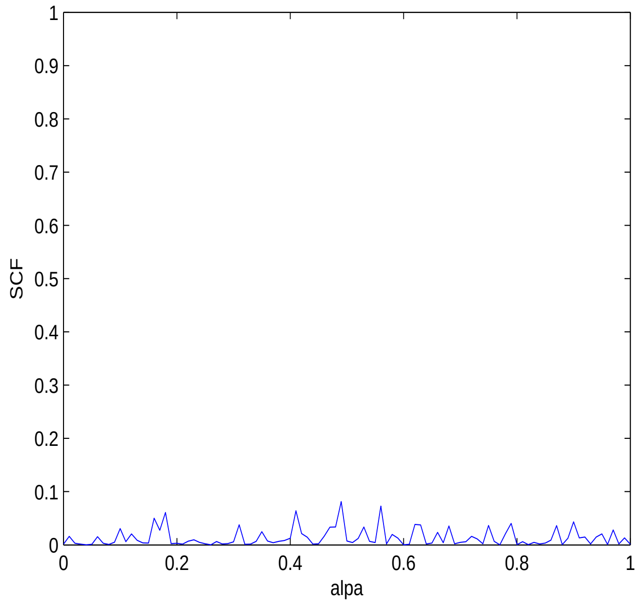


Figure 3.4: spectral coherence verses alpha for the noise signal at cognitive node

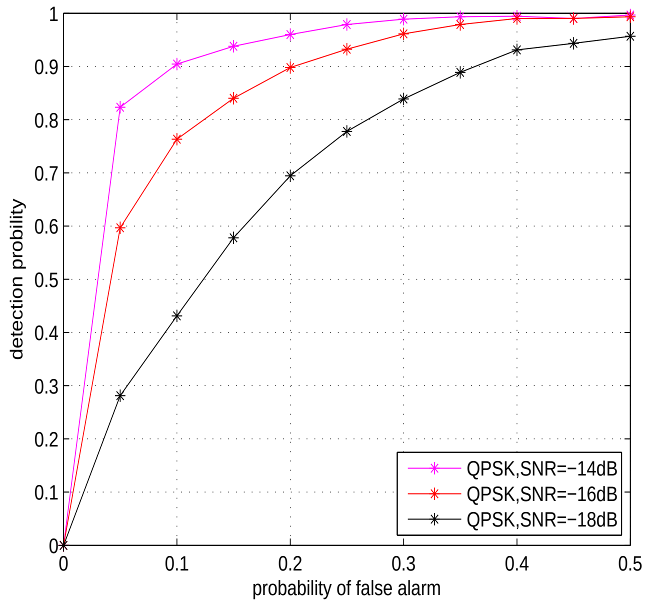


Figure 3.5: ROC curves for QPSK signal under AWGN channel with different SNRs

Figure 3.7 presents the $P_d$ Vs SNR with different $P_{fa}$ values for QPSK and DVB-T signals. This figure reveals that the probability of detection ($P_d$) of the

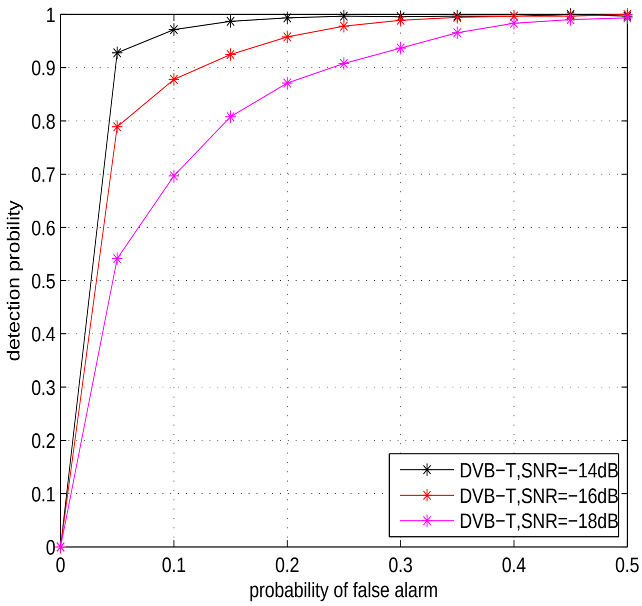


Figure 3.6: ROC curves for DVB-T signal under AWGN channel with different SNRs

sensing increases as the SNR increases. The SCF based cyclostationary detector is able to detect the QPSK signal upto -14dB with $P_{fa}$=0.1, -13dB with $P_{fa}$=0.05 for desired detection probability $P_d$=0.9. In the case of DVB-T signal, it is -16dB with $P_{fa}$=0.1, -15dB with $P_{fa}$=0.05.

### 3.6.2 Cooperative detection

In cooperative detection AND, OR fusion rules for hard decision and EGC for soft decision are considered. Different number of secondary user nodes are used in the simulation (for AND and OR logic M= 3, 5 and EGC logic M=3, 5, and 7 are considered for simulation). In each node the SNR's are different assuming they are shadowed.

The efficiency of fusion rules are determined by using Receiver Operating Characteristics (ROC) ($P_d$ and $P_{fa}$) and SNR Vs $P_d$ curves.

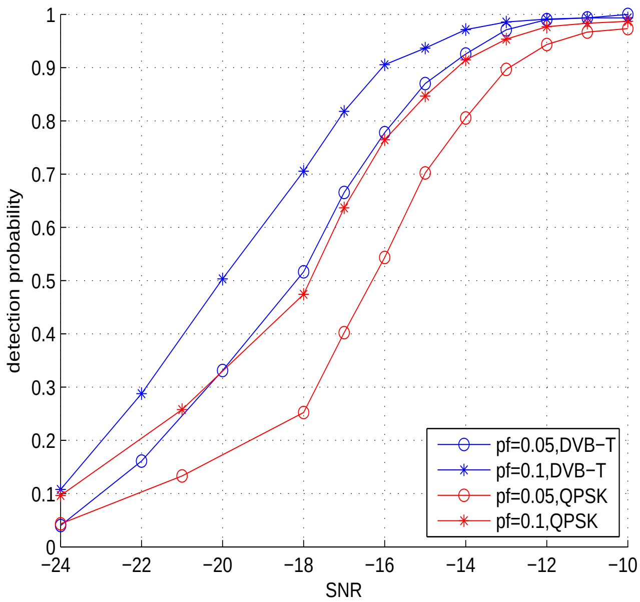


Figure 3.7: SNR Vs Pd curves for QPSK AND DVB-T signals with different fixed probability of false alarm ($P_{fa}$=0.05, 0.1)

#### 3.6.2.1 QPSK test signal

The SNR vs. $P_d$ curves for QPSK test signal with OR fusion rule is shown in figure 3.8. The algorithm is verified for SNRs between -21 to -12 in steps of -1dB, with $P_{fa}$=0.1, 0.2 and with 3 and 5 nodes. From figure it is seen that the probability of detection increases as we increase SNR as well as number of nodes in cooperation. The algoritham can detect the QPSK signal upto -17dB with $P_{fa}$=0.1, -19dB with $P_{fa}$=0.2 for 3 nodes in cooperation and upto -18dB with $P_{fa}$=0.1, -20dB with $P_{fa}$=0.2 for 5 nodes in cooperation for desired probability of detection $P_d$=0.9.

The SNR vs. $P_d$ curves for QPSK test signal with AND fusion rule is shown in figure 3.9. The algorithm is verified for SNRs between -18 to -9 in steps of -1dB, with $p_{fa}$=0.1, 0.2 and with 3 and 5 nodes. From figure it is seen that the probability of detection increases as we increase SNR and it decreaes as well as number of nodes in cooperation. The algoritham can detect the QPSK signal upto -13dB with $P_{fa}$=0.1, -14dB with $P_{fa}$=0.2 for 3 nodes in cooperation and upto -12dB with $P_{fa}$=0.1, -13dB with $P_{fa}$=0.2 for 5 nodes in cooperation for desired

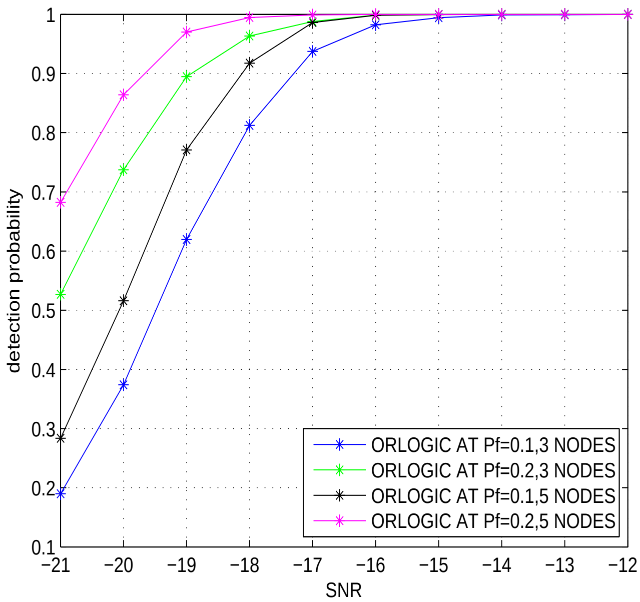


Figure 3.8: SNR Vs $P_d$ curves of OR fusion for QPSK signal with different probability of false alarm ($P_{fa}$=0.1 and 0.2, M=3, 5)

probability of detection $P_d$=0.9.

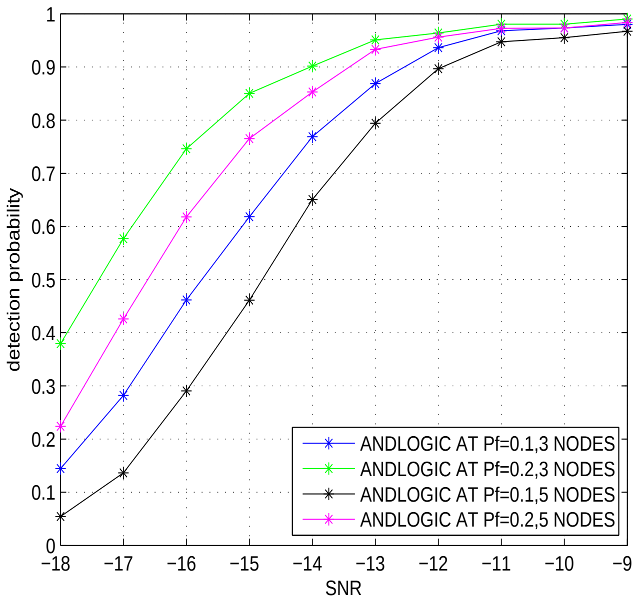


Figure 3.9: SNR Vs $P_d$ curves of AND fusion for QPSK signal with different probability of false alarm ($P_{fa}$=0.1,0.2 M=3, 5)

The SNR vs. $P_d$ curves for QPSK test signal with EGC fusion rule is shown in figure 3.10. The algorithm is verified for SNRs between -26 to -10 in steps of -2dB, with $P_{fa}$=0.1 and with 3, 5, and 7 nodes. From figure it is seen that the probability of detection increases as we increase SNR as well as number of nodes in cooperation. The algoritham can detect the QPSK signal upto -18dB with Pfa=0.1 for 3 nodes in cooperation, upto -20dB with Pfa=0.1 for 5 nodes in cooperation and upto -22dB with $P_{fa}$=0.1 for 7 nodes in cooperation for desired probability of detection $P_d$=0.9.

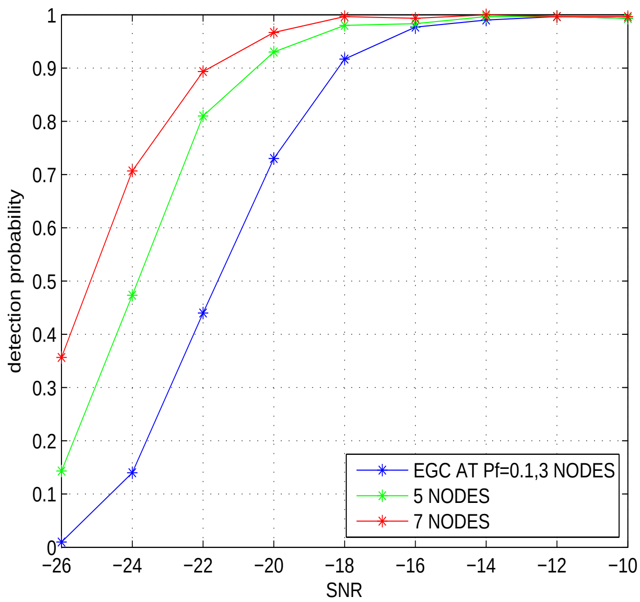


Figure 3.10: SNR Vs $P_d$ curves of EGC fusion for QPSK signal with fixed probability of false alarm ($P_{fa}$=O.1, M=3, 5, 7)

Table 3.2 shows The least SNR required to achieve required ($P_d$) Vs ($P_{fa}$) as a function of no.of nodes(M) using Hard decision logic for QPSK signal based on SCF method.

#### 3.6.2.2 DVB-T test signal

The SNR vs. $P_d$ curves for DVB-T test signal with OR fusion rule is shown in figure 3.11. The algorithm is verified for SNRs between -24 to -12 in steps of -2dB, with $P_{fa}$=0.1, 0.2 and with 3 and 5 nodes. From figure it is seen that the probability of detection increases as we increase SNR as well as number of nodes

| Fusion logic | M=1 | M=3 | M=5 |
|---|---|---|---|
| OR fusion,$P_{fa}$=0.1 | -14dB | -17dB | -18dB |
| OR fusion,$P_{fa}$=0.2 | -16dB | -19dB | -20dB |
| AND fusion,$P_{fa}$=0.1 | -14dB | -13dB | -12dB |
| AND fusion,$P_{fa}$=0.2 | -16dB | -14dB | -13dB |

Table 3.2: Least SNR required to achieve required ($P_d$) Vs ($P_{fa}$) as a function M using OR, AND fusion logic for SCF method (QPSK signal)

in cooperation. The algoritham can detect the DVB-T signal upto -19dB with $P_{fa}$=0.1, -21dB with $P_{fa}$=0.2 for 3 nodes in cooperation and upto -20dB with $P_{fa}$=0.1, -22dB with $P_{fa}$=0.2 for 5 nodes in cooperation for desired probability of detection $P_d$=0.9.

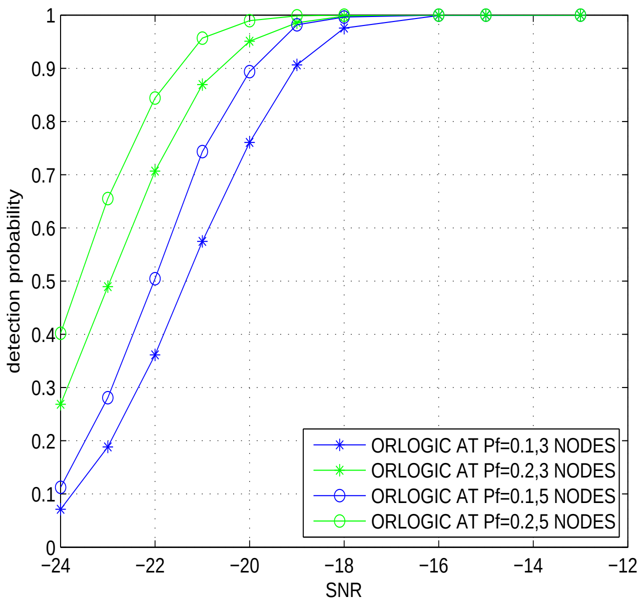


Figure 3.11: SNR Vs $P_d$ curves of OR fusion for DVB-T signal with different probability of false alarm ($P_{fa}$=O.1,0.2 M=3, 5)

The SNR vs. $P_d$ curves for DVB-T test signal with AND fusion rule is shown in figure 3.12. The algorithm is verified for SNRs between -18 to -9 in steps of -1dB, with $P_{fa}$=0.1, 0.2 and with 3 and 5 nodes. From figure it is seen that the probability of detection increases as we increase SNR and it decreaes as well as number of nodes in cooperation. The algoritham can detect the DVB-T signal upto -14dB with Pfa=0.1, -16dB with $P_{fa}$=0.2 for 3 nodes in cooperation and upto -13dB with $P_{fa}$=0.1, -15dB with $P_{fa}$=0.2 for 5 nodes in cooperation for desired probability of detection $P_d$=0.9.

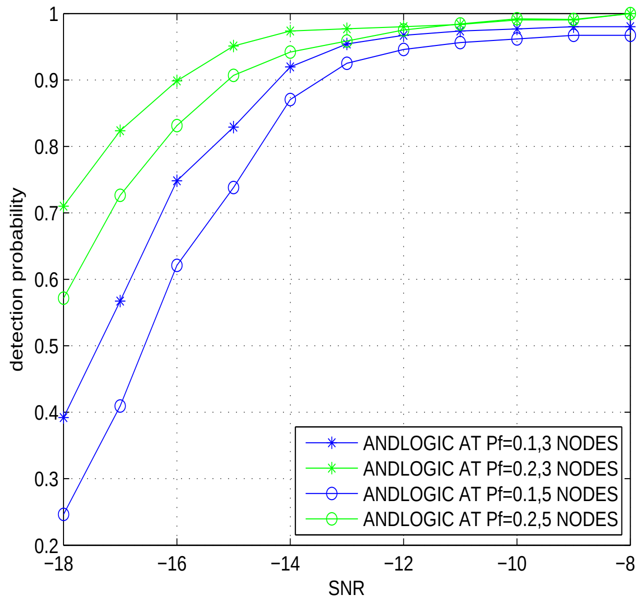


Figure 3.12: SNR Vs $P_d$ curves of AND fusion for DVB-T signal with different probability of false alarm ($P_{fa}$=O.1,0.2 M=3, 5)

Table 3.3 shows The least SNR required to achieve required ($P_d$) Vs ($P_{fa}$) as a function of no.of nodes(M) using Hard decision logic for DVB-T signal based on SCF method.

| Fusion logic | M=1 | M=3 | M=5 |
|---|---|---|---|
| OR fusion,$P_{fa}$=0.1 | -16dB | -19dB | -20dB |
| OR fusion,$P_{fa}$=0.2 | -17dB | -21dB | -22dB |
| AND fusion,$P_{fa}$=0.1 | -16dB | -14dB | -13 |
| AND fusion,$P_{fa}$=0.2 | -17dB | -16dB | -15dB |

Table 3.3: Least SNR required to achieve required ($P_d$) Vs ($P_{fa}$) as a function M using OR, AND fusion logic for SCF method (DVB-T signal)

The SNR vs. $P_d$ curves for DVB-T test signal with EGC fusion rule is shown in figure 3.13. The algorithm is verified for SNRs between -28 to -10 in steps of -2dB, with $P_{fa}$=0.1 and with 3, 5, and 7 nodes. From figure it is seen that the probability of detection increases as we increase SNR as well as number of nodes in cooperation.from the Table 3.4 the algoritham can detect the DVB-T signal upto -20dB with Pfa=0.1 for 3 nodes in cooperation, upto -22dB with $P_{fa}$=0.1 for 5 nodes in cooperation and upto -23dB with $P_{fa}$=0.1 for 7 nodes in cooperation for desired probability of detection $P_d$=0.9. In conclusion cooperative detection increases the performance of the system and it shows superiority compared to energy detection technique [6].

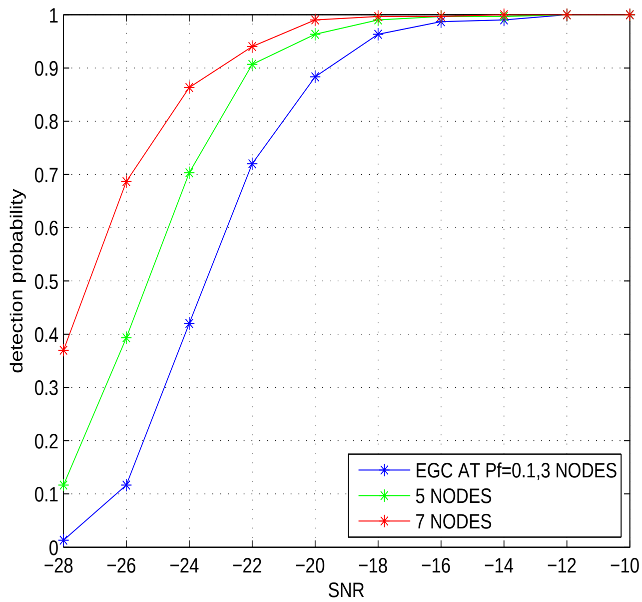


Figure 3.13: SNR Vs $P_d$ curves of EGC fusion for DVB-T signal with fixed probability of false alarm ($P_{fa}$=O.1, M=3, 5, 7)

Table 3.4 shows the least SNR required to achieve $P_d$=0.9 ($P_{fa}$) =0.1 as a function of no.of nodes(M) using soft decision logic for DVB-T and QPSK signals based on SCF method.

| EGC fusion | M=1 | M=3 | M=5 | M=7 |
|---|---|---|---|---|
| SCF method for DVB-T signal | -16dB | -20dB | -22dB | -23dB |
| SCF method for QPSK signal | -14dB | -18dB | -20dB | -22dB |
| Energy detection method[6] | -7dB | -12dB | -14dB | -16dB |

Table 3.4: Least SNR required to achieve $P_d$=0.9 ($P_{fa}$) =0.1 as a function no. of nodes $M$ using EGC fusion logic for SCF method (DVB-T and QPSK signas)

## 3.7 Conclusions

In this work, SCF based cyclostationary feature detector is studied and analyzed for single node and cooperative sensing. From the simulation results, it is clear that the performance of the proposed algorithm shows superiority compared to the energy detection technique. The performance of the cooperative detection is increased compared to single node detection. The soft combining technique using EGC fusion rule is optimal in low SNR environment and also exhibits better performance compared to hard decision techniques. Moreover, as the number of nodes increases the misdetection probability decreases. The detection algorithm able to detect the received signals of signal-to-noise ratio upto -16dB using single node. With cooperation it can detect upto -20dB with 3 nodes, -22dB with 5 nodes, and -23dB with 7 nodes.

## 3.8 References


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# Chapter 4

# Entropy estimation Method

## 4.1 Objective

The aim of this chapter is to develop Entropy estimation method based on cyclostationary features for cognitive radio networks. To compare its performance wth non entropy based cooperative sensing. The main objectives achieved in this chapter are:

1. Spectrum Sensing based on Entropy estimation detects weak licensed user signals and shows superiority compared to SCF based detection in case of both single node and cooperative scheme.

## 4.2 Work done in this chapter

The cyclostationary based spectrum sensing using Entropy detection method is proposed and the algorithm performance is verified using DVB-T signal. Cooperative cyclostationary technique is developed to improve the performance of non cooperative sensing technique. All the simulations are carried out using MATLAB tool.

## 4.3 Sensing algorithm

### 4.3.1 Hypothesis testing

The spectrum sensing problem is modeled as a binary Hypothesis test [1]

$$\begin{aligned} H_0 &: x(t) = w(t) \\ H_1 &: x(t) = hs(t) + w(t) \end{aligned} \tag{4.1}$$

Where $H_0$ stands for the absence of the signal in the channel, $H_1$ is the presence of a primary signal in the band. $x(t)$ is the received signal by the secondary user. $s(t)$ is the primary users transmitted signal, $w(t)$ is the additive white Gaussian noise (AWGN) and $h$ is the channel gain.

### 4.3.2 Entropy detection method

Information entropy is a measure of uncertainty associated with a random variable. In this algorithm entropy estimation is perfromed in frequency domain using cyclostationary features of the signal as follows

Let $x(t)$ be the received signal at the cognitive node, $x(t)$ is second-order cyclostationary if its mean and autocorrelation are periodic in time with some period $T$ [2].

$$m_x(t+T) = m_x(t) \tag{4.2}$$

$$R_x(t+T+\frac{\tau}{2}, t+T-\frac{\tau}{2}) = R_x(t+\frac{\tau}{2}, t-\frac{\tau}{2}) \tag{4.3}$$

In the case of cyclostationary process, the cyclic autocorrelation function (CAF) is non zero for a set of cyclic frequencies $\alpha$=0. The cyclic autocorrelation function at cyclic frequency $\alpha$ can be estimated as

$$R_x^{\alpha}(\tau) = \frac{1}{T}\int_{-T/2}^{T/2} R_x(\tau)e^{-j2\pi\alpha t}dt \tag{4.4}$$

Where $\alpha$= $(m/T)$ ; $m = 0, 1, 2, 3 \ldots\ldots\ldots\ldots\ldots\ldots$
And $R_x(\tau) = \int_{-\infty}^{\infty} x(t)x^*(t-\tau)dt$.

In discrete domain the cyclic autocorrelation is

$$R_x^{\alpha}[k] = \frac{1}{N}\sum_{n=-N/2}^{N/2} R_x[k]e^{-j2\pi\alpha n} \tag{4.5}$$

In our work, the autocorrelation is computed in a particular time interval with $N$= 512 samples, and $k = 0, 1, \ldots N - 1$.

Where $R_x[k]$ the autocorrelation function for $k - 1$ delays of the signal

$$R_x[k] = \sum_{n=1}^{N-k+1} x[n]x^*[n + k - 1]$$

And $x[n]$ is the discrete form of received signal.

By assuming that, the fast fourier transform coefficients of cyclic autocorrelation for different cyclic frequencies follows Gaussian distribution, this can be calculated as

$$S \cong FFT(R_x^{\alpha}[k]) \tag{4.6}$$

Entropy is estimated using Histogram method. The number of states of the random variable is equal to number of bins, let it be $L$ (dimension of probability space). Let $l_i$ denote the total number of occurrences in the i$^{th}$ bin with $\sum_{i=1}^{L} l_i = N$ [3]. The probability in each state $p_i$ is the frequency of occurrences in the i$^{th}$ bin, that is $p_i = l_i/N$.

The bin width $\Delta$ can be calculated as
$\Delta = \frac{[S_{\max} - S_{\min}]}{L}$

Where $S_{max}$ and $S_{min}$ denote the maximum and minimum value of random variable $S$. we fixed the bin number and calculated the bandwidth with the range of spectrum magnitude.

The information entropy of a random variable $S$ can be written as [4]

$$\phi(S) = -\sum_{i=1}^{L} (\frac{l_i}{N}) \log \frac{l_i}{N} \tag{4.7}$$

### 4.3.3 Threshold calculation

The threshold is calculated using the equation 4.8. it depends on the noise variance, number of bins taken for detection ($L$) and probability of false alarm ($P_{fa}$) [5].

$$The = H_L + \sigma_e Q^{-1}(1 - P_{fa}) \tag{4.8}$$

And therotical entropy of noise is $H_L = \ln(\frac{L}{\sqrt{2}}) + \frac{\gamma}{2} + 1$

Where $\gamma$ is the Euler-Mascheroni constant, $L$ is number of bins, $Q^{-1}$ is the inverse $Q$ function and $\sigma_e$ the noise variance.

If $\varphi$(S) is above $The$ we decide that the sensed spectrum is unoccupied otherwise it is occupied.

## 4.4 Simulation results

This section presents the simulation results of entropy based spectrum sensing using cyclostationary features. We have tested the perfromance of this approach for both single node (non cooperative) and cooperative detection. Two cases were considered with number of nodes in cooperation as 3 and 5.The perfromance of the algorithm is studied from $P_{fa}$ vs $P_d$ plot for different SNR values and SNR vs $P_d$ plots for diferent $P_{fa}$ values. In cooperative scheme, different number of secondary user nodes are used in the simulation (for AND and OR logic M= 3, 5 and EGC logic M=3, 5, and 7 are considered for simulation). In each node the SNR's are different assuming they are shadowed.

### 4.4.1 Non cooperative detection

The Entropy based cyclostationary spectrum sensing algorithm is verified by applying DVB-T test signal with the specifications in table 3.1.In this algorithm, the autocorrelation computed in a particular time interval with 512 samples, binwidth (L)=15 and $\gamma$ (Euler-Mascheroni constant)=0.57721.

The detector computes Entropy for the received signal spectral correlation values and compares it with a precomputed threshold (The) as equation 4.8. Threshold is determined by the desired value of probability of false alarm ($P_{fa}$). The algorithm is simulated for SNR range between -30dB to -10dB in steps of 2dB. We computed the detection probability using test statistic in 1000 iterations.

The performance of detector is measured from ROC curve which is the plot between probability of detection ($P_d$) and probability of false alarm ($P_{fa}$). Figure

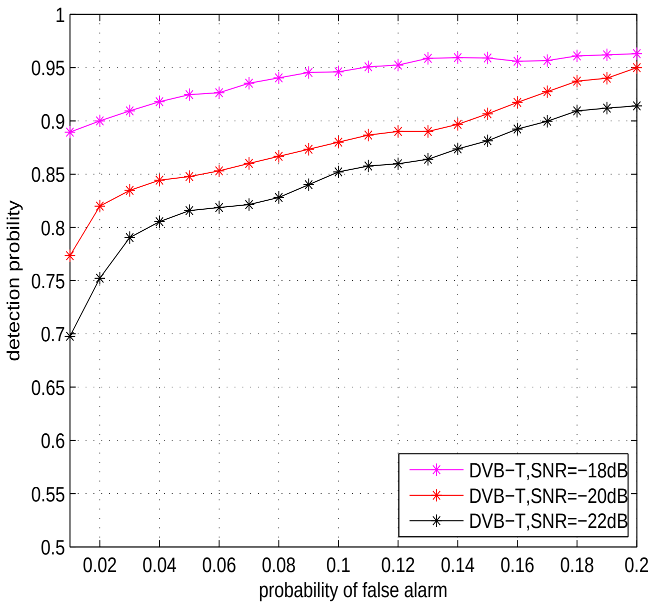


Figure 4.1: ROC curves for DVB-T signal under AWGN channel with different SNRs

4.1 is the ROC curve for DVB-T signal. From this figure it is observed that probability of detection increases as we increase Pf as well as SNR.

Figure 4.2 presents the $P_d$ Vs SNR with different $P_{fa}$ values. This Figure reveals that the probability of detection increases as the SNR increases. The Entropy based cyclostationary detector able to detect the DVB-T signal presence upto -20dB with $P_{fa}$=0.1, -19dB with $P_{fa}$=0.05 for desired detection probability $P_d$=0.9.

## 4.4.2 Cooperative detection

In cooperative detection AND, OR fusion rules for hard decision and EGC for soft decision are considered. Different number of secondary user nodes (varies from 3 to 5) are used in the simulation with each node the SNR's are different.

The efficiency of fusion rules are determined by using Receiver Operating Characteristics (ROC) ($P_d$ and $P_{fa}$) and SNR Vs $P_d$ curves.

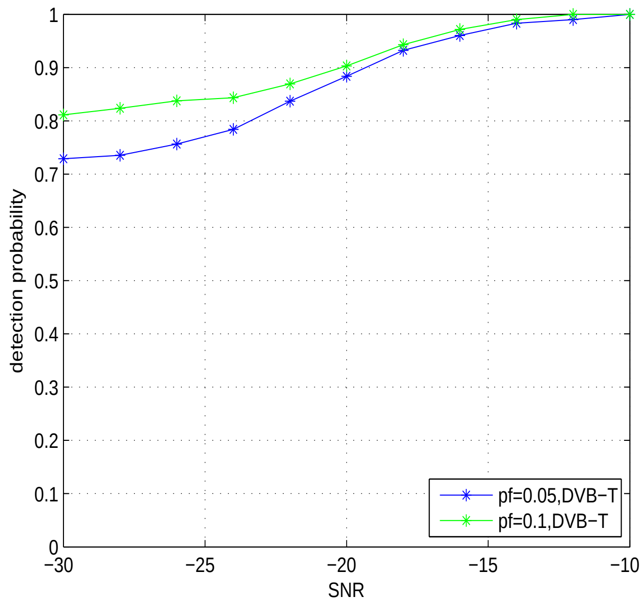


Figure 4.2: SNR Vs $P_d$ curves for DVB-T with different fixed probability of false alarm ($P_{fa}$=0.05, 0.1)

The SNR vs. $P_d$ curves for DVB-T test signal with OR fusion rule is shown in figure 4.3. The algorithm is verified for SNRs between -28 to -10 in steps of -2dB, with $P_{fa}$=0.1 and with 3 and 5 nodes. From figure it is seen that the probability of detection increases as we increase SNR as well as number of nodes in cooperation. The algoritham can detect the DVB-T signal upto -21dB with $P_{fa}$=0.1 for 3 nodes in cooperation and upto -23dB with $P_{fa}$=0.1 for 5 nodes in cooperation for desired probability of detection $P_d$=0.9.

The SNR vs. $P_d$ curves for DVB-T test signal with AND fusion rule is shown in figure 4.4. The algorithm is verified for SNRs between -28 to -10 in steps of -2dB, with $P_{fa}$=0.1 and with 3 and 5 nodes. From figure it is seen that the probability of detection increases as we increase SNR and it decreaes as well as number of nodes in cooperation. The algoritham can detect the DVB-T signal upto -16dB with $P_{fa}$=0.1 for 3 nodes in cooperation and upto -23dB with $P_{fa}$=0.1 for 5 nodes in cooperation for desired probability of detection $P_d$=0.9.

Table 4.1 shows the least SNR required to achieve required ($P_d$) Vs ($P_{fa}$) as a function of no.of nodes ($M$) using Hard decision logic for DVB-T signal based on Entropy method. This table presents the simulation results for $P_{fa}$=0.1.

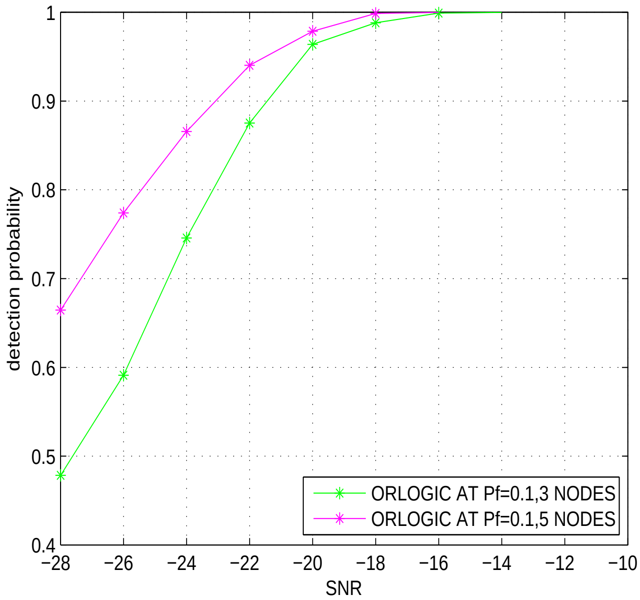


Figure 4.3: SNR Vs $P_d$ curves of OR fusion for DVB-T signal with fixed probability of false alarm ($P_{fa}$=O.1, M=3, 5)

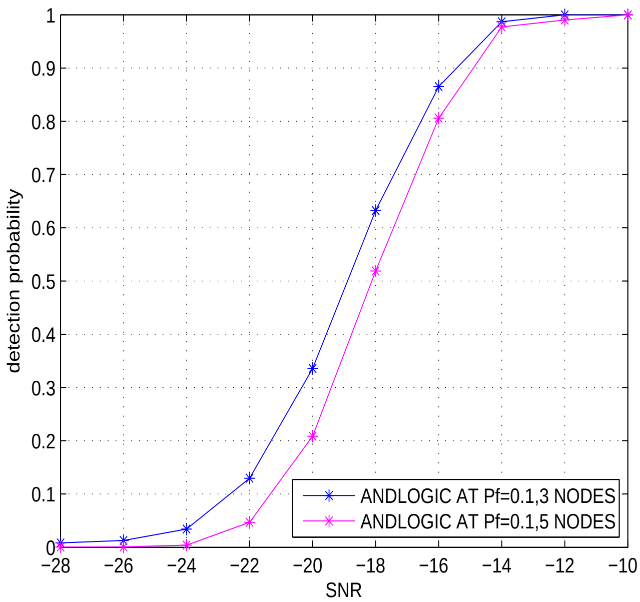


Figure 4.4: SNR Vs $P_d$ curves of AND fusion for DVB-T signal with fixed probability of false alarm ($P_{fa}$=O.1, M=3, 5)

| Fusion logic | M=1 | M=3 | M=5 |
|---|---|---|---|
| OR | -19dB | -22dB | -23dB |
| AND | -19dB | -17dB | -16dB |

Table 4.1: The least SNR required to achieve required ($P_d$) =0.9, ($P_{fa}$) =0.1 as a function of no.of nodes ($M$) using OR, AND fusion logic based on Entropy method

The SNR vs. $P_d$ curves for DVB-T test signal with EGC fusion rule is shown in figure 4.5. The algorithm is verified for SNRs between -30 to -18 in steps of -2dB, with $P_{fa}$=0.1 and with 3, 5, and 7 nodes. From figure it is seen that the probability of detection increases as we increase SNR as well as number of nodes in cooperation. from the Table 4.2 the algoritham can detect the DVB-T signal upto -21dB with $P_{fa}$=0.1 for 3 nodes in cooperation, upto -24dB with $P_{fa}$=0.1 for 5 nodes in cooperation and upto -26dB with $P_{fa}$=0.1 for 7 nodes in cooperation for desired probability of detection $P_d$=0.9. In conclusion cooperative detection increases the performance of the system and it shows superiority compared to SCF based cyclostationary detection technique [11].

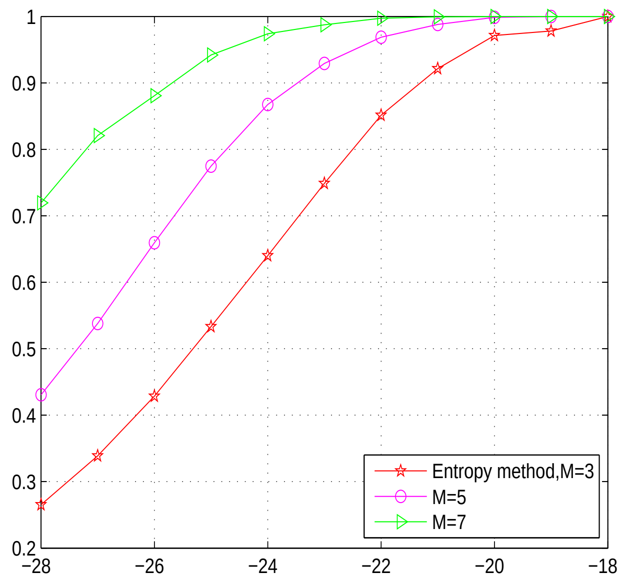


Figure 4.5: SNR Vs $P_d$ curves of EGC fusion for DVB-T signal with fixed probability of false alarm ($P_{fa}$=O.1, M=3, 5))

Table 4.2 shows the least SNR required to achieve required ($P_d$) Vs ($P_{fa}$) as a function of no.of nodes(M) using soft decision logic for DVB-T signal based on Entropy method. The simulation results are for $P_d$ =0.9 and $P_{fa}$ =0.1.

| EGC fusion | M=1 | M=3 | M=5 | M=7 |
|---|---|---|---|---|
| Entropy estimation method | -19dB | -21dB | -24dB | -26dB |
| SCF method | -16dB | -20dB | -22dB | -23dB |

Table 4.2: The least SNR required to achieve $P_d$ =0.9 and $P_{fa}$ =0.1 as a function of no.of nodes($M$) using EGC fusion logic based on Entropy method

## 4.5 Conclusions

In this work, Entropy detection based on cyclostationary features is proposed for single node and cooperative sensing. From the simulation results, it is clear that the performance of the proposed algorithm outperforms the energy and cyclostationary detection techniques. The performance of the cooperative detection is increased compared to single node detection. The soft combining technique using EGC fusion rule is optimal in low SNR environment and also exhibits better performance compared to hard decision techniques. Moreover, as the number of nodes increases the misdetection probability decreases. The detection algorithm able to detect the received signals of signal to noise ratio upto -20dB using single node. With cooperation it can detect upto -21dB with 3 nodes, -24dB with 5 nodes, and -26dB with 7 nodes.

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# Chapter 5

# FPGA implementation of sensing methods

## 5.1 Objective

The aim of this chapter is to implement the cyclostationary sensing technique with SCF method and entropy method in Field Programmable Gate Array (FPGA). For validating the implemented algorithms DVB-T signal under AWGN noise is considered. The performance of architecture are evaluated based on

1. Implementation complexity and feasibility.

2. Minimum computational time required to implement the algorithm.

3. Accuracy of the algorithm when implemented using hardware.

## 5.2 Work done in this chapter

The cyclostationary based spectrum sensing techniques with SCF and entropy methods are studied and implemented on Xilinx Virtex4 (XC4VSX35-10FF668) FPGA [1,5]. Hardware in Loop (HIL) verification technique is carried out for verification of algorithms in FPGA. The resource utilization for each case along with the maximum operating frequency with which the design can run has been observed.

## 5.3 DVB-T signal generation

The signal generation for real time DVB-T (2k mode) signal is taken from the MATLAB communication examples. The block diagram of the block is shown in the figure 5.1. The signal from this block is added with AWGN noise of the required SNR. This signal is considered as the received signal for the cognitive radio to perform spectrum sensing.

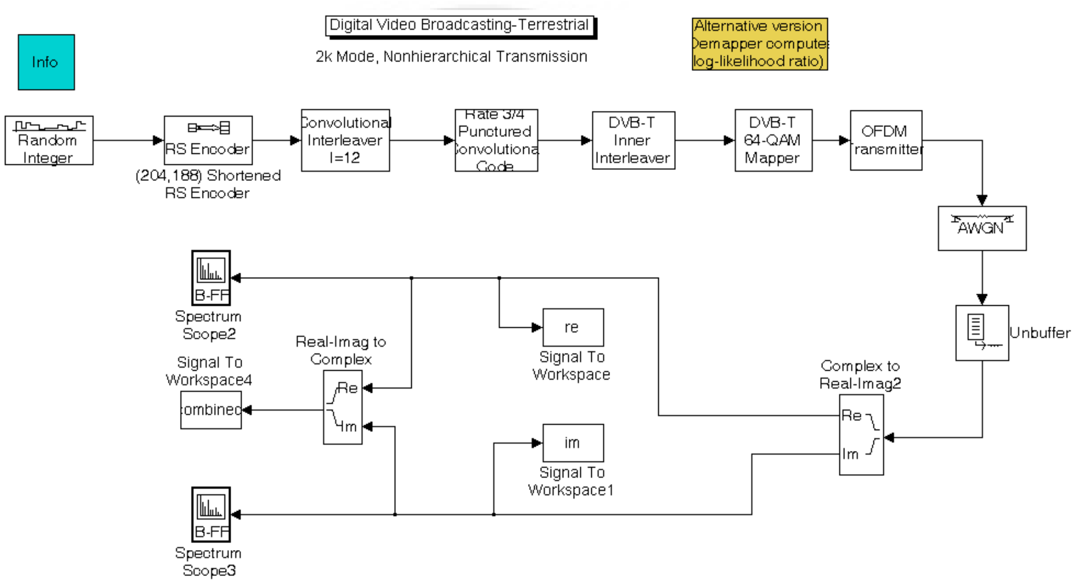


Figure 5.1: DVB-T signal generation model [2]

## 5.4 SCF based spectrum sensing architecture

The complete architecture for cyclostationary based spectrum sensing using SCF method is shown in figure 5.2.

This block consists of the following components.

1. Gateway In: The Xilinx Gateway In blocks are the inputs into the Xilinx portion of your Simulink design. These blocks convert Simulink integer, double and fixed-point data types into the System Generator fixed-point type. Data Type : Signed 16_15

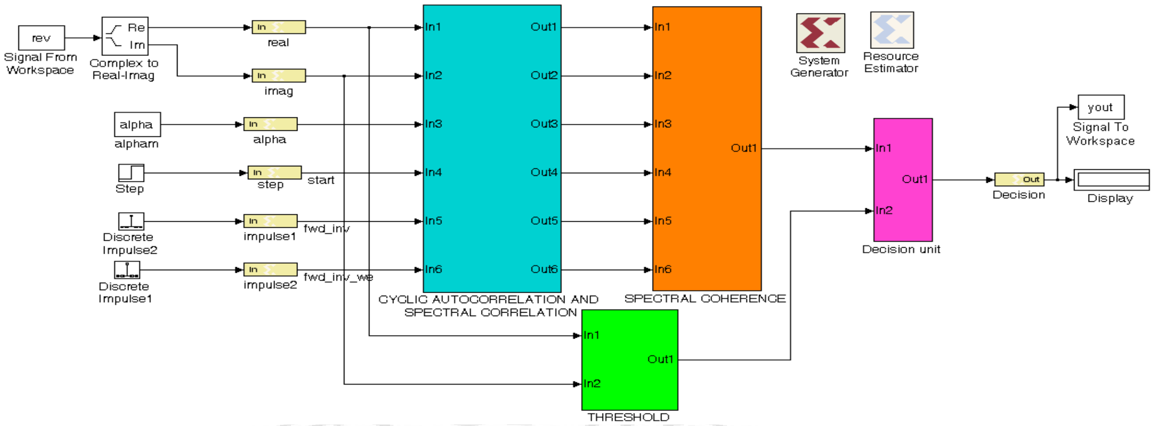


Figure 5.2: Sysgen model for SCF based cyclostationary spectrum sensing [3]

2. Subsystem: A Subsystem block represents a subsystem of the system that contains it. The Subsystem block can represent a virtual subsystem or a true (atomic) subsystem.

3. Multipliers: The Xilinx Mult block implements a multiplier. It computes the product of the data on its two input ports, producing the result on its output port. Precision : Full

4. Adder/Subtractor: This block implements an adder/subtractor. The operation can be fixed (Addition or Subtraction) or changed dynamically under control of the sub mode signal. Precision : Full

5. Accumulator: Implements an adder or subtractor-based scaling accumulator. The blocks current input is accumulated with a scaled current stored value. The scale factor is a block parameter.

6. Counter: Counter block implements a free running or count-limited type of an up, down, or up/down counter. The counter output can be specified as a signed or unsigned fixed-point number.

7. Signal from workspace: The Signal From Workspace block imports a signal from the MATLAB workspace into the Simulink model. The Signal parameter specifies the name of a MATLAB workspace variable containing the signal to import, or any valid MATLAB expression defining a matrix or 3-D array.

8. Relational: The Xilinx Relational block implements a comparator. The supported comparisons are the following: Equal-to (a = b) Not-equal-to (a != b) Less-than (a ¡ b) Greater-than (a ¿ b) Less-than-or-equal-to (a ¡= b) Greater-than-or-equal-to (a ¿= b) The output of the block is a Bool.

9. Gateway Out: Xilinx Gateway Out blocks are the outputs from the Xilinx portion of your Simulink design. This block converts the System Generator fixed-point data type into Simulink Double. According to its configuration, the Gateway Out block can either define an output port for the top level of the HDL design generated by System Generator, or be used simply as a test point that will be trimmed from the hardware representation

10. Display: The Display block shows the value of its input on its icon. We can control the display format using the Format parameter

11. Constant: The Xilinx Constant block generates a constant that can be a fixed-point value, a Boolean value, or a DSP48 instruction. This block is similar to the Simulink constant block, but can be used to directly drive the inputs on Xilinx blocks.

12. CORDIC SQRT: This block implements a square root circuit using a fully parallel CORDIC algorithm in hyperbolic vectoring mode i.e given input x it computes sqrt(x).

13. CORDIC DIVIDER: This block implements a divider circuit using a fully parallel CORDIC algorithm in linear vectoring mode i.e given input (x,y) it computes y/x.

14. Mcode block: The Xilinx MCode block is a container for executing a user-supplied MATLAB function within Simulink. A parameter on the block specifies the M-function name. The block executes the M-code to calculate block outputs during a Simulink simulation. The same code is translated in a straightforward way into equivalent behavioral VHDL/Verilog when hardware is generated.

15. FFT: This block implements an efficient algorithm for computing Discrete Fourier Transform (DFT). It supports only for virtex-4, virtex-II, virtex-II pro and sparten-3 devices.

16. FIFO: This block implements a FIFO memory queue. Values presented at the module's data-input port are written to the next available empty memory location when the write-enable input is one. By asserting the read-enable input port, data can be read out of the FIFO via the data output port in the order in which they were written.

### 5.4.1 Autocorrelation

Autocorrelation with one time delay is shown in figure 5.3. In practice the number of delays sholud be more for higher accuracy.

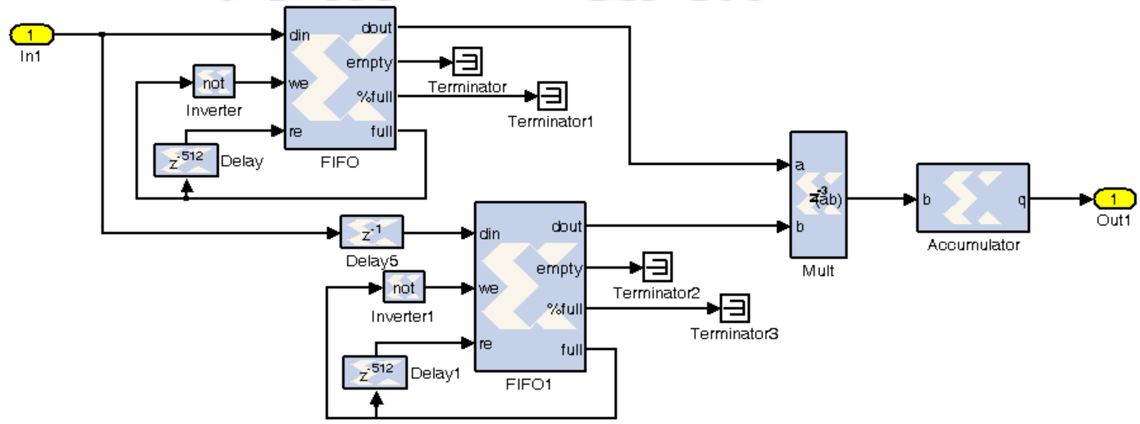


Figure 5.3: Sysgen model for Autocorrelation

### 5.4.2 SCF block

The SCF block computes the cyclic autocorrelation and from that it calculates the average SCF over number of cyclic frequencies as per equations 3.6. Spectral correlation is calculated by applying FFT to autocorrelation function. Shifting in frequency domain is equal to multiplying corresponding time domain signal with exponential signal. This is converted into frequency domain. This analysis is done in cyclic autocorrelation and spectral correlation block which is shown in figure 5.4. The corresponding equations are [4]

$$S_x^{\alpha}(\Omega) = fft([R_x[k]) \tag{5.1}$$

$$S_x(\Omega + \alpha/2) = fft([R_x[k] \exp(-i2\pi(\alpha/2)\frac{k}{n})) \tag{5.2}$$

$$S_x(\Omega - \alpha/2) = fft([R_x[k] \exp(i2\pi(\alpha/2)\frac{k}{n})) \tag{5.3}$$

Where $[R_x[k]$ the autocorrelation function

The outputs of cyclic autocorrelation and spectral correlation block are passed through set of multipliers, adders, CORDIC sqrt and CORDIC divider to calculate SCF. Then the average SCF over number of cyclic frequencies is calculated by an accumulator and a multiplier. The output of SCF block is the test statistic for signal detection.

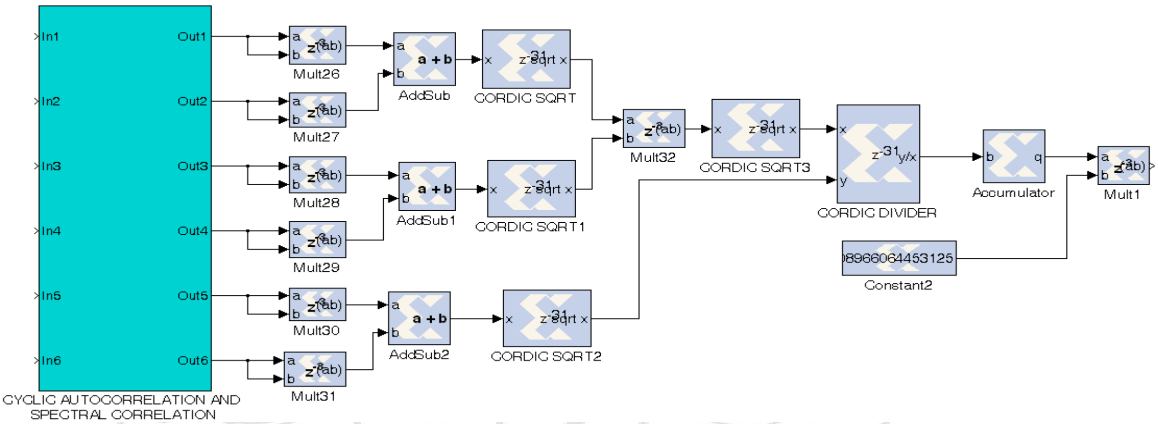


Figure 5.4: Sysgen model for SCF block

### 5.4.3 Threshold block

The threshold block computes the value of threshold required to make a decision about signal status. The architecture of this block in shown in the figure 5.5.

### 5.4.4 Decision logic

The decision logic block which is shown in figure 5.6 compares the threshold and the estimated SCF value to make the decision about the existence of the signal in a particular frequency band. The output of detector block displays 1 if primary signal is present and 0 if primary signal is absent.

The complete hardware co simulation architecture for cyclostationary based spectrum sensing using SCF method is shown in figure 5.7. The Hardware in

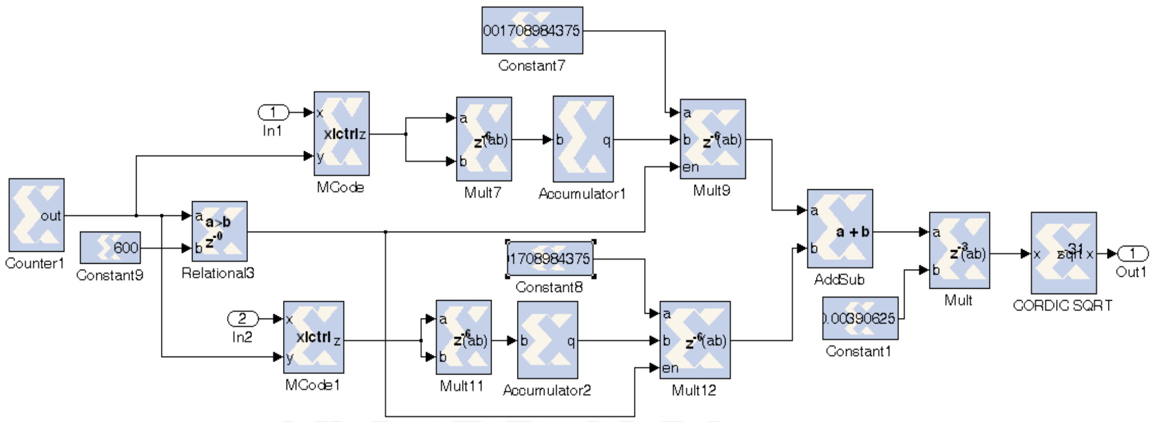


Figure 5.5: Sysgen model for Threshold block

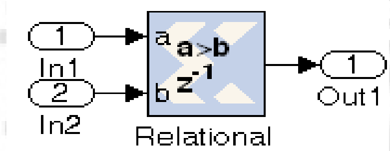


Figure 5.6: Sysgen model for decision block

Loop (HIL) verification is carried out by using Virtex 4 (XC4VSX35-10FF668) FPGA. The performance of algorithm using this hardware is tested.

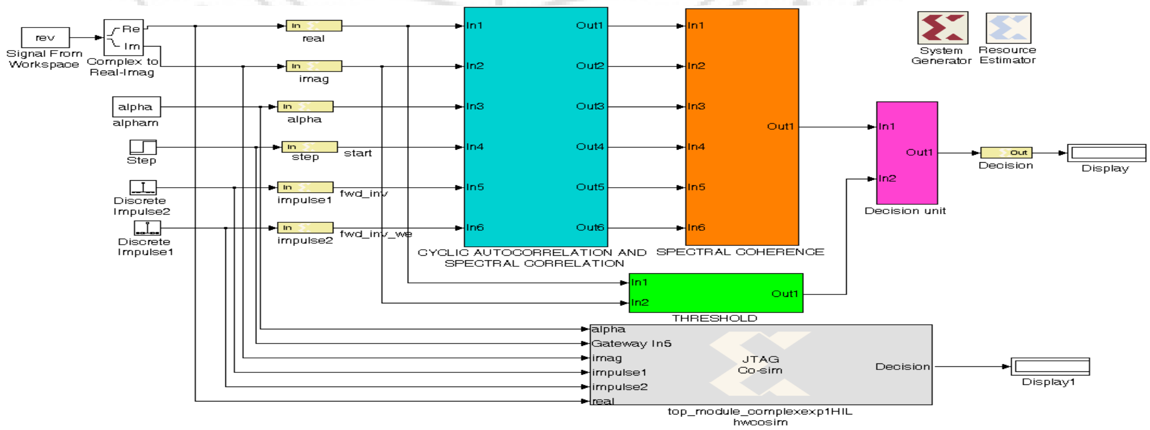


Figure 5.7: HIL simulation model for SCF based cyclostationary spectrum sensing

## 5.5 Entropy based spectrum sensing architecture

The complete architecture for cyclostationary based spectrum sensing using Entropy method is shown in figure 5.8.

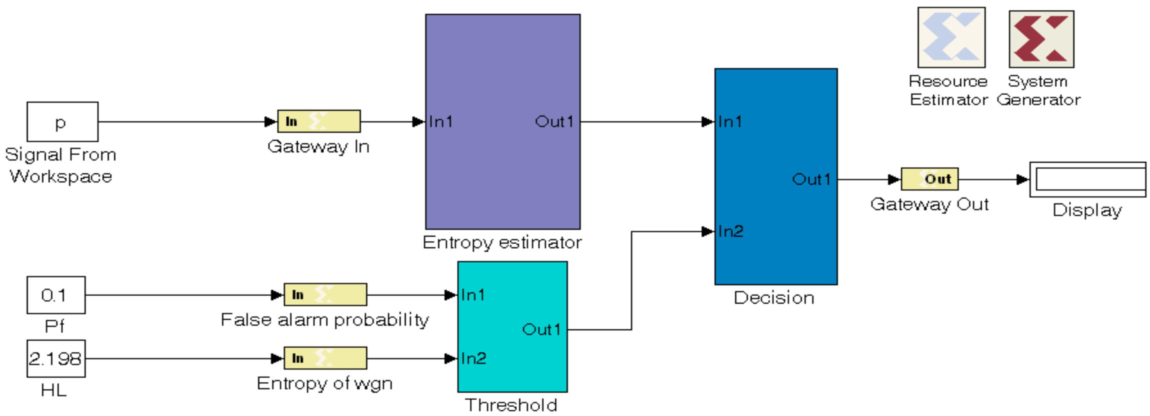


Figure 5.8: Sysgen model for Entropy based cyclostationary spectrum sensing

This block consists of the following components.

1. Gateway In
2. Subsystem
3. Multipliers
4. Adder/Subtractor
5. Accumulator:
6. Signal from workspace
7. Relational
8. Gateway Out
9. Display
10. Constant
11. FIFO

12. CORDIC LOG: This block implements a natural logarithm circuit using a fully parallel CORDIC algorithm in hyperbolic vectoring mode i.e. given input x it computes log(x).

### 5.5.1 Entropy block

The Entropy block computes the entropy for the spectral correlation values of the received signal. The sysgen model for Entropy calculation is shown in figure 5.9.

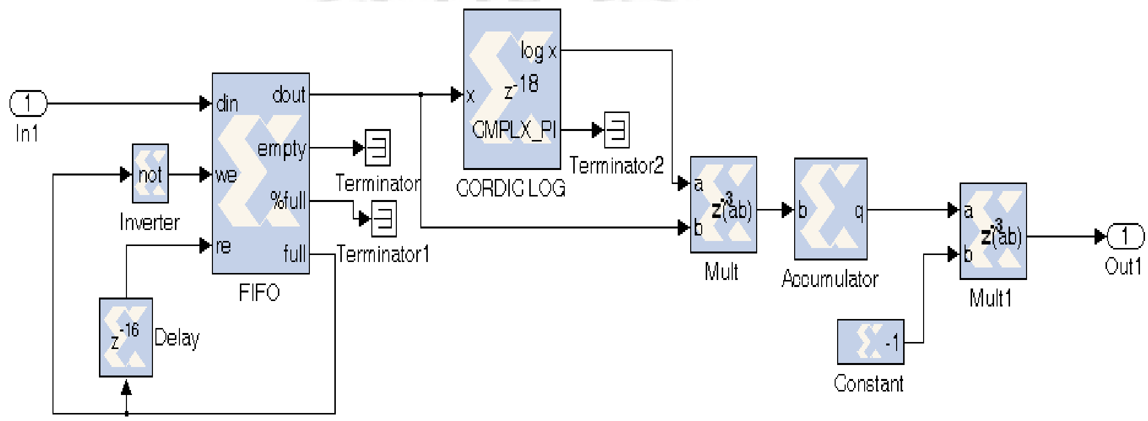


Figure 5.9: Sysgen model for Entropy block

### 5.5.2 Threshold block

The threshold block computes the value of threshold required to make a decision about signal status. The architecture of this block in shown in the figure 5.10.

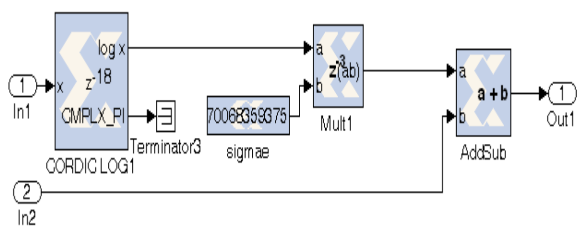


Figure 5.10: Sysgen model of Threshold block for entropy detection

### 5.5.3 Decision logic

The decision logic block which is shown in figure 5.6 compares the threshold and the estimated Entropy value to make the decision about the existence of the signal in a particular frequency band. The output of detector block displays 1 if primary signal is present and 0 if primary signal is absent.

The complete hardware co simulation architecture for cyclostationary based spectrum sensing using Entropy detection method is shown in figure 5.11. The Hardware In Loop (HIL) verification is carried out by using Virtex 4 (XC4VSX35-10FF668) FPGA. The performance of algorithm using this hardware is tested.

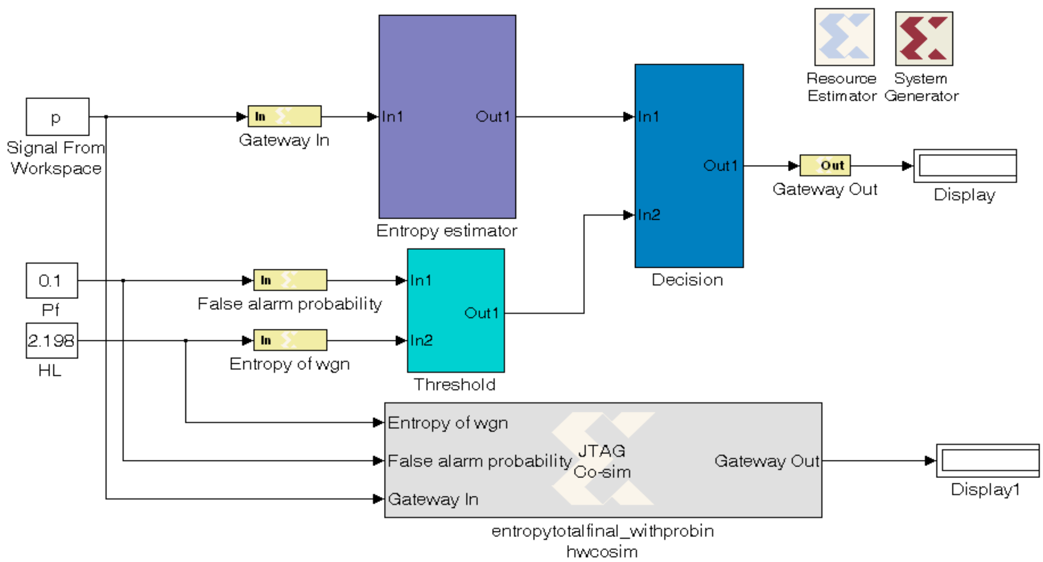


Figure 5.11: HIL simulation model for Entropy based cyclostationary spectrum sensing

## 5.6 Results

The performance requirements of the detector can be summarized using the following parameters

### 5.6.1 SCF based detection

The maximum frequency of operation of the algorithm in FPGA is 31.166MHz. Table 5.1 shows the resource utilization of the sensing algorithm.

| Logic Utilization | Used | Available | Utilization (%) |
|---|---|---|---|
| Number of BSCANs | 1 | 4 | 25 |
| Number of BUFGs | 3 | 32 | 9 |
| Number of BUFGCTRLs | 3 | 32 | 9 |
| Number of DCM$_{A}DVs$ | 1 | 8 | 12 |
| Number of DSP48s | 190 | 192 | 98 |
| Number of External IOBs | 1 | 448 | 1 |
| Number of LOCed IOBs | 1 | 1 | 100 |
| Number of RAMB16s | 17 | 192 | 8 |
| Number of Slices | 14301 | 15360 | 93 |
| Number of SLICEMs | 1767 | 7680 | 23 |

Table 5.1: Device Utilization summary for SCF based method

### 5.6.2 Entropy based detection

The maximum frequency of operation of the algorithm in FPGA is 151.814MHz. Table 5.2 shows the resource utilization of the sensing algorithm.

| Logic Utilization | Used | Available | Utilization (%) |
|---|---|---|---|
| Number of BSCANs | 1 | 4 | 25 |
| Number of BUFGs | 2 | 32 | 6 |
| Number of BUFGCTRLs | 2 | 32 | 6 |
| Number of DSP48s | 4 | 192 | 2 |
| Number of External IOBs | 1 | 448 | 1 |
| Number of LOCed IOBs | 1 | 1 | 100 |
| Number of RAMB16s | 3 | 192 | 1 |
| Number of Slices | 785 | 15360 | 5 |
| Number of SLICEMs | 12 | 7680 | 1 |

Table 5.2: Device Utilization summary for Entropy based method

## 5.7 Conclusion

The SCF based and Entropy based cyclostationary spectrum sensing techniques are studied and implemented in FPGA. The single node detectors for both were designed using Xilinx Sysgen. From implementation results, proposed entropy detector occupies fewer resources compared to cyclostationary detection technique. The maximum frequency of operation for SCF detector is 31.166MHz and entropy detector is 151.814MHz. The software and hardware results are matched with Matlab simulation results for desired probability of false alarm ($P_{fa}0.1$).

## 5.8 References

1. www.xilinx.com, “Xilinx University program Virtex-4 Development system, hardware reference manual”, Xilinx.

2. www.mathworks.com.

3. Xilinx System generator 10.1 user guide.

4. Ning Han; SungHwan Shon; Jae Hak Chung; Jae Moung Kim; , "Spectral correlation based signal detection method for spectrum sensing in IEEE 802.22 WRAN systems,"The 8th International Conference on Advanced Communication Technology (ICACT), vol.3, pp. 1766-1770, Feb-2006.

5. Srinu, S; Sabat, S.L; Udgata, S.K, "FPGA implementation of cooperative spectrum sensing for Cognitive Radio networks,"Second UK-India-IDRC International Workshop on Cognitive Wireless Systems (UKIWCWS), pp.1-5, Dec-2010.

# Chapter 6

# Conclusions and Future work

## 6.1 Conclusions

In this work, spectrum sensing was performed by using cyclostationry features of the received signal. Cyclostationary feature detection technique was studied because of its better sensing ability for low signal to noise ratio (SNR) signals. We studied spectrum sensing using Spectral Coherence Function (SCF) . We proposed entropy based detection using cyclostationary properties for spectrum sensing because from studies we found that entropy detection method is based on the concept that the entropy or uncertainty of the received signal reduces if the received signal is a modulated signal. Two different kind of modulated signals were considered such as QPSK, DVB-T under additive white Gaussian noise (AWGN) for validating the algorithms. Sensing performance of both algorithms were analyzed by considering probability of detection, probability of false alarm as performance metrics. We used Monte-Carlo methods for studying the perfromance of the algorithm.

In practice, sensing performance is often compromised with multipath fading, shadowing and receiver uncertainty issues. To mitigate the impact of these issues, the proposed approach (entropy + cyclostationary) was extended for cooperative sensing using different fusion rules (Hard and Soft decision rules). The performance of proposed entropy detection was compared with SCF detection technique. Simulation results discloses that, Entropy detection algorithm detect signals of signal-to-noise ratio upto -26dB using seven nodes in cooperation for detection probability $P_d \geq 0.9$ and false alarm probability $P_{fa} \leq 0.1$, whereas, SCF method detects signal upto -23dB. Proposed sensing algorithm for single node is implemented in Xilinx Virtex4 (XC4VSX35-10FF668) Field Programmable Gate Arrays (FPGA).

Finally it is concluded that i) Entropy can be used as an important feature of the signal that helps to detect the low SNR signals ii) every detection technique has an SNR threshold below which it will fail to operate robustly.

## 6.2 Future work

These techniques can be extended further to eliminate problems in the control channel by applying forward error correction techniques. We can optimize the designs using advanced digital design techniques to speed up the algorithm and reduce the complexity. The designs can be tested on Wireless application Research Platfrom (WARP) board which has the necessary hardware to test this type of applications.