# TWO STAGE SPECTRUM SENSING FOR COGNITIVE RADIO

*A Thesis submitted in partial fulfillment of the Requirements for the degree of*

Master of Technology
In
Electronics and Communication Engineering
Specialization: Communication and Networks

By

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May 2014

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Under the Guidance of
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Department of Electronics and Communication Engineering
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*Dedicated to…*

*My parents, my younger Sisters and my Best Friend*

**DEPT. OF ELECTRONICS AND COMMUNICATION ENGINEERING**

**NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA**

**ROURKELA – 769008, ODISHA, INDIA**

# Certificate

This is to certify that the work in the thesis entitled **Two Stage Spectrum Sensing for Cognitive Radio** by **Khushboo Mawatwal** is a record of an original research work carried out by her during 2013 - 2014 under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Master of Technology in Electronics and Communication Engineering (Communication and Networks), National Institute of Technology, Rourkela. Neither this thesis nor any part of it, to the best of my knowledge, has been submitted for any degree or diploma elsewhere.

Place: NIT Rourkela

Date: 25 May 2014

**Prof. S.M.Hiremath**

Professor

**DEPT. OF ELECTRONICS AND COMMUNICATION ENGINEERING**

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**ROURKELA – 769008, ODISHA, INDIA**

# Declaration

I certify that

a) The work contained in the thesis is original and has been done by myself under the general supervision of my supervisor.

b) The work has not been submitted to any other Institute for any degree or diploma.

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*Khushboo Mawatwal*

*25th May 2014*

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# ABSTRACT

In past few decades the need for high data rate wireless communication has experienced a booming growth indicating a huge commercial potential. The growing demand of wireless devices is restricted by the spectrum access policy of radio regulatory regime. Large part of the spectrum is allocated for exclusive use by the licensed users and only a small portion of the spectrum is given for open access. The commercial success of the unlicensed spectrum has encouraged FCC to frame policies towards more flexible and open spectrum access.

Most of the licensed bands suffer from under-utilization and less spectral occupancy of spectrum. The exclusive usage criteria in the licensed spectrum have resulted in wastage of limited and precious spectrum. The so called ‘spectrum scarcity’ and ‘limited radio spectrum’ is a result of the way the spectrum is being regulated.

Cognitive radio has emerged as a solution to the problem of low spectral occupancy and inefficient utilization of the licensed radio spectrum. It enables the unlicensed users to access the licensed band without violating the exclusive usage facility for the licensed user. It identifies the unused portions of the licensed spectrum known as spectrum holes and makes them available for unlicensed or secondary users.

Spectrum sensing is a technique in which the surrounding radio environment is sensed in order to determine the presence or absence of the licensed user in the licensed band. It enables the CR to get an overview on the radio environment usage and in determining the spectrum holes.

The two-stage spectrum sensing method utilizes the strength of both energy and cyclostationary schemes. It contains two stages of spectrum sensing, in which the received signal first passes through the energy detection stage. If the signal is not detected in this

stage, it goes to the cyclostationary detection stage. It was observed that the two-stage spectrum sensing method outperforms both the energy detection and cyclostationary detection method in terms of its detection capability. This dissertation discusses a modified detection scheme for cyclostationary method and the two-stage detection scheme for wireless microphone signals and amplitude modulation signals.

# CONTENTS

# NOMENCLATURE

| | | |
|---|---|---|
| $\Delta t$ | : | Total observation interval |
| $T$ | : | Sliding window interval |
| $N$ | : | Number of samples in the observation interval $\Delta t$ |
| $N_p$ | : | Number of samples in sliding window $T$ |
| $f_s$ | : | Sampling frequency |
| $T_s$ | : | Sampling Period |
| f | : | Spectral frequency |
| $\Delta f$ | : | Spectral frequency resolution |
| $\Delta\alpha$ | : | Cyclic frequency resolution |
| $S_x^\alpha(f)$ | : | SCD function |
| $P_{fa}$ | : | Probability of false alarm |
| $P_d$ | : | Probability of detection |
| $K_f$ | : | Frequency sensitivity of the FM modulator |
| $I_0(u)$ | : | Modified Bessel function of 1st kind and order zero |
| $\Delta f$ | : | Frequency deviation |
| $\alpha$ | : | Cyclic frequency |
| $R_x^\alpha(\tau)$ | : | Cyclic autocorrelation function of $x(t)$ |
| $X_T(n,f)$ | : | Complex demodulate of $x(t)$ over interval $T$ |
| λ | : | Threshold |
| $\sigma_w^2$ | : | Variance of the noise signal |
| $\sigma_s^2$ | | Variance of the primary user signal |

# ABBREVIATIONS

| | | |
|---|---|---|
| A/D | : | Analog-to-Digital converter |
| AM | : | Analog Modulation |
| AWGN | : | Additive White Gaussian Noise |
| CAF | : | Cyclic auto-correlation function |
| CDP | : | Cyclic Domain Profile |
| CR | : | Cognitive Radio |
| CS | : | Cyclostationary |
| ED | : | Energy Detection |
| FAM | : | FFT Accumulation Method |
| FCC | : | Federal Communication Commission |
| FFT | : | Fast Fourier Transform |
| FM | : | Frequency Modulation |
| FS | : | Frequency Smoothing |
| GSM | : | Global System for Mobile |
| IEEE | : | Institute of Electrical and Electronics Engineers |
| LO | : | Local Oscillator |
| MAC | : | Media Access Control |
| MF | : | Matched Filter |
| NLOS | : | Non- Line-of-Sight |
| pdf | : | Probability density function |
| PHY | : | Physical |
| PSD | : | Power Spectral Density |
| PU | : | Primary User |
| RF | : | Radio Frequency |
| ROC | : | Receiver Operating Characteristics |
| SCD | : | Spectral Correlation Density |
| SCF | : | Spectral Correlation Function |
| SNR | : | Signal-to-Noise Ratio |
| SSCA | : | Strip Spectral Correlation Algorithm |
| TS | : | Time Smoothing |
| TV | : | Television |
| UHF | : | Ultra High Frequency |
| VHF | : | Very High Frequency |

| | | |
|---|---|---|
| WM | : | Wireless Microphone |
| WRAN | : | Wireless Regional Area Network |

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# 1

# COGNITIVE RADIO: AN INTRODUCTION

In last few decades a booming growth is experienced in the Wireless Communication [1], due to increase in consumer electronics applications and personal high-data-rate networks. Devices based on wireless standards and technologies will remain increasing in future, which in turn will lead to spectrum scarcity in wireless communication. The limited availability of spectrum has become a bottleneck in the fulfillment of the consumers demand.

The Federal Communication Commission (FCC) [2] report has shown that spectrum scarcity is mostly due to under-utilization of licensed spectrum. The licensed bands are exclusive usage band which provides protection against interference from other radio systems. It is observed that around 90-95% of the licensed radio spectrum is not in use at any location at any given time. The under-utilization of licensed spectrum has lead to the problem of artificial spectrum scarcity.

In order to overcome the inefficient spectrum utilization and to meet the increasing demand has lead to the coining of new concept "Cognitive Radio". The Cognitive Radio is a technology which efficiently utilizes the licensed spectrum without causing any harm to the licensed users. It searches the licensed frequency bands for unused spectrum, and uses them efficiently. The unused licensed spectrum is also known as ‘white spaces’ [1].

## 1.1 Cognitive Radio Concept

Cognitive Radio derives its name from the word ‘cognitive’ which means process of acquiring knowledge by the use of reasoning, intuition or perception. It is a new technology which scans the radio spectrum and searches for white spaces in it. It enables the unlicensed user to use the licensed bands without causing any significant interference to the licensed user. The licensed user is also known as primary user (PU). The users which are having no rights to access the licensed bands are known as secondary users (SU) [1].

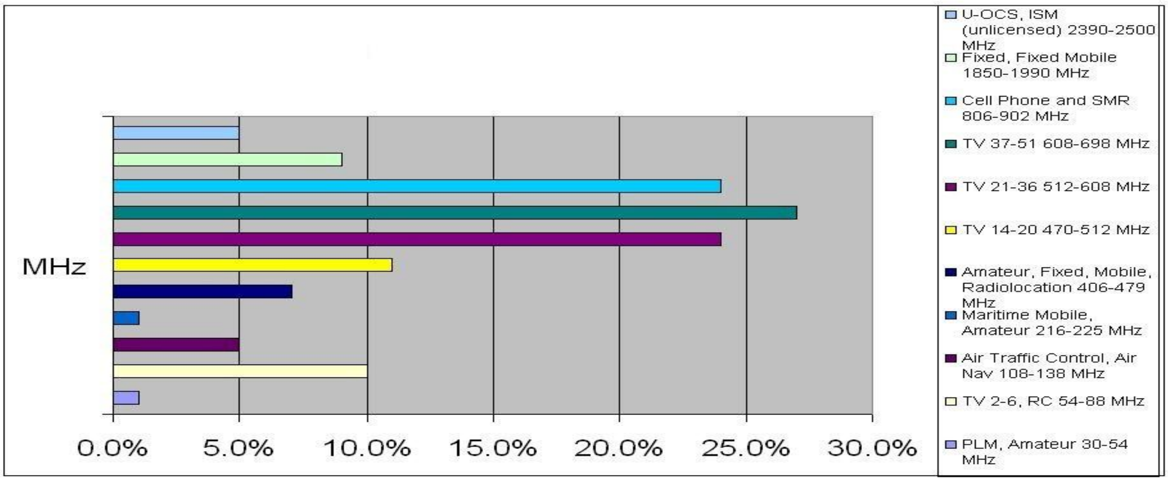



Fig 1-1 Measured Spectrum Occupancy Average from 6 locations [3]

## 1.2 Cognitive Radio Cycle

Cognitive radio operation can be explained by a Cognitive radio cycle [4]

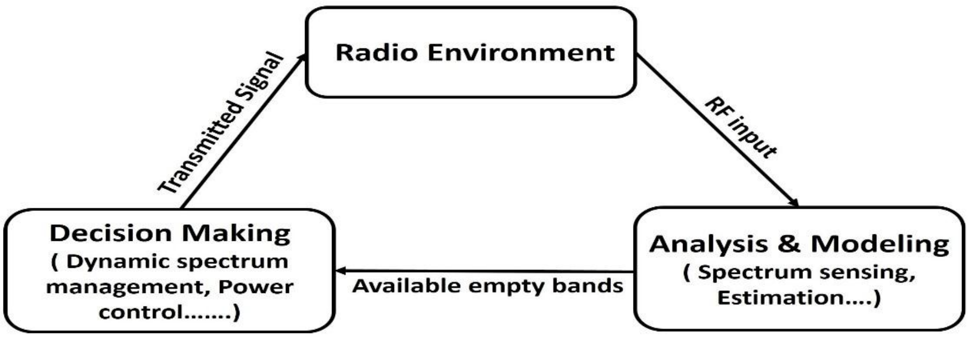



Fig 1-2 Cognitive Radio cycle

The cognitive radio cycle starts from the sensing of the radio environment and its characteristics is modeled and analyzed. It is the first and most important step in cognitive radio. The analysis and modeling section performs spectrum sensing in order to study the radio characteristics and find unused channels. Channel estimation is also performed in this section in order to determine the channel characteristics on the received signal, which in turn will help in better reception of the licensed user signal. The data's thus obtained from sensing and estimating the radio environment is used in predictive modeling of the channel. The predictive model is used to predict the behavior of the channels on the future and even the traffic patterns. Predictive modeling uses the current observations along with the previous observations and based on some statistical measures it tries to find the model that will most likely suits the channel or the traffic in the near future. The models will increase the efficiency and will improve and ease the decision taking procedures. The data's thus collected, processed and analyzed with analysis and modeling section are then sent to the next section namely decision making section.

The decision making section is the core of the CR cycle since it makes the decision regarding the availability of the spectrum, its usage and allocation, and best configuration for transmitter and receiver. The spectrum allocation process is highly complex since the user demand for spectrum is highly dynamic. Thus, the allocation process must also be dynamic. The dynamic spectrum allocation is like distributing the available spectrum holes among the aspirant users.

In this section, power control is also taken in consideration. In cognitive radio each user should take care of it is own transmission power control and gives some feedbacks regarding the signals that it received. As a result, the power control process will be done in a distributed manner. In other words, each user must make sure that the signal that is transmitted will reach the receiver in a certain level high enough to be detected by the receiver and low enough to avoid interfering with other users. At the same time each user has to inform the users, about the reception signal level. The power control operation plays a crucial part in minimizing the interference and in ensuring the needed quality of service in many communication systems.

### 1.2.1 Characteristics of Cognitive Radio (CR)

CR is an intelligent radio system which adapts to the conditions of the environment by analyzing, observing and learning. CR has the following characteristics which help in achieving this goal [5]-

1. ***Flexibility:*** CR should be able to change its parameter like modulation technique, data rate, etc. in order to utilize the spectrum holes present in different communication standards.
2. ***Agility*:** CR should be able to operate in several spectrum bands in order to utilize white spaces observed in different frequency bands. For example a cell phone can operate in two or more different frequencies i.e., GSM 900 and GSM 1900. So CR device should be able to jump between different frequency bands whenever spectrum is available.
3. ***Sensing***: CR should be able to sense the RF environment and internal working parameters in order to sense the existence of spectrum holes and to provide an overview of the radio spectrum utilisation.
4. ***Networking*:** CR should be able to communicate between different nodes of the wireless communication to bring synergy in using the radio resources. Sharing of information and cooperatively passing decisions on the radio resources.

### 1.2.2 Terms related to Cognitive Radio Network

Following are some important terms related to cognitive radio network-

1. Primary user- A user is said to be primary if it has authorized right to access the licensed band. It is also known as licensed user.
2. Secondary user- A user is said to be secondary if it has no rights to utilize the licensed spectrum. It is also known as CR user. It senses the radio spectrum and searches for the un-utilized portions of the radio spectrum. It uses this un-utilized spectrum to transmit it signals without affecting the primary user.
3. White spaces- un-utilized part of the licensed spectrum is known as white space. It provides opportunity for other unlicensed users to access it with the help of CR technology. One of the main aims of CR is to search for white spaces. It is also known as spectrum holes.

## 1.3 IEEE 802.22- an exclusive standard for Cognitive Radio [6]

It has been observed by FCC, spectrum scarcity is an artificial result of the way the bands are regulated. Large part of the licensed radio spectrum is used inefficiently by the licensed user adds to the problem of growing demand for additional spectrum. The commercial success of unlicensed bands has compelled FCC to provide more unlicensed spectrum. In order to increase the spectrum utilization of licensed bands, FCC has allowed unlicensed users to access the licensed bands without affecting the PU.

IEEE 802.22 is a standard which gives the opportunity of utilizing the unoccupied TV bands for CR users without causing any significant interference to the licensed user. This standard is also known as WRAN standard [6]. It concentrates mainly on VHF/UHF TV bands due to their highly favorable propagation characteristics and worldwide move from analog to digital TV creating spectrum opportunities called “White Spaces”.

IEEE 802.22 concentrates on rural areas, which constitutes around 45% of the world’s population where wireless is a viable source of communication. It specifies the PHY layer and MAC layer specification for different methods and under different operating conditions in order to exploit the unutilized licensed spectrum.

The IEEE 802.22 devices shall sense mainly TV signals and Wireless Microphone signal for the detection of white spaces in the VHF/UHF band. The Wireless Microphone signal is described in details in the below section.

### 1.3.1 The Wireless Microphone Signal

Wireless microphone (WM) [7] uses UHF/VHF TV bands as a low power licensed signal. Generally it uses FM modulation scheme with BW less than 200 kHz. Spectrum sensing module in the WRAN devices searches for the FM WM signal in the UHF/VHF TV bands for spectral opportunity.

The general expression for FM wireless microphone signal $x_{wm}(t)$ is defined as

$$x_{wm}\ (t) = A_c(\cos 2\pi f_c\, t + 2\pi k_f \int_0^t m(u)du)1 \tag{1.1}$$

where, $A_c$= Amplitude of the carrier signal

$K_f$ = frequency sensitivity of the FM modulator

$m(t)$ = message signal

$f_{dev}$= $K_f$ max{m(t)} = frequency deviation

For simulation of WM signal, there are three operating conditions [7, 8]

- Silent speaker: In this case user is silent with message tone frequency of 32 kHz and frequency deviation of ±5 kHz.

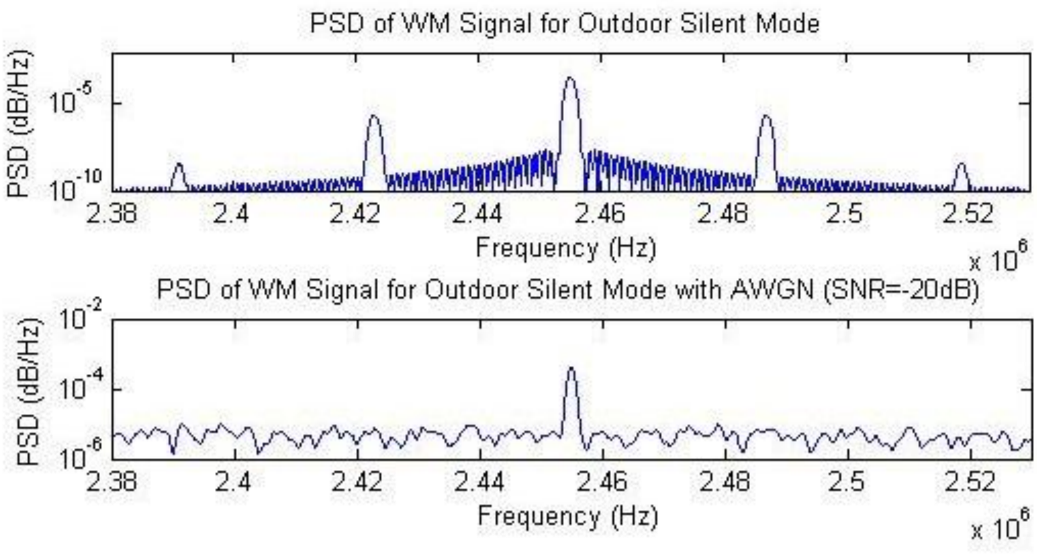



Fig 1-3 PSD of Silent Speaker

- Soft speaker: In this case user is a soft speaker with message tone frequency of 3.9 kHz and frequency deviation of ±15 kHz.

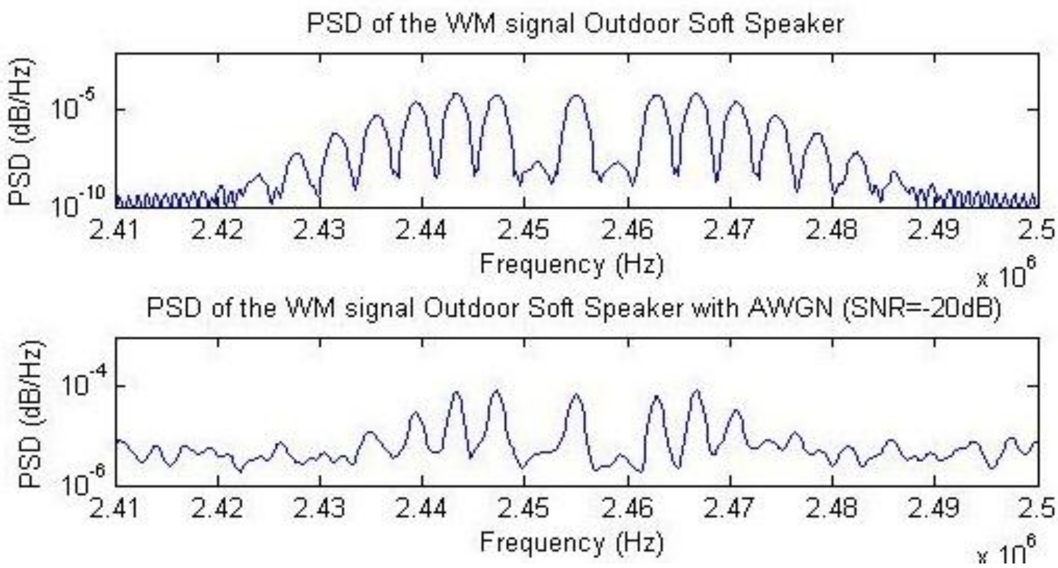



Fig 1-4 PSD of Soft Speaker

- Loud speaker: In this case user is a loud speaker with message tone frequency of 13.4 kHz and frequency deviation of ±32.6 kHz.

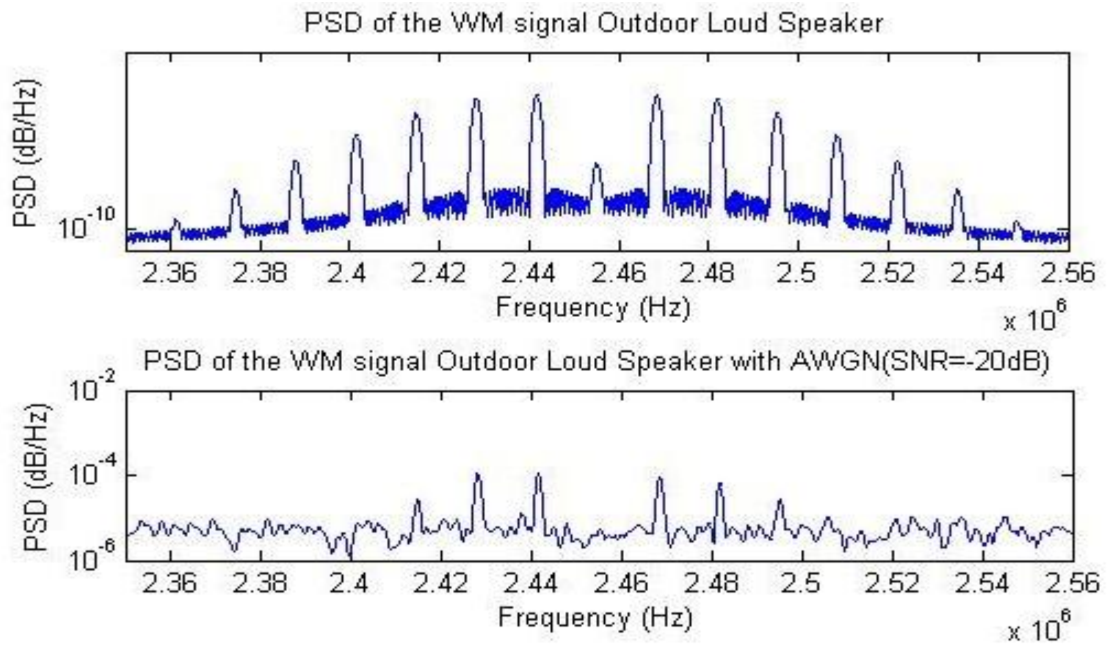



Fig 1-5 PSD of Loud Speaker

## 1.4 Motivation

The limited availability of radio spectrum is a bottleneck for the growing consumer electronics in wireless communication. It was observed that the spectrum scarcity is the result of inefficient and under-utilization of the licensed spectrum by the licensed user. Large part of the radio spectrum is assigned to licensed users and only small portions are allowed for open access to the unlicensed user.

Unlicensed spectrum bands are commercially successful bands but constitute only a small fraction of the radio spectrum and less likely to increase its span in near future. Keeping in view of the increasing demands for the new spectrum possibilities, inefficient and low spectral utilization of licensed bands, the FCC has made a standard IEEE 802.22 exclusively for the utilization of white spaces in the UHF/VHF TV bands.

Spectrum sensing is the key enabler in the identification of spectrum holes in the licensed bands. There are conventional methods like energy detection and cyclostationary detection method used for the spectrum sensing. A lot of research works are carried out in the spectrum sensing area in order to increase the probability of detection and reduce the probability of false alarm for the detection scheme. The advantages of both the energy detection and cyclostationary detection have motivated to frame a technique which combine their merits and overcome their drawbacks.

## 1.5 Objective of the Work

In this dissertation a two-stage spectrum sensing method is implemented. The objective for the implementation of the two stage spectrum sensing can be summarized as follows

- To construct a low computational complex detection scheme for cyclostationary detection.
- To study and analyze the cyclostationary and energy detection scheme.
- To combine the energy and cyclostationary detection technique in order to construct a two-stage spectrum sensing method.
- To compare the performance of the two-stage spectrum sensing scheme with the energy detection and cyclostationary detection method.

## 1.6 Thesis Organization

The thesis has been organized into five chapters. The current chapter gives the introduction to the concept of CR, its operation, characteristics and need. It also gives a brief overview of IEEE 802.22 standard and WM signal. The motivation and the objective present an essence of the dissertation.

**Chapter** 2: It describes the importance and different types of spectrum sensing techniques in CR. A brief overview on binary hypothesis testing problem and Receiver operating Characteristics are also described.

**Chapter** 3: It presents the overview on the cyclostationary detection and energy detection method. Expression for the probability of detection ($P_d$) and false alarm are derived for both the methods.

**Chapter** 4: It presents the two-stage spectrum sensing method for CR.

**Chapter Error! Reference source not found.**: It describes the conclusion and scope of uture work of the two-stage spectrum sensing for cognitive radio.

# 2

# SPECTRUM SENSING IN COGNITIVE RADIO

One of the main tasks of Cognitive radio is to sense the radio environment and search for white spaces in it. Spectrum sensing is one of the important sections in CR cycle. It enables the CR to observe its surrounding environment and to utilize the radio environment by determining spectrum holes, without causing interference to the primary network.

## 2.1 Types of Spectrum Sensing

Spectrum sensing can be classified in four groups [1]. They are

(i) Primary transmitter detection

(ii) Cooperative detection

(iii) Primary receiver detection

(iv) Interference temperature management.

These spectrum sensing types are described in the following sections

### 2.1.1 Primary Transmitter Detection

In this detection method, CR users sense the radio environment in order to detect the presence of PU signal. Since the CR users have no prior information regarding the PU signal type and characteristics so, it has to distinguish between the noise and the PU signal. It is the most widely used method since it directly gives an idea regarding the usage pattern of a given radio spectrum. CR uses binary hypothesis problem formulation for detecting the PU signal against the noise. The binary hypothesis problem is described in details in subsequent section.

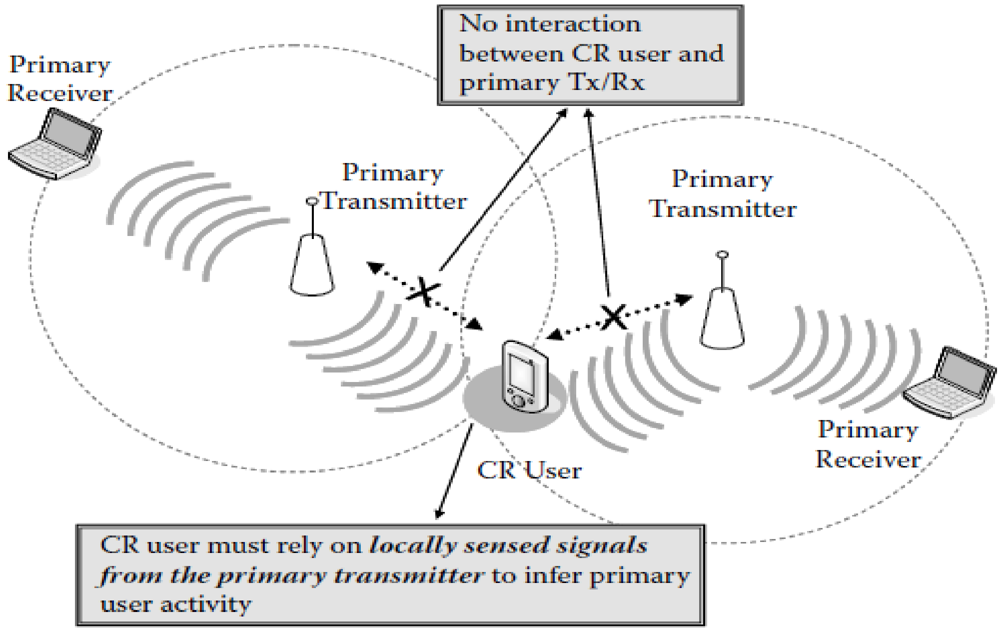



Fig 2-1 Primary Transmitter Detection [1]

The primary detection can be performed by various methods, out of which there are three popular methods, (a) Energy detection method, (b) Matched Filter detection method and (c) Feature based Detection method. These methods are described in details in the following section.

### 2.1.1.1 Energy Detection Method

It is a blind detection scheme and optimal detection method when the primary user signal is unknown. It is the most widely used method for the detection of PU signal since, it doesn't require any *a priori* information. In this method, the energy of the received signal is calculated which is compared against some given threshold to determine the presence or absence of PU signal. For the calculation of energy of the received signal, firstly the samples are squared and integrated over the observation interval and the output of the integrator is then compared against the threshold. If the output of the integrator exceeds the threshold then it is assumed that the given radio spectrum is occupied otherwise it is treated as vacant. The detection problem can be written as

$$\text{Decision} \begin{cases} H_0, & \text{if } \sum_{n=1}^{N} |y[n]|^2 \le \lambda \\ H_1, & \text{otherwise} \end{cases}$$

where y[n] is the received signal at the CR receiver, λ is the threshold which depends on the receiver noise, $H_0$ is noise only hypothesis and $H_1$ is signal plus noise hypothesis.

Energy detection method can be performed both in frequency domain and time domain. Frequency domain energy detection can

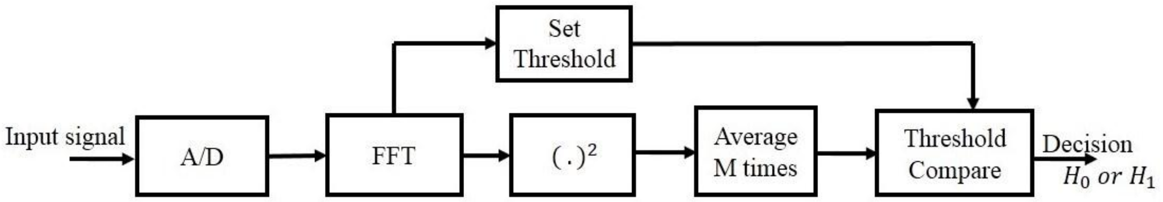



Fig 2-2 Energy detection method [5]

It requires *O(1/SNR²)*number of Samples for the calculation of decision statistics. It is the simplest and easier to implement among all the three methods, but it suffers from some drawbacks. Firstly, the threshold is highly susceptible to receiver noise uncertainty. Secondly, it cannot discriminate among the PU signal and noise and performs poor in low SNR environment.

#### 2.1.1.2 Matched Filter Detection Method

It is a signal specific detection technique and it maximizes the SNR of the received signal in the presence of AWGN environment. It is an optimal detector where a *priori* information is available. In this CR user requires some *a priori* information like modulation type, pilot carriers, etc. regarding the PU. Matched filter performs correlation between unknown signals with the known signal. The output of the MF is then compared against the threshold to decide the presence or absence of PU signal in the specified band. The detection problem for this scheme can be written as

$$\begin{cases} H_0, & \text{if } \sum_{n=1}^{N} y[n]x[n]^* \leq \lambda \\ H_1, & \text{otherwise} \end{cases}$$

where y[n] is the received signal at the CR receiver, x[n] is the known signal, λ is the threshold, $H_0$ is noise only hypothesis and $H_1$ is signal plus noise hypothesis.

It is the best among all the three methods but not widely in use in CR scenario. Its main drawback lies in a *priori* knowledge requirement for its implementation. CR has limited information regarding the signal structure of the PU. In licensed spectrums the pilot carrier information of PU is available with the CR. The pilot based matched filter detector is given in

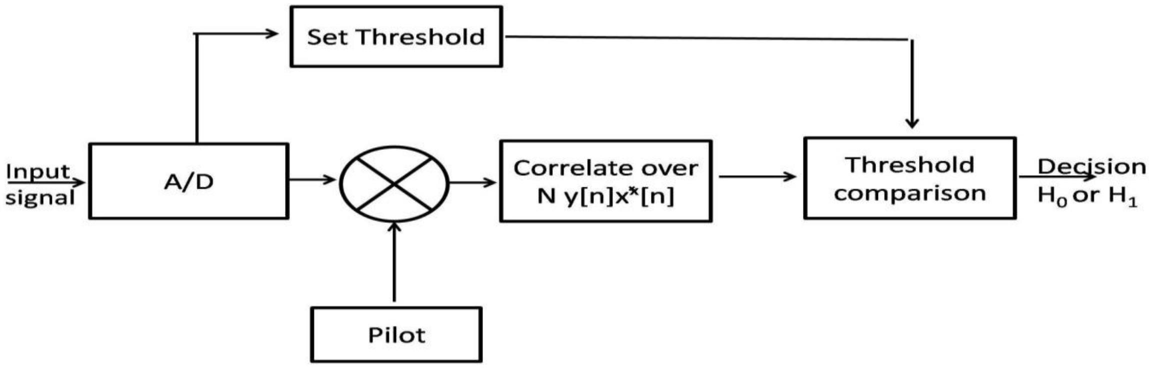



Fig 2-3Pilot based Matched Filter Detection [5]

It requires only *O(1/SNR)* number of samples for the calculation of decision statistics. It performs very poor when no information or incorrect information is available with the CR user. Its main advantage is it needs less number of samples for detection. Its main drawback comes in demodulation process which requires perfect timing, carrier synchronization, etc. which requires a dedicated receiver for different PU signals, which increases complexity of the system.

#### 2.1.1.3 Feature Based Detection Method

In this technique, CR user uses the periodic feature of the modulated signal in order to discriminate the PU signal from the noise. It is a complex method among the three techniques. It takes the advantage of the cyclostationary property to distinguish between the PU signal and noise. Generally, the modulated signals exhibit the cyclostationary property due to sampling, cyclic prefix, sine wave carriers, etc. The noise signal doesn't exhibit cyclostationary property since it is a wide sense stationary signal with no correlation among its samples. A signal is said to be cyclostationary if its autocorrelation function is periodic in time. The cyclic autocorrelation function is used for discriminating the signal from noise, which can be described as

$$R_x^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x\left(t+\frac{\tau}{2}\right) x(t-\frac{\tau}{2}) e^{-i2\pi\alpha t} dt \tag{2.1}$$

whereα is cyclic frequency. Fourier transform of CAF gives Spectral correlation density (SCD) function. The SCD is given as

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-2\pi f\tau} d\tau \tag{2.2}$$

The cyclostationary feature detection is done by correlating the spectral components of the received signal. The decision statistic is derived from SCD function. The detection problem can be represented as

$$\begin{cases} \mathrm{H_0}, \text{ if } \ T(S_x^{\alpha}(f)) \le \lambda \\ \mathrm{H_1}, \text{ otherwise} \end{cases}$$

where λ is the threshold and $T(S_x^{\alpha}(f))$ is test statistic which is a function of SCD.

Cyclostationary based feature based detection implementation can be shown by Fig 2-4.

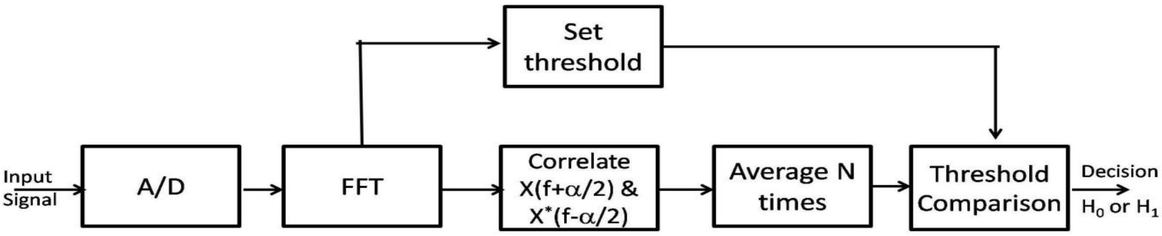



Fig 2-4 Cyclostationary Detection Method [5]

It performs better than the energy detection scheme in low SNR condition. The cyclostationary property is also capable of differentiating signal on the basis of its type. Its main drawback is its large computationally complexity and longer observation interval. It cannot utilize the short duration spectrum holes effectively.

The advantages and disadvantages for the above mentioned detection scheme is presented in.

Table 2-1 Comparison among different spectrum sensing methods [5]

| Spectrum sensing | Advantages | Disadvantages |
|---|---|---|
| **Energy Detection** | ✓ Doesn't need any a priori information<br>✓ Low computational cost | ✓ Poor performance at low SNR<br>✓ Can't distinguish users sharing the same channel |
| **Matched Filter Detection** | ✓Optimal detection performance<br>✓Low computational cost | ✓ Requires a priori information of the PU<br>✓ Design for each kind of PU signal |
| **Cyclostationary Detection** | ✓Robust in low SNR<br>✓Robust in interference | ✓ Requires partial information of PU<br>✓ High computational cost |

### 2.1.2 Cooperative Detection

The primary transmitter detection scheme depends on the primary transmitter signal strength and the distance between the primary transmitter and CR user. The signals from the primary transmitter get attenuated with the distance and may not be visible at the CR receiver due to NLOS path between them. These two problems can be solved by cooperative detection scheme. In this scheme, a number of CR receivers make a network through which sensing information's are exchanged among them. It takes the advantage of spatial diversity to increase the detection accuracy. It is more accurate than a single CR's detection. It performs well in low SNR, shadowing, fading and NLOS conditions.

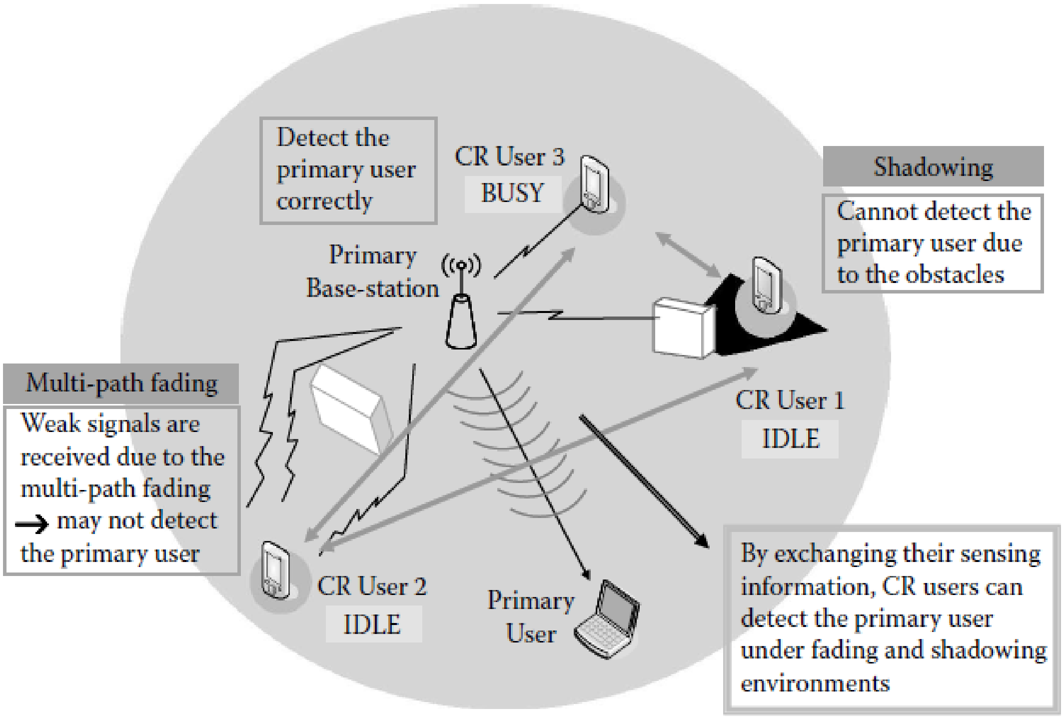



Fig 2-5 Cooperative Transmitter detection [1]

In this, spectrum band is said to be available only when all the CR's involved in the network have found no PU's activity in the given radio spectrum. The spectrum band is assumed to be occupied, even if one CR has sensed the PU signal in it. This method has high probability of detection in shadowing and fading environment. The increase in CR in network leads to increase in detection probability along with increase in probability of false alarm ($P_{fa}$). Due to the increase in $P_{fa}$ the spectrum opportunities decreases which tends to less spectral utilization. Its main drawback is the increase in traffic overhead.

### 2.1.3 Primary receiver detection

In this scheme, the primary receiver is sensed instead of primary transmitter for the determination of spectral occupancy. It is similar to primary transmitter detection method. Generally the receiver part of a communication system emits local oscillator (LO) leakage power from its RF front-end while receiving the signal. The CR user uses the leakage power from the primary receiver to determine whether the band is occupied or not. It is not a widely used method.

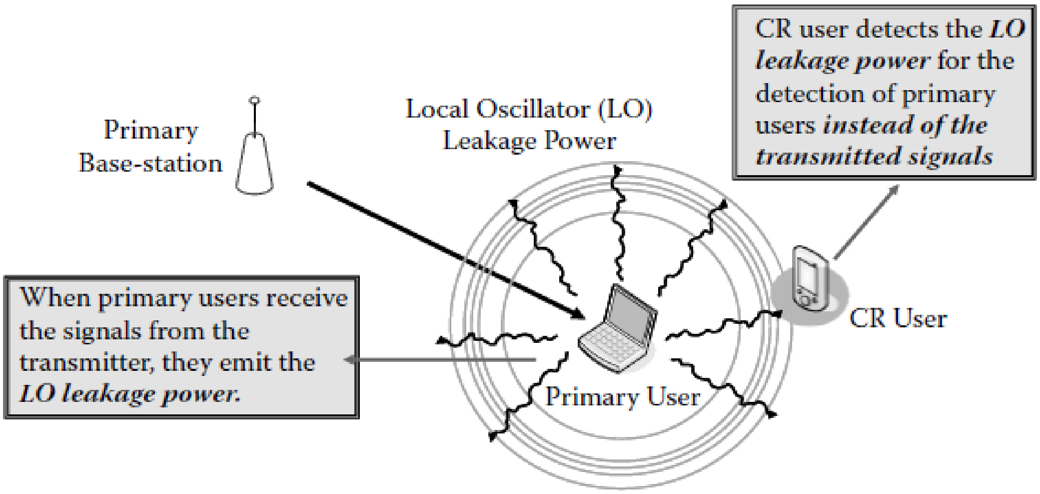



Fig 2-6 Primary Receiver Detection [1]

### 2.1.4 Interference temperature management

In this method, CR users are allowed to transmit their signals in presence of PU provided that the CR users signal strength is within a specified limit. The limit is determined by the amount of interference a primary receiver can tolerate. The CR users can access the spectrum band if they don’t exceed the limit. The interference is measured with the help of interference temperature. The main drawback of this method is the difficulty in measuring or estimating the interference temperature.

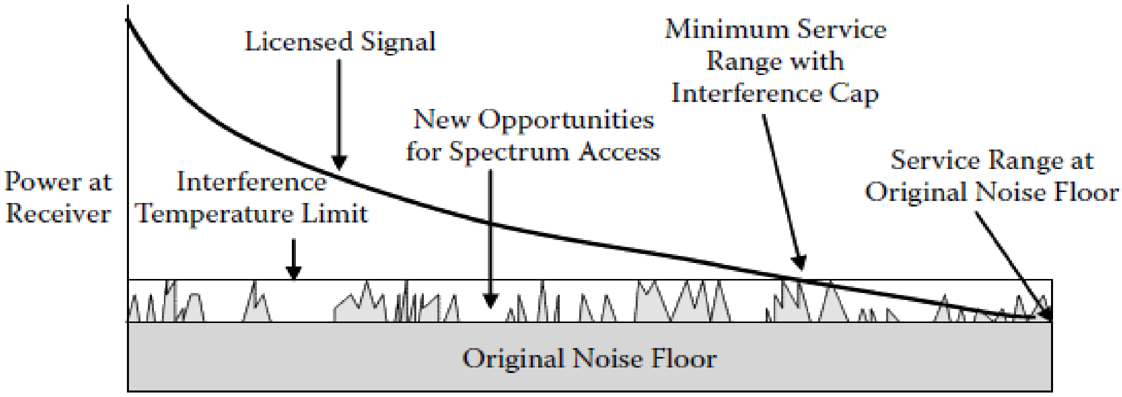



Fig 2-7 Interference Temperature Management [1]

## 2.2 Binary Hypothesis Testing

The major task of spectrum sensing is to determine whether the PU signal is present or not in the specified spectrum band. The CR detection problem can be considered as *binary hypothesis testing problem.* In this, CR has to distinguish between the PU signal and noise signal. The binary hypothesis testing model can be described as

$$y(t)= \begin{cases} n(t) & ; H_0 \text{hypothesis} \\ x(t)+n(t) & ; H_1 \text{ hypothesis} \end{cases}$$

where, $y(t)$ = received signal by the CR user

$x(t)$ = transmitted signal of the primary user

$n(t)$ = zero-mean additive white Gaussian noise (AWGN)

$H_0$ = null hypothesis, which indicates the absence of PU signal

$H_1$ = alternative hypothesis, which indicates the presence of PU signal

Hypothesis $H_0$ indicates, the received signal consist of noise only whereas hypothesis $H_1$ determines that the received signal contains both PU signal and noise. In binary hypothesis test, the CR user has to choose between these two hypotheses on the basis of test statistic. A test statistic is a function of the received signal, which is compared against the threshold.

Test statistic is also known as decision statistic since, it decides between the two hypotheses for the CR. The binary hypothesis model in terms of decision statistic can be described as

$$Y = \begin{cases} H_0 \,;\, T \leq \lambda \\ H_1 \,;\, T > \lambda \end{cases}$$

where $Y$ = Decision made by the CR user

$T$ =Test statistics

$\lambda$= Predetermined threshold

In this two parameters are of great importance, they are defined as

**(i)** ***Probability of detection,*** $\boldsymbol{P_d}$ It is defined as the probability of deciding $H_1$ when $H_1$ is true

$$P_d = Pr\{T > \lambda | H_1\}$$

**(ii)** ***Probability of false alarm*** $\boldsymbol{P_{fa}}$ It is defined as the probability of deciding $H_1$ when $H_0$ is true

$$P_{fa} = Pr\{T > \lambda | H_0\}$$

## 2.3 Receiver Operating Characteristics (ROC) [9, 10]

It is an important tool in analyzing performance of a detector. It is generally used in binary hypothesis testing problem. ROC curves provide graphical representation of the performance of binary classifier system. A ROC curve is generated by plotting the *probability of detection* ($P_d$) versus *probability of false alarm* ($P_{fa}$).

In a binary classification problem, there are two possible outcomes, positive (P) and negative (N) where, P denotes the presence of PU signal and N denotes its absence [9]. There are four possible conditions in binary classification system. They are as follows

**(i) True positive (TP)**

In this condition, the PU signal is present and the detector also decides the $H_1$ hypothesis i.e. presence of PU signal.

**(ii) False positive (FP)**

In this condition, the PU signal is present but the detector decides the $H_0$ hypothesis i.e. absence of PU signal.

**(iii) True negative (TN)**

In this condition, there is no PU signal and the detector also decides the $H_0$ hypothesis i.e. absence of PU signal.

**(iv) False negative (FN)**

In this condition, the PU signal is absent but the detector decides the $H_1$ hypothesis i.e. presence of PU signal.

The above mentioned conditions in binary classification system can be presented in form of 2×2 matrix known as contingency or confusion matrix given in Table 2-2

Table 2-2 Confusion matrix or Contingency Table

| | **Condition Positive (P)** | **Condition Negative (N)** |
|---|---|---|
| **Detector output Positive (P)** | True Positive<br>(Sensitivity) | False Positive<br>( Type I Error) |
| **Detector output Negative (N)** | False Negative<br>(Type II Error) | True Negative<br>(Specificity) |

From the above mentioned conditions four important parameters can be calculated. They are as follows

**(i) Sensitivity**

It is also known as true positive rate (TPR) or probability of Detection ($P_d$). It determines the number of times the detector has correctly detected the PU signal.

$$Sensitivity\ or\ (TPR) = \frac{TP}{P} = \frac{TP}{TP + FN}$$

**(ii) Specificity**

It is also known as true negative rate (TNR). It determines the number of times the detector has correctly decided that the band is unoccupied or vacant.

$$Specificity\ or\ (TNR) = \frac{TN}{N} = \frac{TN}{TN+FP}$$

**(iii) Type I error**

It is also known as false positive rate (FPR) or probability of false alarm ($P_{fa}$). It determines the number of times the detector has incorrectly decided that the band is occupied.

$$Probability\ of\ False\ alarm\ or\ (FPR) = \frac{FP}{N} = \frac{FP}{TN+FP}$$

**(iv) Type II error**

It is also known as false negative rate (FNR) or probability of Missed Detection ($P_{md}$). It determines the number of times the detector has incorrectly decided that the band is vacant.

$$Probability\ of\ Missed\ Detection\ or\ (FNR) = \frac{FN}{P} = \frac{FN}{TP+FN}$$

The probability of False alarm and probability of detection lies in the range of 0 to 1. The point [0, 1] in the ROC curve represents perfect classification. The upper left portion of the ROC curve is of prime interest for the CR. The upper left portion denotes high probability of detection and low probability of false alarm, which provides security to the PU from the secondary users and increases the spectrum holes utilization by the CR users.

# 3

# CYCLOSTATIONARY AND ENERGY DETECTION

This chapter describes in details, the cyclostationary and energy detection concept along with mathematical analysis and simulations.

According to Gardener, cyclostationarity can be extracted from a random data by applying certain non-linear transformations. Let a signal *x(t)* is said to be cyclostationary in wide sense if and only if its nth order transformation, *y(t)=f(x(t))* will generate finite amplitude additive sine wave components which produces spectral lines.

## 3.1 Cyclostationary: An Insight

Over the past few decades communication has become an essence of life. Wireless Communication signals undergo a lot of problem like interference from other communication sources, time varying nature of the channel and noise. Due to these, it becomes difficult for a receiver to extract useful information from the received signal.

Periodicity is an important characteristic of communication signals which distinguishes it from noise [11]. The periodicity in communication signal cannot be seen in terms of signal values but their statistical parameters vary periodically with time. Signals showing statistical periodicity are known as cyclostationary signals. It arises in communication due to sampling, modulation, multiplexing, coding operations, etc. [11].

A signal is said to be cyclostationary of order n, if nth order nonlinear transformation results in spectral lines at non-zero cyclic frequency. Cyclostationary process is a process in which statistical parameters like mean, autocorrelation function varies periodically with time. Mathematically, let *x(t)*is a cyclostationary process and it's mean and auto-correlation is periodic with period $T_0$ [12].

$$m_x(t) = m_x(t + T_0) \tag{3.1}$$

$$R_x(t, \tau) = R_x(t + T_0, \tau) \tag{3.2}$$

In general, Communication signals can be modeled as stationary random process. Let, for a zero mean random process *x(t)* the autocorrelation function is given by

$$R_x(t, \tau) = E[X(t)X^*(t - \tau)] \tag{3.3}$$

Since the autocorrelation function is a periodic function, so it can be represented as a Fourier series

$$R_x(t, \tau) = \sum_{\alpha} R_x^{\alpha}(\tau) e^{i2\pi\alpha t} \tag{3.4}$$

where, $R_x^{\alpha}(\tau)$ is the Fourier coefficient also known as the cyclic autocorrelation function (CAF/ACF) and $\alpha$ is the cyclic frequency which includes all integral multiples of the reciprocal of the fundamental period $T_0$.The CAF is given by [13]

$$R_x^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} R_x\left(t + \tau/2, t - \tau/2\right) e^{-i2\pi\alpha t} dt \tag{3.5}$$

The CAF in discrete domain is given by

$$R_x^{\alpha}(k) = \lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{n=N} \left[x(n+k)e^{-j\pi\alpha(n+k)}\right] [x(n)e^{j\pi\alpha n}]^* \tag{3.6}$$

A signal is said to be wide sense cyclostationary if and only if $R_x^{\alpha}(\tau) \neq 0$ for nonzero $\alpha$. The Fourier transform of CAF is known as spectral correlation density function (SCD), which is used for the detection and identification of the desired signal against noise. The SCD is given by [13]

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-i2\pi f\tau}\, d\tau \tag{3.7}$$

where, $\alpha$ is the cyclic frequency and $f$ is the spectral frequency. The SCD in discrete domain is given by

$$S_x^{\alpha}(f) = \sum_{k=-\infty}^{\infty} R_x^{\alpha}(k) e^{-i2\pi fk} \tag{3.8}$$

The SCD can also be considered as the correlation among the spectral components of signals, therefore also known as spectral correlation function (SCF). It is computationally complex and time consuming. Mainly there are two approach to estimate the SCD function - Frequency domain averaging/Frequency smoothing (FS) and Time domain averaging/Time smoothing (TS) [14].

- Frequency domain averaging (FS)- In this, $S_x^{\alpha}(f)$ is averaged over $\Delta f$ (frequency), over double limits

$$S_x^{\alpha}(f) = \lim_{\Delta f \to 0} \lim_{\Delta t \to \infty} S_{x_{\Delta t}}^{\alpha}(n, f)_{\Delta f} \tag{3.9}$$

where

$$S_{x_{\Delta t}}^{\alpha}(n, f)_{\Delta f} = \frac{1}{\Delta f} \int_{f-\Delta f/2}^{f+\Delta f/2} X_{\Delta t}(n, f + \alpha/2) X_{\Delta t}^{*}(n, f - \alpha/2) df \tag{3.10}$$

$S_{x_{\Delta t}}^{\alpha}(n, f)_{\Delta f}$, is the frequency smoothed cyclic periodogram and

$$X_{\Delta t}(n, f) = \frac{1}{\Delta t} \sum_{m=n-\frac{\Delta t}{2}}^{n+\frac{\Delta t}{2}} x(m)\, e^{-i2\pi f m T_s} \tag{3.11}$$

is the complex demodulate of *x(n)*, where *x(n)* is a discrete time signal sampled at$f_s=1/T_s$, $\Delta f$ and $\Delta t$ are frequency and time resolution respectively. A good estimate for $S_x^{\alpha}(f)$ can be obtained from $S_{x_{\Delta t}}^{\alpha}(n, f)_{\Delta f}$ for $\Delta t \Delta f \gg 1$

- Time domain averaging (TS)- In this, $S_x^\alpha(f)$ is averaged over $\Delta t$ (time), over double limits [14]

$$S_x^\alpha(f) = \lim_{T\to\infty} \lim_{\Delta t\to\infty} S_{x_T}^\alpha(n,f)_{\Delta t} \tag{3.12}$$

where

$$S_{x_T}^\alpha(n,f)_{\Delta t} = \frac{1}{\Delta t} \sum_{m=n-\frac{\Delta t}{2}}^{n+\frac{\Delta t}{2}} X_T(m,f+\alpha/2) X_T^*(m,f-\alpha/2) \tag{3.13}$$

$S_{x_T}^\alpha(n,f)_{\Delta t}$, is the time smoothed cyclic periodogram and

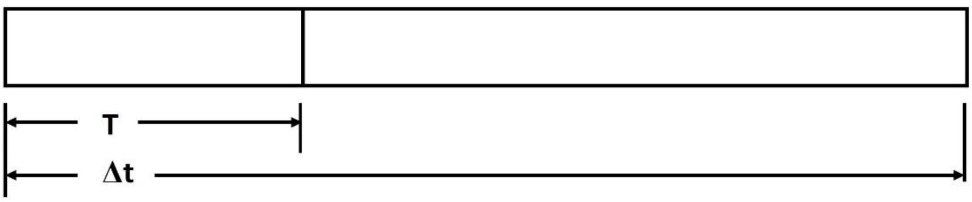
$$X_T(n,f) = \frac{1}{T} \sum_{m=n-\frac{T}{2}}^{n+\frac{T}{2}} x(m)\, e^{-i2\pi f m T_s} \tag{3.14}$$

is the complex demodulate of *x(n)* for a smaller time duration since $\Delta t \gg T$. $S_{x_T}^\alpha(n,f)_{\Delta t}$is the discrete time average of spectral correlation components of x(n) over a time $\Delta t$.

TS and FS methods are equivalent if and only if time-frequency resolution product $(\Delta t\Delta f)$ is much greater than 1, i.e. $\Delta t\Delta f \gg 1$.

$S_{x_T}^\alpha(n,f)_{\Delta t} \approx S_{x_{\Delta t}}^\alpha(n,f)_{\Delta f}$ for $\Delta t\Delta f \gg 1$ and thus reliable estimate for SCD function is obtained if and only if $\Delta t\Delta f \gg 1$.

In this $\Delta t$ is the total observation time interval and $T$ is the sliding window interval and $\Delta f = \frac{1}{T}$.




The TS algorithms are more computationally efficient than the FS algorithms for general cyclic spectral analysis.

The Time smoothing for SCD function can be done in two popular ways- FFT Accumulation Method (FAM) and Strip Spectral correlation algorithm (SSCA) method.

*a)* FFT Accumulation Method (FAM)-It is a Fourier transform of correlation products between spectral components smoothed over time. The complex demodulates $X_T(n, f)$, are estimated by means of sliding $N_p$ point FFT followed by a downshift in frequency to baseband. For reducing the computational complexity and minimizing cycle leakage and cycle aliasing, $L$ data points are skipped between successive computations of the $N_p$ point FFT. The $N_p$ point is determined by the desired spectral resolution (Δf) i.e. $N_p=f_s/\Delta f$.

 After the calculation of the complex demodulates, they are multiplied with their complex conjugate forms. The time smoothing is done by P point FFT, where P is determined by the desired cyclic frequency resolution $\Delta\alpha$, $P=fs/L\Delta\alpha$.

*b)* Strip Spectral Correlation Algorithm (SSCA) Method- It is a Fourier transform of correlation products between spectral and temporal components smoothed over time. The complex demodulates $X_T(n, f)$ is calculated in the same way as described for FAM.For reducing the computational complexity and minimizing cycle leakage and cycle aliasing, $L$ data points are skipped between successive computations of the $N_p$ point FFT. The $N_p$ point is determined by the desired spectral resolution (Δf) i.e. $N_p=f_s/\Delta f$.

 The complex demodulated sequence is directly multiplied by the complex conjugate of the received signal. Then the resultant signal is smoothed in time by means of P point FFT [14].

### 3.1.1 Modified Cyclostationary Detection Method

The modified detection method is a blind detection technique and it directly uses SCD function as test statistic for detection. The SCD function determines the correlation between the frequency shifted versions of the complex demodulates i.e. frequency components $f+\frac{\alpha}{2}$ and $f-\frac{\alpha}{2}$ for appropriate value of *f*.

The detection problem can be modeled as binary hypothesis model. Let x[n] be the received signal samples,

$$x[n] = s[n] + w[n] \tag{3.15}$$

where s[n] is the PU signal and w[n] is an AWGN noise signal and it is assumed to be complex circularly symmetric Gaussian random variable with zero mean and $\sigma_w^2$ variance.

For the estimation of SCD function, time smoothed cyclic periodogram function can be expressed as

$$S_{x_T}^{\alpha}(n,f)_{\Delta t} = \frac{1}{\Delta t}\sum_{m=n-\frac{\Delta t}{2}}^{n+\frac{\Delta t}{2}} X_T\,(m, f+\alpha/2)X_T^*(m, f-\alpha/2) \tag{3.16}$$

where $X_T$ is the spectral component of the received signal x[n] and can be defined as

$$X_T(n,f) = \frac{1}{T}\sum_{m=n-\frac{T}{2}}^{n+\frac{T}{2}} x(m)\, e^{-i2\pi f m T_s} \tag{3.17}$$

where T is the duration of sliding window.

In the SSCA method, the time smoothed cyclic periodogram can be written as

$$S_{x_T}^{\alpha}(n,f)_{\Delta t} = \frac{1}{N}\sum_{m=-\frac{N}{2}}^{\frac{N}{2}-1} X_T(n+m, f+\alpha/2)x^*(n+m)e^{i2\pi\left(f-\frac{\alpha}{2}\right)m} \tag{3.18}$$

where N is the number of samples in the observation interval Δt i.e. $\Delta t = NT_s$ and complex demodulate is given as

$$X_T(n,f) = \frac{1}{N_p} \sum_{m=-\frac{N_p}{2}}^{\frac{N_p}{2}} x(n+m)\, e^{-i2\pi f(n+m)T_s} \tag{3.19}$$

For large time and frequency resolution product i.e.$\Delta t \Delta f \gg 1$, the SCD function can be approximated as, $S_x^{\alpha}(f) \approx S_{x_T}^{\alpha}(n,f)_{\Delta t}$. So,

$$S_x^{\alpha}(f) = \frac{1}{N} \sum_{m=-\frac{N}{2}}^{\frac{N}{2}-1} X_T(n+m, f+\alpha/2) x^*(n+m) e^{i2\pi\left(f-\frac{\alpha}{2}\right)m} \tag{3.20}$$

where $N_p$ is the number of samples in the n smoothing window interval T i.e. $T=N_pT_s$

For the determination of decision statistic initially, the peak value across the spectral frequency $f$ for all the cyclic frequency $\alpha$ is searched and these peak values are known as cyclic domain profile (CDP) or α-profile which is defined as

$$C(\alpha) = \max_{\forall f} |S_x^{\alpha}(f)| \tag{3.21}$$

Since we know that cyclostationary property is observed by the presence of spectral lines for non-zero α. So the decision statistic can be described as the maximum across the *C(α)* for non-zero cyclic frequency i.e. $\alpha \neq 0$

$$T = \max_{\forall\, \alpha, \alpha \neq 0} \{C(\alpha)\} \tag{3.22}$$

Test statistic T can also be written as

$$T = \max_{\forall f\ \forall \alpha, \alpha \neq 0} |S_x^{\alpha}(f)| \tag{3.23}$$

From the central limit theorem [10], large value of $NN_p$, the pdf of $S_x^{\alpha}(f)$ for both hypothesis $H_1$ and $H_0$ will tend to circularly symmetric complex Gaussian distributions which is given as

$$H_0 \;:\; S_x^{\alpha}(f) \sim CN\left(0, \frac{\sigma_w^4}{NN_p}\right)$$

$$H_1 \;:\; S_x^{\alpha}(f) \sim CN\left(\sigma_s^2, \frac{2\sigma_s^2\sigma_w^2 + \sigma_w^4}{NN_p}\right)$$

where $CN(\mu,\sigma^2)$ denotes a complex Gaussian distribution with mean μ and variance $\sigma^2$

$\sigma_s^2$ is the average energy of the received PU signal s[n] [15]

For the test statistic T, it is Rayleigh distributed for $H_0$ (noise only) hypothesis and Rician distributed for $H_1$ (signal plus noise) hypothesis [15]

$$p(T:H_0) = \frac{T}{\sigma_0^2}\exp\left(\frac{-T^2}{2\sigma_0^2}\right)$$

$$p(T:H_1) = \frac{T}{\sigma_1^2}\exp(\frac{-(T^2+A^2)}{2\sigma_1^2})I_0(\frac{AT}{\sigma_1^2})$$

where $A$ is the non-centrality parameter

$\sigma_0^2 = \frac{\sigma_w^4}{NN_p}$ and $\sigma_1^2 = \frac{2\sigma_s^2\sigma_w^2+\sigma_w^4}{NN_p}$

#### 3.1.1.1 *Probability of False Alarm ($P_{fa}$) and Probability of Detection ($P_d$)*

We know that $P_{fa}$ can be defined for the test statistic T and threshold λ as

$$P_{fa} = Pr(T > \lambda|H_0)$$

$$= \int_{\lambda}^{\infty} p\,(T:H_0)dT$$

$$= \int_{\lambda}^{\infty} \frac{T}{\sigma_0^2}\exp\left(\frac{-T^2}{2\sigma_0^2}\right)dT \tag{3.24}$$

After solving the above equation, we get

$$P_{fa} = \exp\left(\frac{\lambda^2}{2\sigma_0^2}\right) = \exp\left(\frac{NN_p\lambda^2}{2\sigma_w^4}\right) \tag{3.25}$$

The threshold can be calculated from the expression of $P_{fa}$, which is defined as

$$\lambda = \sqrt{\frac{-2\sigma_w^4\ln(P_{fa})}{NN_p}} \tag{3.26}$$

The probability of detection, $P_d$ is defined as

$$P_d = Pr(T > \lambda|H_1)$$

$$= \int_{\lambda}^{\infty} p\,(T:H_1)dT$$

$$= \int_{\lambda}^{\infty} \frac{T}{\sigma_1^2} \exp(\frac{-(T^2 + A^2)}{2\sigma_1^2}) I_0(\frac{AT}{\sigma_1^2})\ dT \tag{3.27}$$

By solving the above equations we get

$$P_d = Q_{\chi'^2_2(B)}(\frac{\lambda^2}{\sigma_1^2}) \tag{3.28}$$

where $Q_{\chi'^2_2(m)}(x) = \int_x^{\infty} \frac{1}{2} \exp\left[\frac{-1}{2}(t+\lambda)\right] I_0(\sqrt{\lambda t})dt$

is the right tail probability of the non-central Chi-Squared distribution with two degrees of freedom and the non-centrality parameter $m = |\mu|^2/\sigma_1^2$ and

$$I_0(u) = \int_0^{2\pi} \exp(ucos\theta)\frac{d\theta}{2\pi} \tag{3.29}$$

$I_0(u)$is the modified Bessel function of 1st kind and order zero.

### 3.1.2 Simulation Results

In this section, simulation results for cyclostationary detection technique for WM signal and AM signal is presented and discussed.

#### 3.1.2.1 *Wireless Microphone Signal*

WM signal uses FM scheme. The WM signal can be mathematically represented as

$$x(t) = A_c \cos(2\pi F_c t + 2\pi\Delta f \int_0^t m(u)du) \tag{3.30}$$

The signal can also be written as

$$x(t) = A_c co\,s[2\pi F_c t + \varphi(t)] \tag{3.31}$$

where $\varphi$(t)=phase of the FM signal

In discrete domain, (3.31)can be written as

$$x[n] = A_c \cos(2\pi f_c n + \varphi(n)) \tag{3.32}$$

Where, $f_c$=$\frac{F_c}{F_s}$ = discrete carrier frequency and$F_s$ is the sampling frequency

The CAF of the WM FM signal is calculated by putting the x[n] in $R_x^{\alpha}[l]$ expression given by,

$$R_x^\alpha[l] = \langle x[n]x^*[n-l]e^{-j2\pi\alpha n}\rangle e^{j\pi\alpha l}$$

$$= \langle \cos(2\pi f_c n + \varphi(n))\cos(2\pi f_c(n-l) + \varphi(n-l))e^{-j2\pi\alpha n}\rangle e^{j\pi\alpha l}$$

$$= \frac{1}{2}\langle [\cos\big(2\pi f_c(2n-l) + \varphi(n) + \varphi(n-l)\big) + \cos(2\pi f_c l + \varphi(n) + \varphi(n-l))]e^{-j2\pi\alpha n}\rangle e^{j\pi\alpha l} \quad (3.33)$$

Let, $\varphi_1 = \varphi(n) + \varphi(n-l)$ and $\varphi_2 = \varphi(n) - \varphi(n-l)$

$$= \frac{1}{2}\langle [co\,s(2\pi f_c(2n-l) + \varphi_1) \;\; co\,s(2\pi f_c\, l + \varphi_2)]e^{-j2\pi\alpha n}\rangle e^{j\pi\alpha l} \quad (3.34)$$

By solving we get the CAF as

$$R_x^\alpha[l] = \begin{cases} \frac{e^{-j2\pi f_c l}}{4}\langle e^{-j\varphi_2}\rangle + \frac{e^{j2\pi f_c l}}{4}\langle e^{j\varphi_2}\rangle, & \alpha = 0 \\ \frac{1}{4}\langle e^{j\varphi_1}\rangle, & \alpha = 2f_c \\ \frac{1}{4}\langle e^{-j\varphi_1}\rangle, & \alpha = -2f_c \\ 0, & otherwise \end{cases}$$

Since the pdf is even for WSS Gaussian random process, $\langle e^{-j\varphi_2}\rangle = \langle e^{j\varphi_2}\rangle$ and $\langle e^{-j\varphi_1}\rangle = \langle e^{j\varphi_1}\rangle$

The modified CAF is then given by

$$R_x^\alpha[l] = \begin{cases} \frac{cos 2\pi f_c l}{2}\langle e^{j\varphi_2}\rangle, & \alpha = 0 \\ \frac{1}{4}\langle e^{j\varphi_1}\rangle, & \alpha = \pm 2f_c \\ 0, & otherwise \end{cases}$$

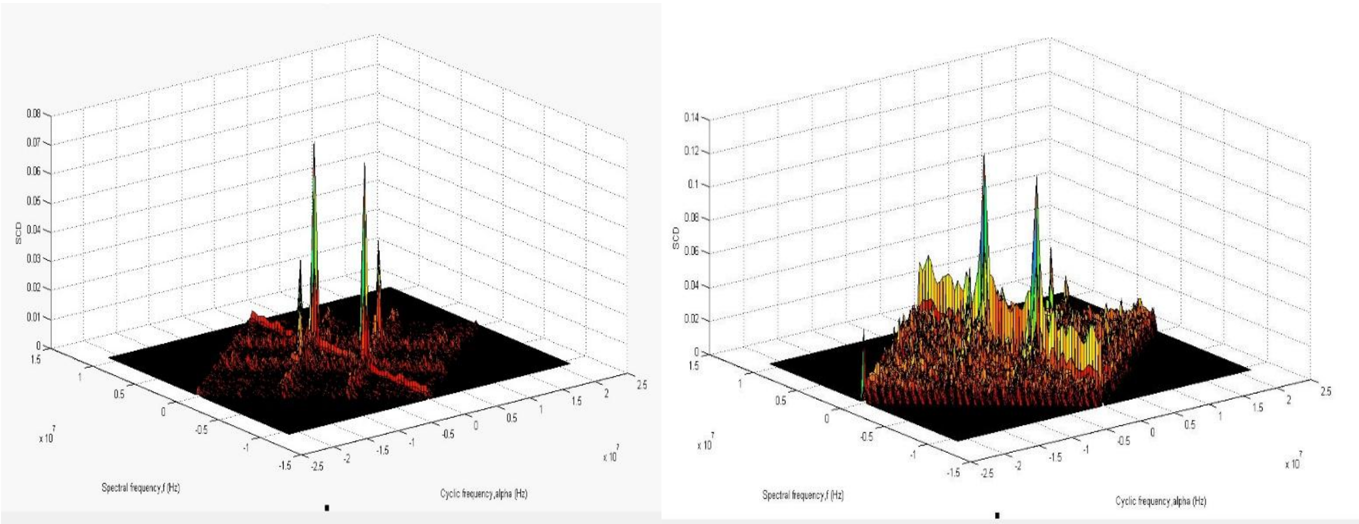
Let, $\Phi_1$(f)is the FT of $\langle e^{j\varphi_1}\rangle$and $\Phi_2$(f) is the FT of $\langle e^{j\varphi_2}\rangle$

The SCD function is the FT of ACF is given by

$$S_x^\alpha(f) = \begin{cases} \frac{1}{4}[\Phi_1(f+f_c) + \Phi_2(f-f_c)], & \alpha = 0 \\ \frac{1}{4}\Phi_2(f), & \alpha = \pm 2f_c \\ 0, & Otherwise \end{cases}$$

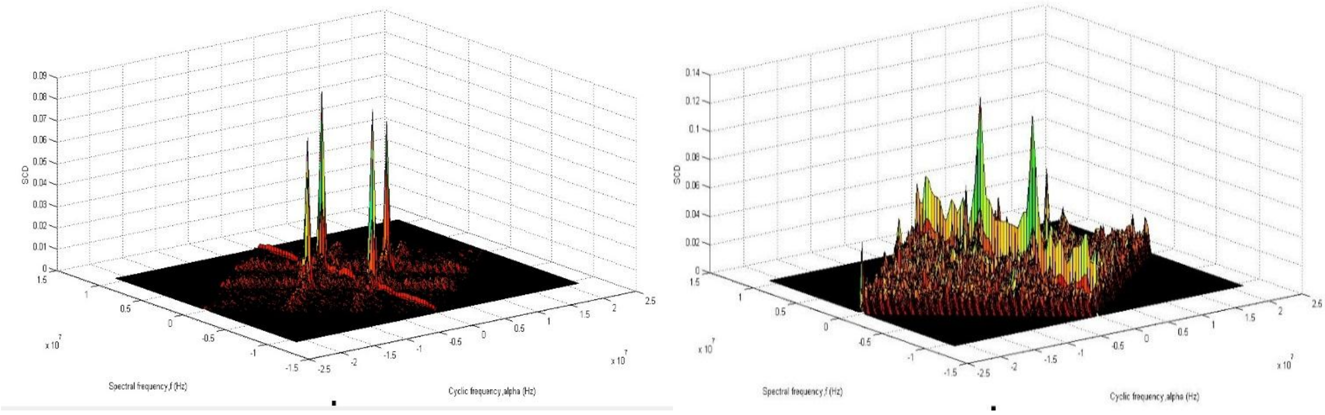
From the above equations the SCD peaks of WM signal will occur at $\alpha = 0, f = \pm f_c$and $\alpha = \pm 2f_c, f = 0$.

The simulations were carried out for all the three operating conditions of WM signal in AWGN environment. The FM WM signal is sampled at a sampling frequency of 21.52MHz [8] with a carrier frequency of 6MHz.The cyclostationary feature of WM signal is estimated by the SSCA method for 1024 number of received samples i.e. total duration of the sensed signal frame ($N$) and the sliding window length ($N_p$) as 64 samples. The received signal samples are passed through Hamming window.



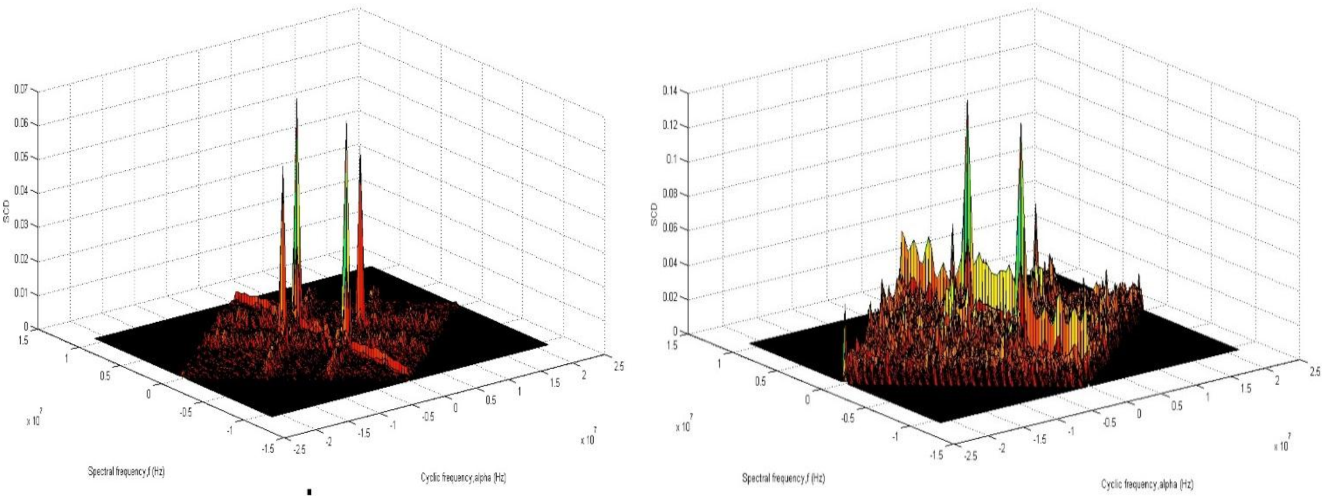
(a) (b)

Fig 3-1 Surface curve of Loud speaker at (a) SNR=0dB, (b) SNR=-10dB



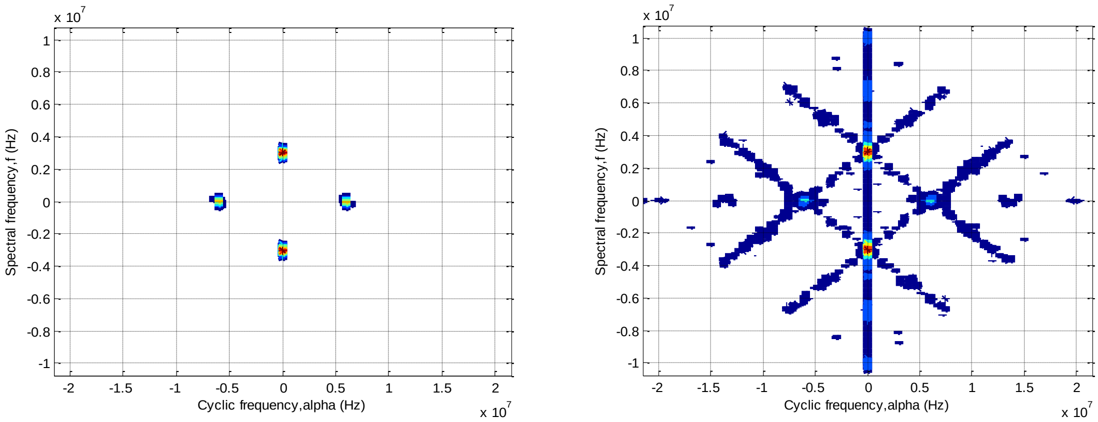
(a) (b)

Fig 3-2 Surface curve of Soft speaker at (a) SNR=0dB, (b)SNR=-10dB



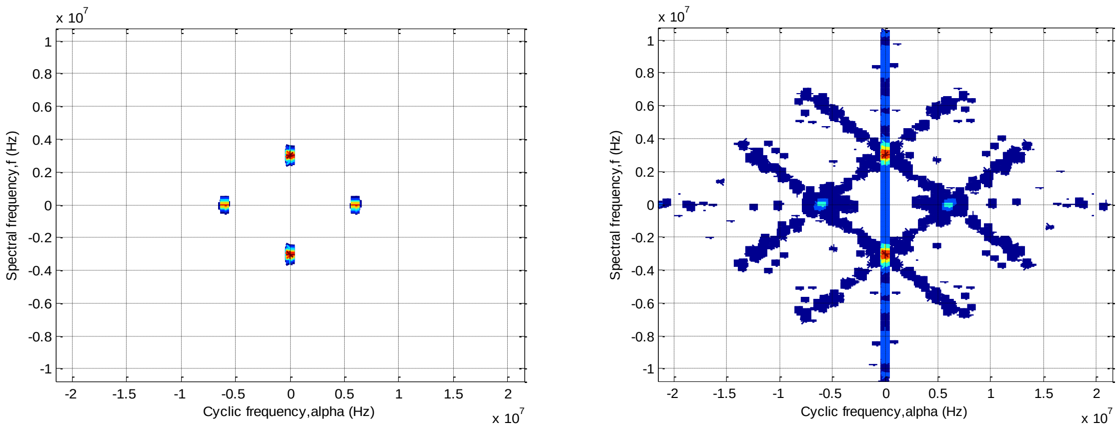

(a) (b)

Fig 3-3 Surface curve of Silent speaker at (a) SNR=0dB, (b)SNR= -10dB



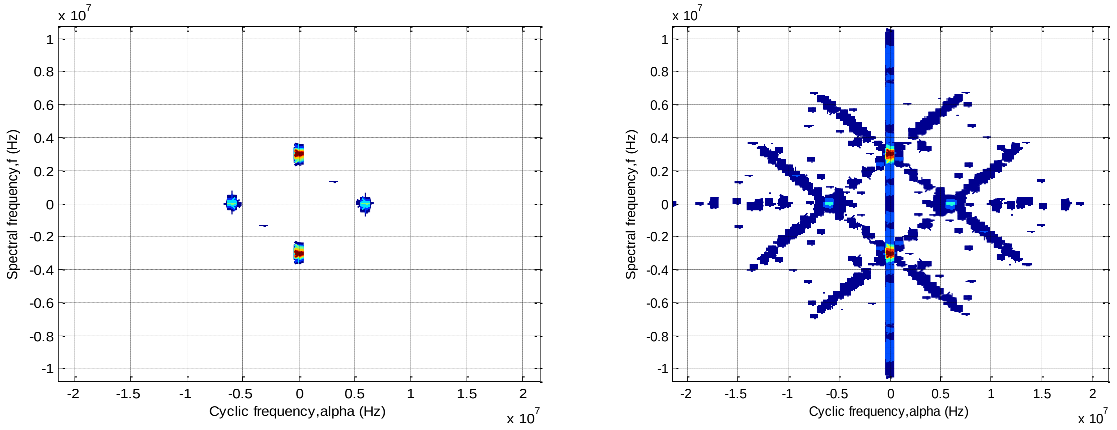

(a) (b)

Fig 3-4 Contour plot of Silent speaker at (a) SNR= 0dB and (b) SNR= -10dB




(a) (b)

Fig 3-5 Contour plot of Soft speaker at a) SNR= 0dB and b) SNR= -10dB




(a) (b)

Fig 3-6 Contour plot of Loud speaker at a) SNR= 0dB and b) SNR= -10dB

From the surface and contour plot of different operating conditions of WM signal, four peaks are observed, out of which two peaks are at $\alpha=0$, $f=\pm f_c$ and the other two are at $\alpha=\pm 2f_c$ , $f=0$. At SNR value of -10dB, the peaks are clearly visible and the PU signal can be easily distinguished from the noise signal.

#### 3.1.2.2 *Amplitude Modulated signal*

Let x[n] be the AM signal which can be mathematically written a

$$x[n] = (1+\cos 2\pi f_m n)\cos 2\pi f_c n$$

$$= \cos 2\pi f_c n + \frac{1}{2}\cos 2\pi(f_c+f_m)\,n + \frac{1}{2}\cos 2\pi(f_c-f_m)\,n \qquad (3.35)$$

The CAF of the AM signal is calculated by putting the x[n] in $R_x^{\alpha}[l]$ expression as

$$R_x^{\alpha}[l] = \langle x[n]x^*[n-l]e^{-j2\pi\alpha n}\rangle e^{j\pi\alpha l}$$

$$= \langle[\cos 2\pi f_c n + \frac{1}{2}\cos 2\pi(f_c+f_m)\,n + \frac{1}{2}\cos 2\pi(f_c-f_m)\,n][\cos 2\pi f_c(n-l)$$

$$+\frac{1}{2}\cos 2\pi(f_c+f_m)\,(n-l) + \frac{1}{2}\cos 2\pi(f_c-f_m)\,(n-l)]e^{-j2\pi\alpha n}\rangle\, e^{j\pi\alpha l}$$

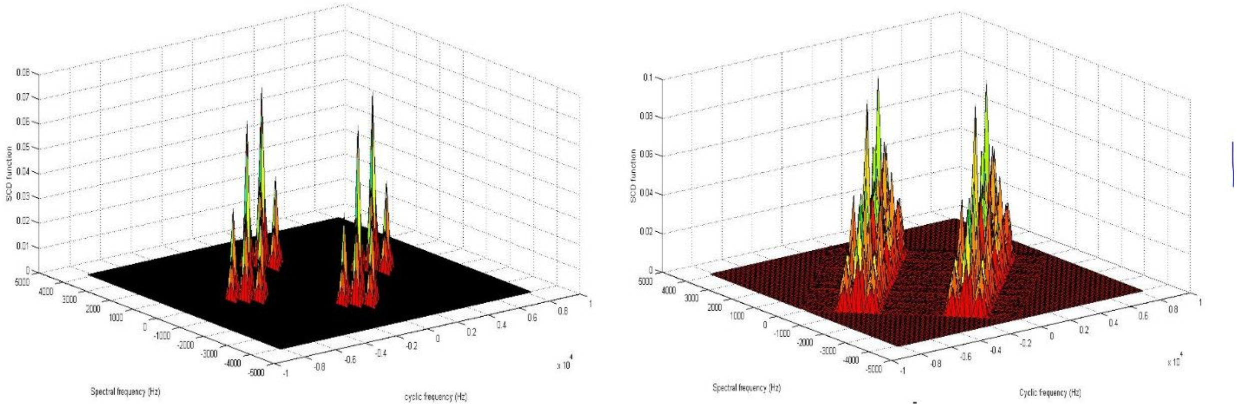
On simplifying the above equation we obtain the CAF as

$$R_x^{\alpha}[l] = \begin{cases} \frac{1}{8}\cos 2\pi(f_c \pm f_m)l + \frac{1}{2}\cos 2\pi f_c l\,, & \alpha = 0 \\ \frac{1}{4}\cos \pi(2f_c \pm f_m)l, & \alpha = \pm f_m \\ \frac{1}{8}\cos 2\pi f_c l, & \alpha = \pm 2f_m \\ \frac{1}{16}, & \alpha = \pm 2(f_c \pm f_m) \\ \frac{1}{4}\cos \pi f_m l, & \alpha = \pm(2f_c \pm f_m) \\ \frac{1}{4} + \frac{1}{8}\cos 2\pi f_m l, & \alpha = \pm 2f_c \end{cases}$$

The SCD function is the FT of ACF, which is given as

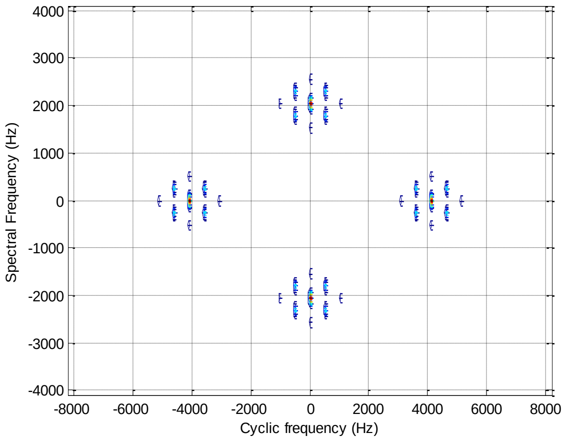
$$S_x^{\alpha}(f) = \begin{cases} \frac{1}{16}\delta(f \pm f_c \pm f_m) + \frac{1}{4}\delta(f \pm f_c), & \alpha = 0 \\ \frac{1}{8}\delta\left(f \pm f_c \pm \frac{f_m}{2}\right), & \alpha = \pm f_m \\ \frac{1}{16}\delta(f \pm f_c), & \alpha = \pm 2f_m \\ \frac{1}{16}\delta(f), & \alpha = \pm 2(f_c \pm f_m) \\ \frac{1}{8}\delta\left(f \pm \frac{f_m}{2}\right), & \alpha = \pm(2f_c \pm f_m) \\ \frac{1}{16}\delta(f \pm f_m) + \frac{1}{4}\delta(f), & \alpha = \pm 2f_c \end{cases} \qquad (3.36)$$

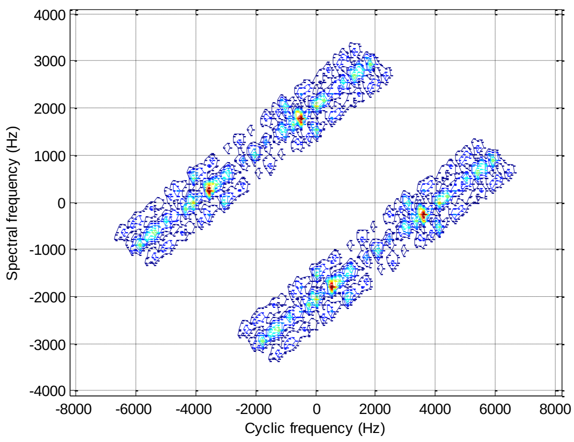
The SCD function of AM signal is generated by using SSCA method. For the simulation of surface and contour plot, $N$ and $N_p$ are 64 samples each. The received signal is AM signal in which message signal is a tone signal of frequency ($f_m$) of 512 Hz and carrier frequency ($f_c$) of 1024 Hz are sampled at 8192 Hz.




(a) (b)

Fig 3-7 Surface plot of AM signal at (a) SNR=0dB, (b) SNR= -10dB




(a) (b)

Fig 3-8 Contour plot of AM signal at (a) SNR=0dB, (b) SNR= -10dB

From the surface and contour plot, peaks of AM signal are observed for given values of $\alpha$ presented by(3.36). At SNR= -10dB, peaks are visible along with noise.

For the simulation of ROC and SNR Vs $P_d$curve for AM signal, the sampling frequency ($f_s$) is taken to be 8192 Hz and the message signal is a tone signal of frequency ($f_m$) 512Hz along with a carrier frequency ($f_c$) of 1024Hz.

In this section, a complete analysis of cyclostationary detection method is presented.

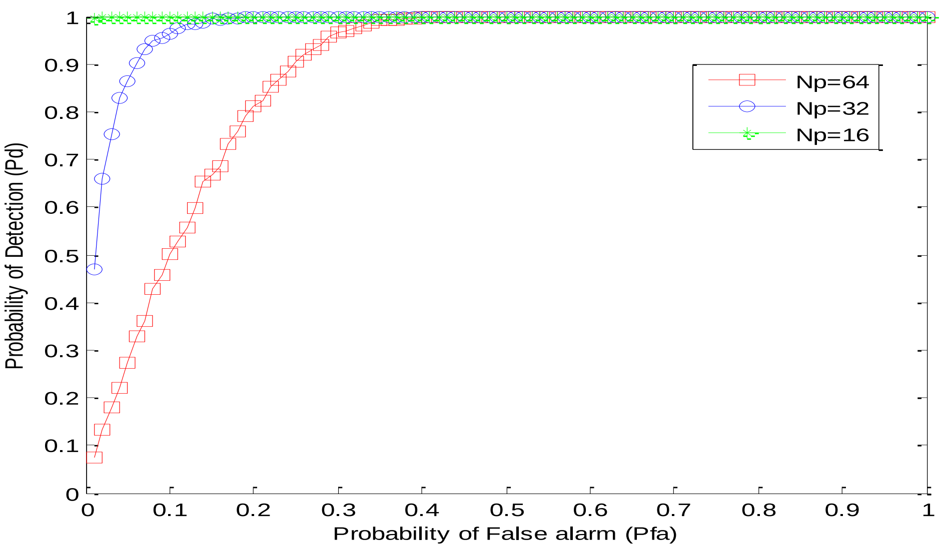



Fig 3-9 ROC curve with $N_p$ varying at N=1024 and SNR=-25dB

Fig 3-9 hows ROC curve of AM signal for different values of$N_p$.it can be observed that, with increase in $N_p$ value performance of the cyclostationary detection method deteriorates,since for reliable estimate of $S_x^\alpha(f)$, $\Delta t \Delta f \gg 1$ i.e. $\frac{N}{N_p} \gg 1$.

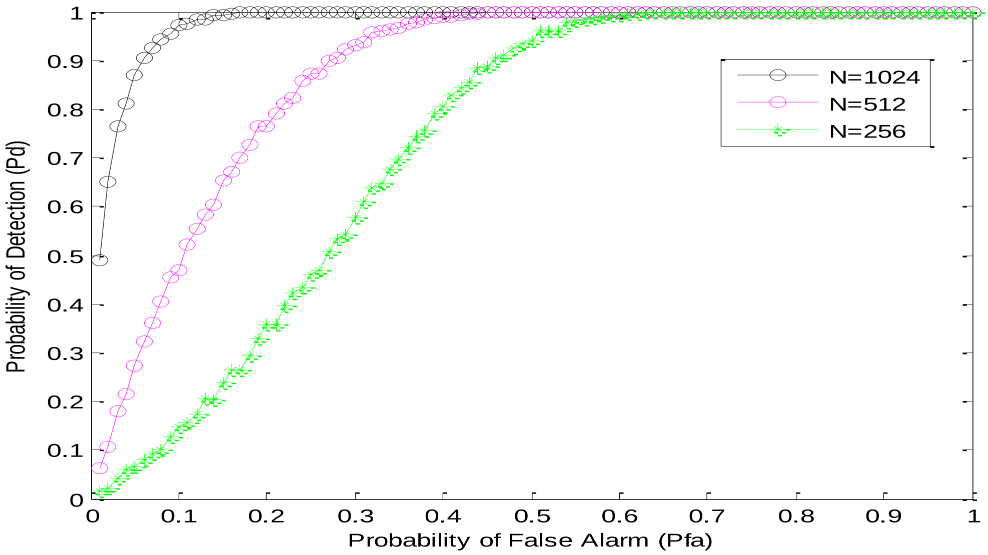



Fig 3-10 ROC curve with N varying at $N_p$=32, SNR= -25dB

Fig 3-10 shows ROC curve of AM signal for different values of N. It can be observed thatwith increase in N the performance of the cyclostationary detection method also increasessince, it increases the time and frequency resolution product i.e. $\Delta t \Delta f \gg 1$

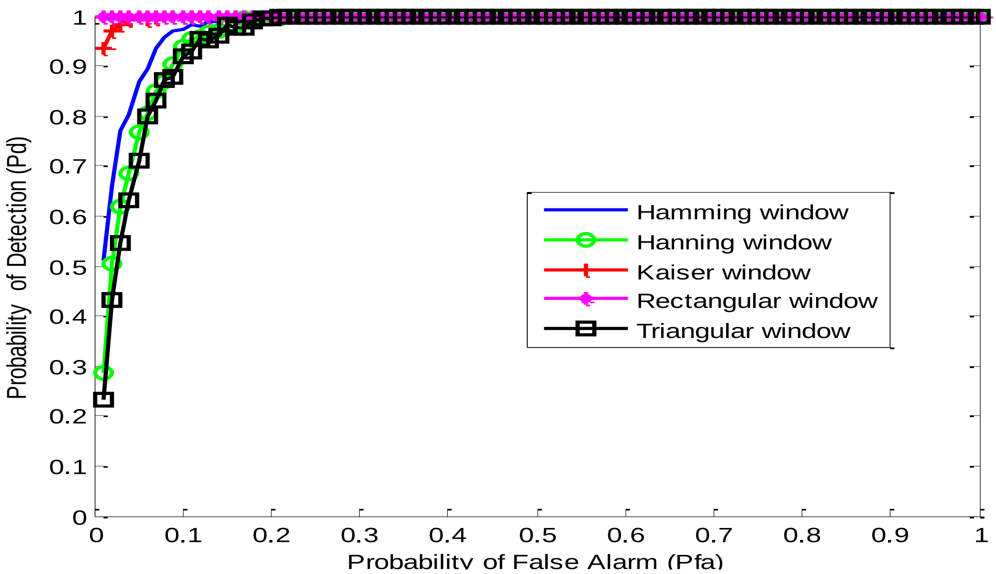



Fig 3-11ROC curve with window varying

Fig 3-11 shows ROC curve for different windows. It can be observed that rectangular windowperforms the best and triangular window performs the worst.

## 3.2 Energy Detection Overview

It is the most simplest and popular detection method, in which the energy of the received signal is compared against the threshold for the determination of presence or absence of PU signal in a given licensed band [16].

Let the received signal be x[n] defined as

x[n]=s[n]+w[n]

where s[n] is the PU signal with zero mean and $\sigma_s^2$variance and w[n] is AWGN signal with zero mean and $\sigma_w^2$ variance.

The hypothesis testing problem can be written as

x[n]=s[n]+w[n]   for $H_1$ hypothesis

x[n]=w[n]   for $H_0$ hypothesis

let N number of samples are used for the calculation decision statistic, which is given by

$$T(x) = \frac{1}{N}\sum_{n=1}^{N} |x[n]|^2 \tag{3.37}$$

### 3.2.1 Probability of false alarm ($P_{fa}$) and Probability of Detection ($P_d$)

The test statistic T(x) under$H_0$ hypothesis follows a chi-square distribution with 2N degrees of freedom for complex valued signal and N degrees of freedom for real valued signal [16].

Let λ is the threshold value for the energy detector then the $P_{fa}$can be calculated as

$$P_{fa} = \Pr(T(x) > \lambda | H_0) = \int_{\lambda}^{\infty} p_{H_0}(x)dx \tag{3.38}$$

From central limit theorem, large N the pdf of test statistic T(x) for $H_0\ hypothsis$, follows Gaussian distribution with mean$\mu = \sigma_w^2$and variance $\sigma^2 = \frac{\sigma_w^4}{N}$

$$P_{fa} = \int_{\lambda}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(T(x)-\mu)^2}{2\sigma^2}} dT(x) \tag{3.39}$$

By solving the above equation we get

$$P_{fa} = Q\left(\frac{\lambda-\mu}{\sigma}\right) = Q(\left(\frac{\lambda}{\sigma_w^2} - 1\right)\sqrt{N}\,) \tag{3.40}$$

where Q(.) is the Q function given by

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_{x}^{\infty} e^{\frac{-u^2}{2}} du \tag{3.41}$$

The probability of detection, $P_d$ is defined as

$$P_d = Pr(T > \lambda | H_1) = \int_{\lambda}^{\infty} p\,(T\colon H_1) dT$$

From central limit theorem, large N the pdf of test statistic T(x) for $H_1\ hypothsis,$ follows Gaussian distribution with mean $\mu = \sigma_s^2 + \sigma_w^2$ and variance $\sigma^2 = \frac{2}{N}(\sigma_s^2 + \sigma_w^2)^2$

$$P_d = \int_{\lambda}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(T(x)-\mu)^2}{2\sigma^2}} dT(x)$$

By solving the above equation we get

$$P_d = Q\left(\left(\frac{\lambda - (\sigma_s^2 + \sigma_w^2)}{\sigma_w^2}\right)\sqrt{\frac{N\sigma_w^2}{2\sigma_s^2 + \sigma_w^2}}\right) \tag{3.42}$$

### 3.2.2 Simulation Results

In this section, performance of energy detection scheme for AM signal in AWGN environment is discussed. For the simulation of AM signal, a tone signal of frequency 128Hz is used as a message signal with a carrier of frequency 1024Hz and sampled at 8192Hz.

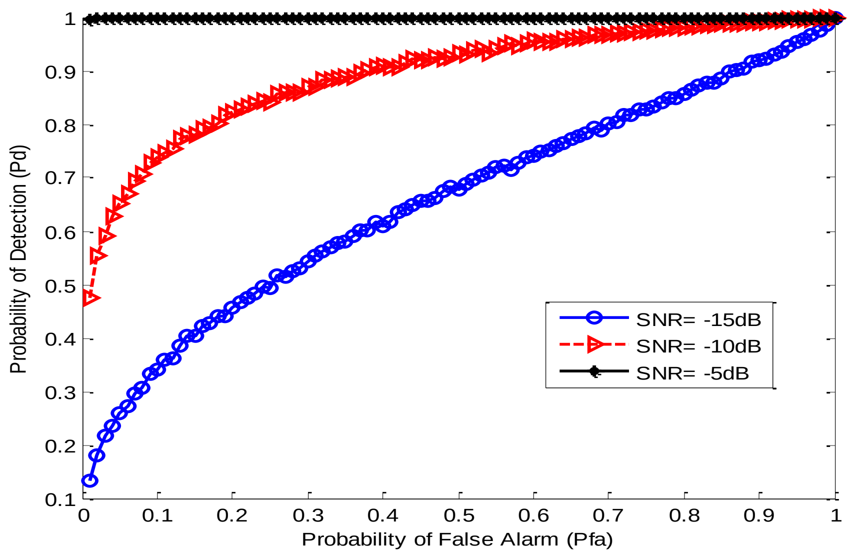



Fig 3-12 ROC Curve of AM signal with varying SNR

From fig 3-12 it can be seen that with increase in SNR, the detection performance of the energy detection improves.

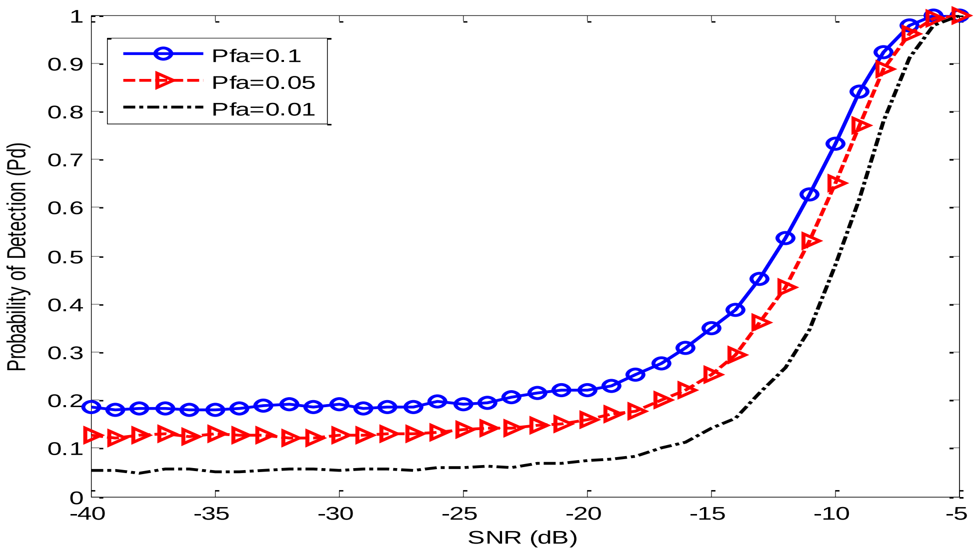



Fig 3-13 SNRVsProbability of detection ($P_d$) curve

Fig 3-13 shows the variation of probability of detectionwith SNR for different values of $P_{fa}$. It can be observed that with increase in the $P_{fa}$the detection performance increases.

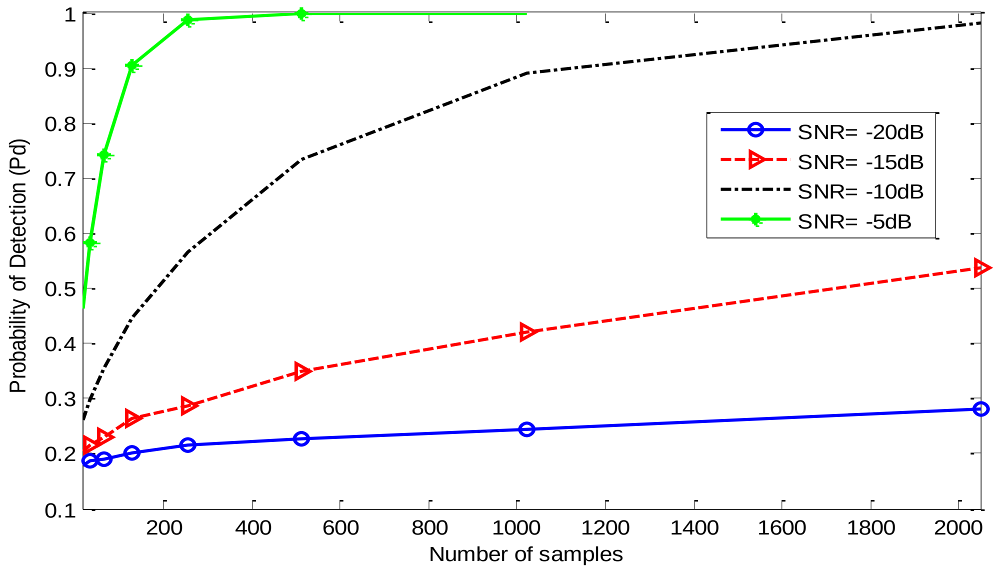



Fig 3-14 Number of Samples Vs $P_d$Curve with Varying SNR

Fig 3-14 shows the variation of $P_d$ with number of samples used to calculate the test statistic for different values of SNR. It can be observed that with increase in the SNR, number of samples required to obtain a given $P_d$decreases.

# 4

# TWO-STAGE SPECTRUM SENSING FOR COGNITIVE RADIO

The energy detection and cyclostationary detection method suffer from some demerits which are overcome in the two-stage detection method. The ED method is simple to operate and requires less number of samples for the calculation of decision statistics but it performs poor in low SNR condition. The cyclostationary method is robust to noise and interference signals but incurs large computational complexity.

The proposed two-stage spectrum sensing method is a blind detection method. It is a combination of energy and cyclostationary method and performs better than the energy as well as cyclostationary detection scheme.

## 4.1 Introduction to Two-stage Spectrum Sensing Method

The two-stage spectrum sensing carries the merits of both the schemes. In this method, the received samples are first passed through the energy detection method and the decision statistic is compared against the threshold$\lambda_e$ ($\lambda_e$ is the threshold defined for the energy detection stage) in order to determine the presence or absence of the PU signal. If the decision statistic is above the predetermined threshold$\lambda_e$, then it is assumed that the channel is occupied else cyclostationary detection is applied on the received signal [17]. Again the decision statistic derived from the received samples is compared with the threshold $\lambda_c$, if the test statistic exceeds the threshold $\lambda_c$ then the band is unavailable for the secondary users else the band is declared as vacant.

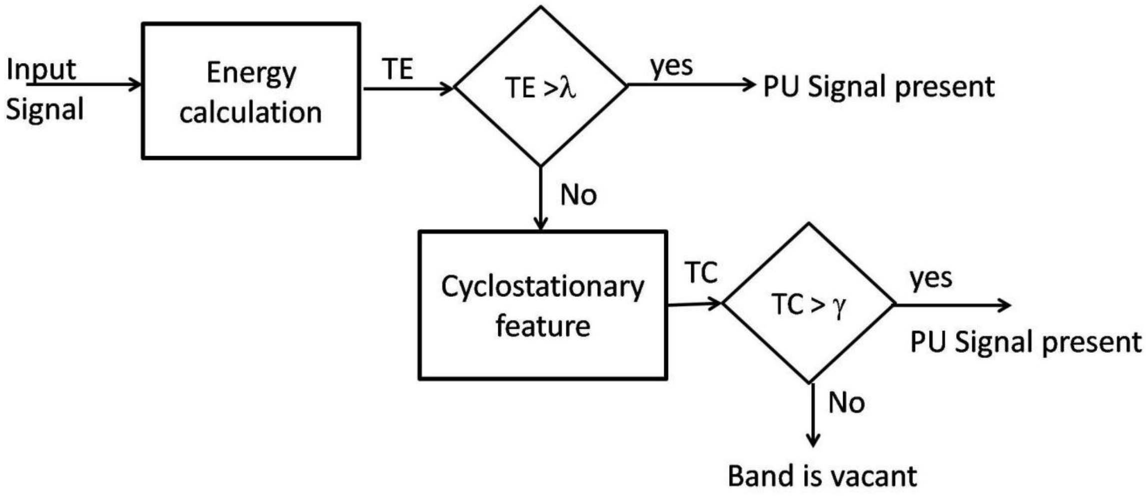



Fig 4-1 Block Diagram of Two-stage spectrum sensing

The received signal samples in the two-stage method are first passed through the energy detection stage.

**Energy Detection Stage:**

Let the received signal be x[n], the detection problem in energy detection stage can be represented as

$$x[n]=s[n]+w[n] \qquad \text{for } H_1 \text{ hypothesis}$$

$$x[n]=w[n] \qquad \text{for } H_0 \text{ hypothesis}$$

where s[n] is the PU signal with zero mean and $\sigma_s^2$ variance

w[n] is the AWGN noise with zero mean and $\sigma_w^2$ variance let N number of samples are received, then the decision statistic TE(x) can be defined as

$$TE = \frac{1}{N}\sum_{n=1}^{N}|x[n]|^2 \tag{4.1}$$

The detection problem can be formulated as

$$Y = \begin{cases} H_0 \text{ hypothesis; } TE \leq \lambda \\ H_1 \text{ hypothesis; } TE > \lambda \end{cases}$$

The expression for $P_{fa}$ is described in the previous chapter in sec 3.2.1, which is defined as

$$P_{fa} = Q\left(\frac{\lambda-\mu}{\sigma}\right) = Q(\left(\frac{\lambda}{\sigma_w^2}-1\right)\sqrt{N}) \tag{4.2}$$

where $\lambda$ is the threshold for energy detection stage and $Q(.)$ is the Q function.

If the decision statistic TE(x) exceeds the threshold $\lambda$ then it is decided that the band is occupied by the PU signal else no decision can be derived from the energy detection stage. The ambiguity on the status of the received signal can be resolved by the cyclostationary detection method which can distinguish between the PU signal and noise. The received signal is then moved to the cyclostationary stage.

**Cyclostationary detection stage:**

Cyclostationary detection method is described in detail in chapter 3 in sec 3.1 SCD function is determined which gives the correlation among the spectral components of the signal. The test statistic is the peak value across the SCD function which is compared against the predetermined threshold γ. The SCD function is estimated as

$$S_x^\alpha(f) = \frac{1}{N}\sum_{m=-\frac{N}{2}}^{\frac{N}{2}-1} X_T(n+m, f+\alpha/2)x^*(n+m)e^{i2\pi\left(f-\frac{\alpha}{2}\right)m} \tag{4.3}$$

The decision statistic can be described as

$$TC = \max_{\forall f\ \forall \alpha, \alpha\neq 0} |S_x^\alpha(f)| \tag{4.4}$$

The detection problem in cyclostationary detection stage can be given by

$$Y = \begin{cases} H_0 \textit{ hypothesis; } TC \leq \gamma \\ H_1 \textit{hypothesis; } TC > \gamma \end{cases}$$

The probability of false alarm ($P_{fa}$) expression is already described in detail in

$$P_{fa} = \exp\left(\frac{\lambda^2}{2\sigma_0^2}\right) = \exp\left(\frac{NN_p\lambda^2}{2\sigma_w^4}\right) \tag{4.5}$$

## 4.2 Simulation Results

In this section, we compare the performance of the two-stage spectrum sensing with the conventional spectrum sensing scheme like energy detection and cyclostationary detection method. For comparison WM signal and AM signal are considered and their results are described in the following sections.

### 4.2.1 Wireless Microphone Signal

The performance of two-stage spectrum sensing method, energy detection method and cyclostationary detection method is shown in terms of ROC curves and SNR Vs $P_d$ curves. All the simulation results were performed for the silent speaker, soft speaker and loud speaker under AWGN environment.

The cyclostationary feature of WM signal is estimated by the SSCA method and the simulations were carried out for 1024 number of received samples i.e. total duration of the sensed signal frame ($N$) and the sliding window length ($N_p$) as 64 samples. The received signal samples are passed through Hamming window. In these simulations, WM signal under different operating conditions are used with carrier frequency ($f_c$) of 3MHz, sampled at a sampling rate of ($f_s$) 21.52 MHz and number of iteration is taken as3000.

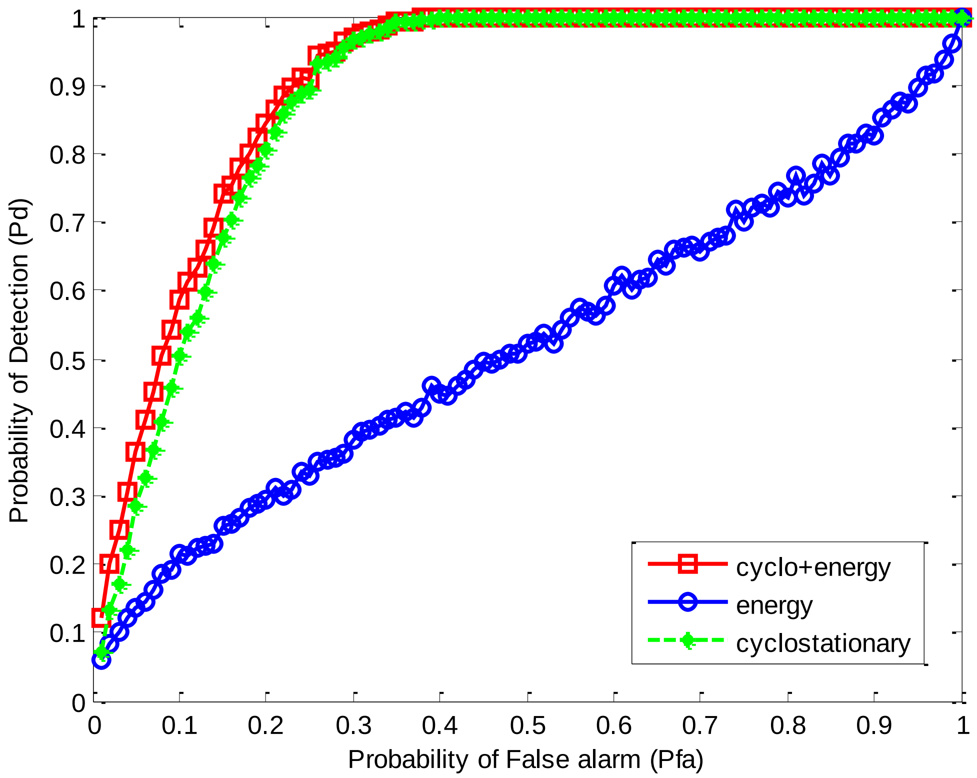



Fig 4-2 Receiver Operating Characteristics Curve of Silent Speaker at SNR= -25dB

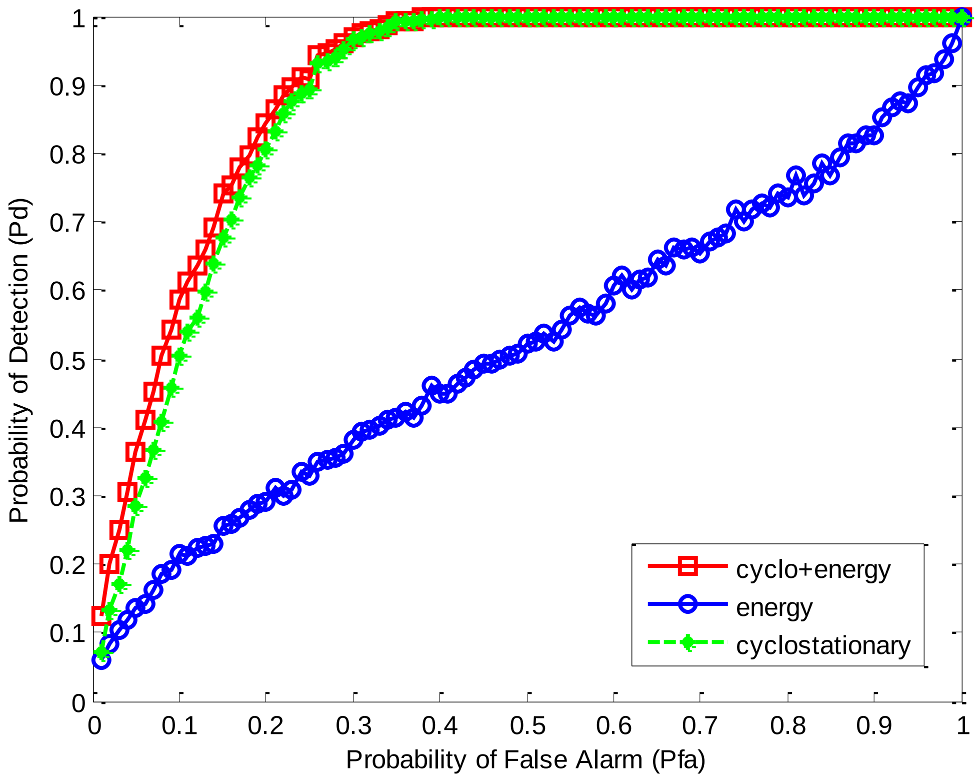



Fig 4-3 Receiver Operating Characteristics Curve of Soft Speaker at SNR= -25dB

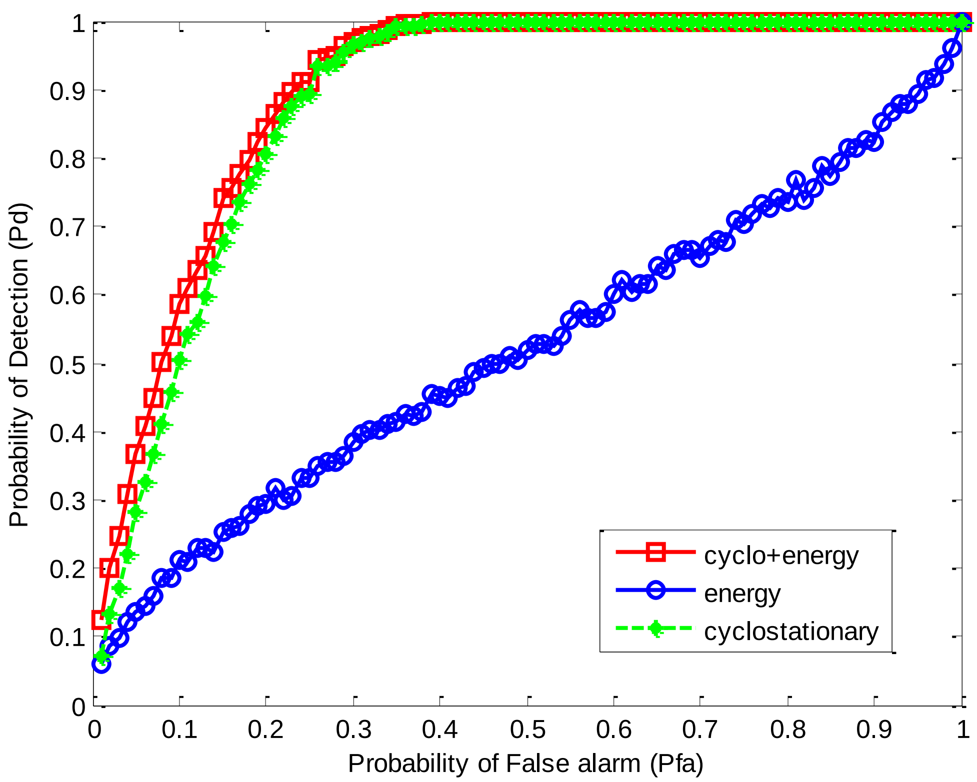



Fig 4-4 Receiver Operating Characteristics Curve of Loud Speaker at SNR= -25dB

Fig 4-2, 4-3 and 4-4 shows the ROC curve for different operating conditions of WM signals. The figures show the superior performance of two-stage spectrum sensing method than both the energy detection and cyclostationary method at SNR -25dB.

FCC has defined performance metric to measure the sensing performance of a detection scheme. It is defined as the SNR at which, probability of detection is 90% and probability of false alarm is 10%. The higher the value of performance metric the better is the performance of the detection scheme. Performance metric can be observed from the SNR Vs $P_d$ curve plotted for $P_{fa} = 0.1$. It indicates that if SNR is greater than the performance metric given for a detection scheme,$P_d$will be greater than or equal to 90% and $P_{fa}$ will be less than or equal to 10%, which is the desired performance of a detector.

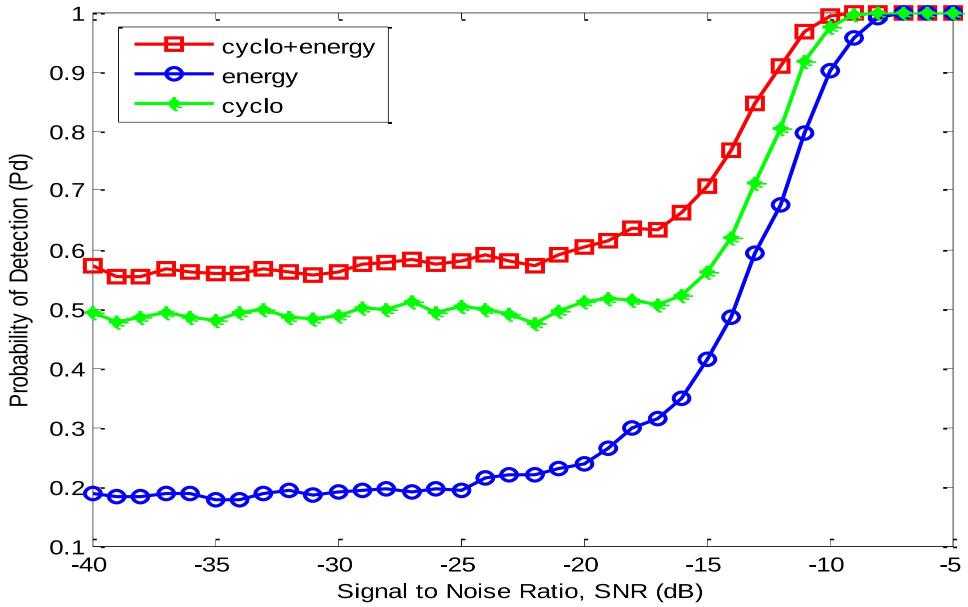



Fig 4-5 SNRVs Probability of detection ($P_d$) of Silent Speaker

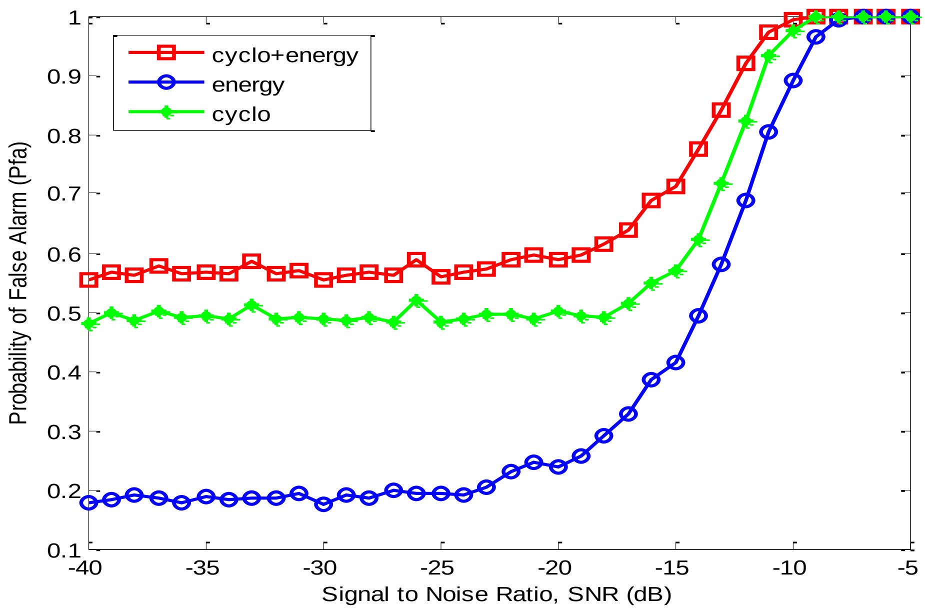



Fig 4-6 SNR Vs Probability of detection ($P_d$) of Soft Speaker

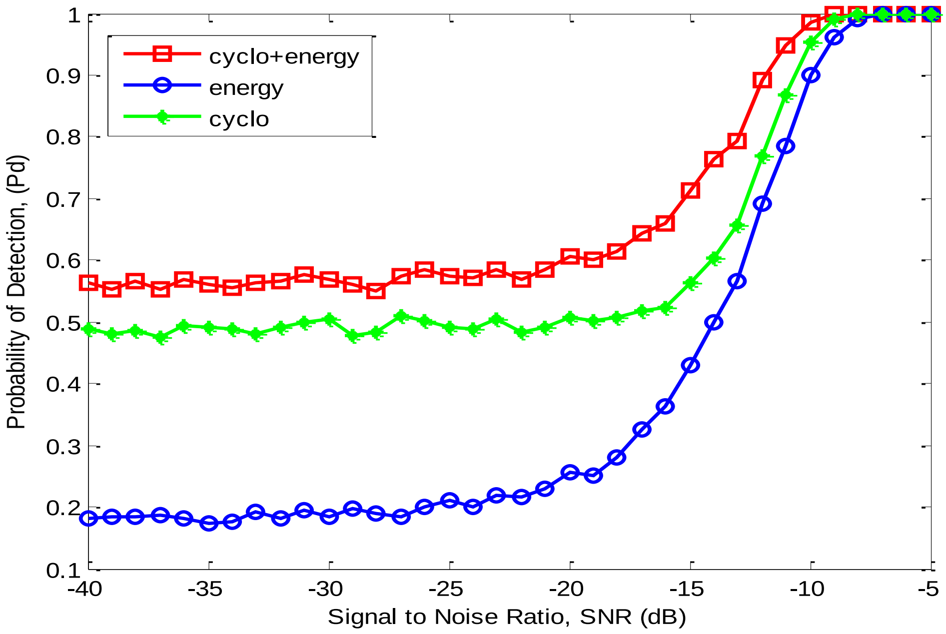



Fig 4-7 SNR Vs Probability of detection ($P_d$) of Loud Speaker

Fig 4-5, 4-6 and4-7 shows the detection performance against the SNR for different operating condition of WM signal. It can be observed that for SNR value less than -10dB, the two-stage spectrum sensing detection scheme out performs both the energy and cyclostationary detection method. At SNR greater than -10dB, all the detection schemes performance are same.

The performance metric for WM signal for different operating conditions are summarized in the following tables

Table 4-1 Performance metric for Silent speaker

| **Detection Method** | **Performance metric** |
|---|---|
| 2-stage method | -12.15dB |
| Cyclostationary detection | -11.16dB |
| Energy detection | -10.00dB |

Table 4-2 Performance metric for Soft speaker

| **Detection Method** | **Performance metric** |
|---|---|
| 2-stage method | -12.25dB |
| Cyclostationary detection | -11.30dB |
| Energy detection | -9.90dB |

Table 4-3 Performance metric for Loud speaker

| Detection Method | Performance metric |
|---|---|
| 2-stage method | -11.86dB |
| Cyclostationary detection | -11.16dB |
| Energy detection | -10.02dB |

### 4.2.2 Amplitude Modulated Signal

In this section, the performance comparison of two-stage detection method with the energy detection and cyclostationary detection for AM signal is presented. For simulations, the message is considered to be a tone signal of frequency 128 Hz and carrier frequency of 1024 Hz, sampled at sampling frequency of 8192 Hz. The total observation interval is taken to be 1024 samples and sliding window length as 32 samples.

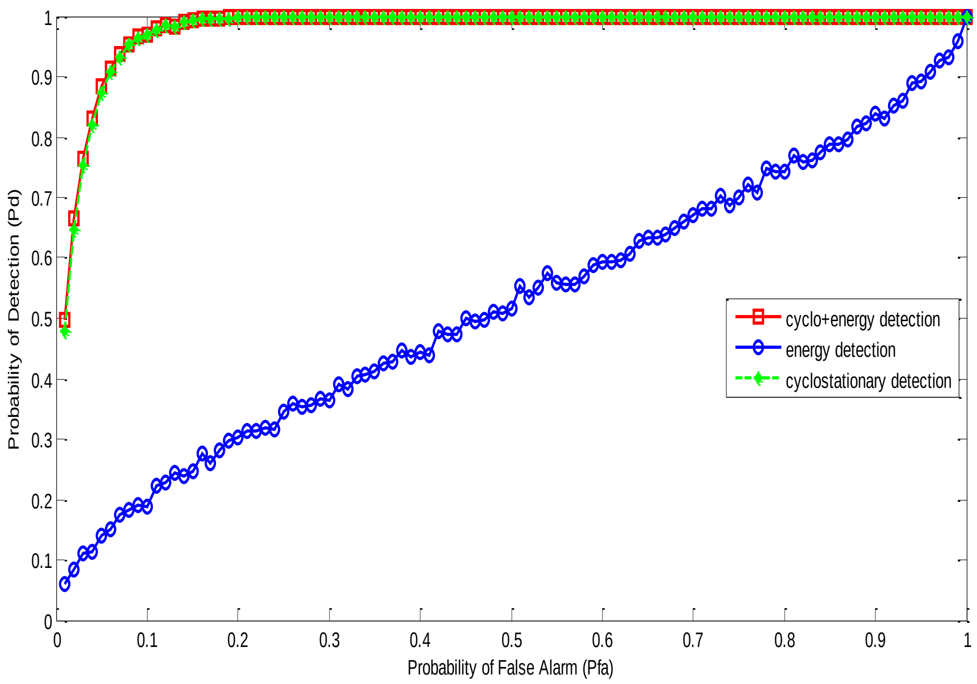



Fig 4-8 Receiver Operating Characteristics curve for AM signal at SNR= -25dB

From the Fig 4-8, it is observed that two-stage sensing scheme detection performance is better than the cyclostationary detection as well as energy detection.

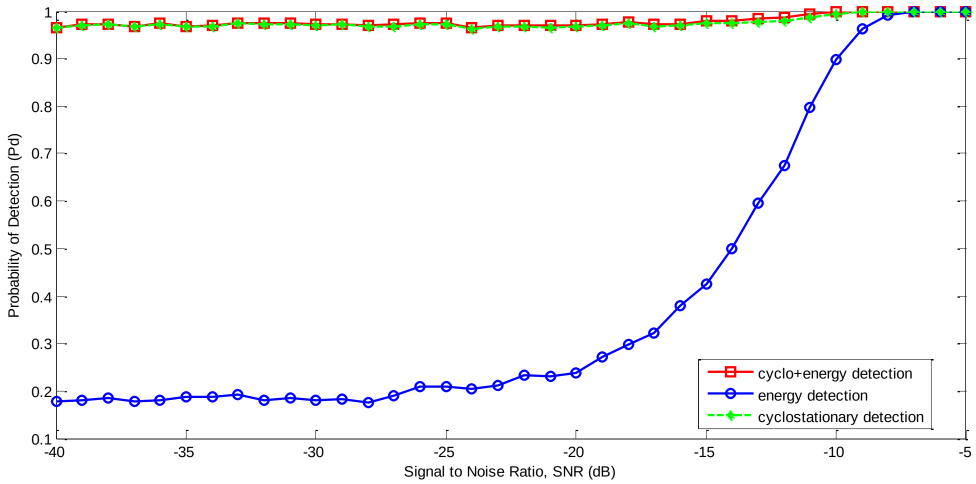



Fig 4-9 SNR Vs Probability of detection ($P_d$) of AM signal at $P_{fa} = 0.1$

Fig 4-9 shows the probability of detection against the SNR for different detection schemes at $P_{fa} = 0.1$. For SNR less than -10dB the two stage sensing method and cyclostationary detection method detection capability are nearly the same whereas energy detection performs poor. SNR value greater than -10dB, all the detection scheme performance is nearly the same.

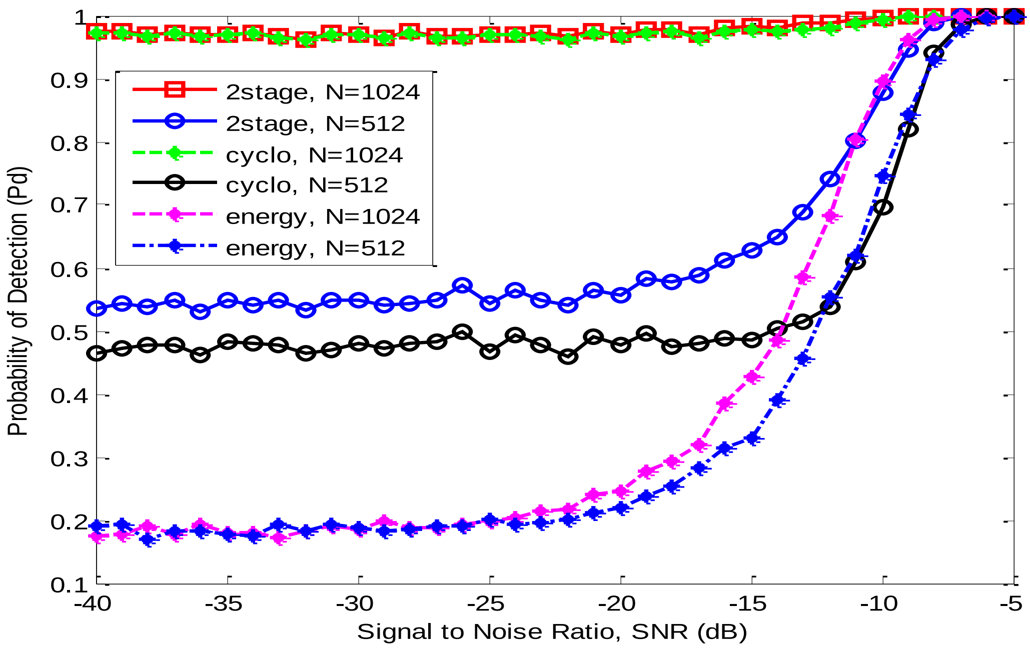



Fig 4-10 SNR Vs Probability of detection ($P_d$) for varying N

From Fig 4-10 we can observe that with decrease in $N$, performance of two-stage detection method deteriorates marginally in comparison to cyclostationary. It can also be observed that the decrease in no of samples have less effect on energy detection performance.

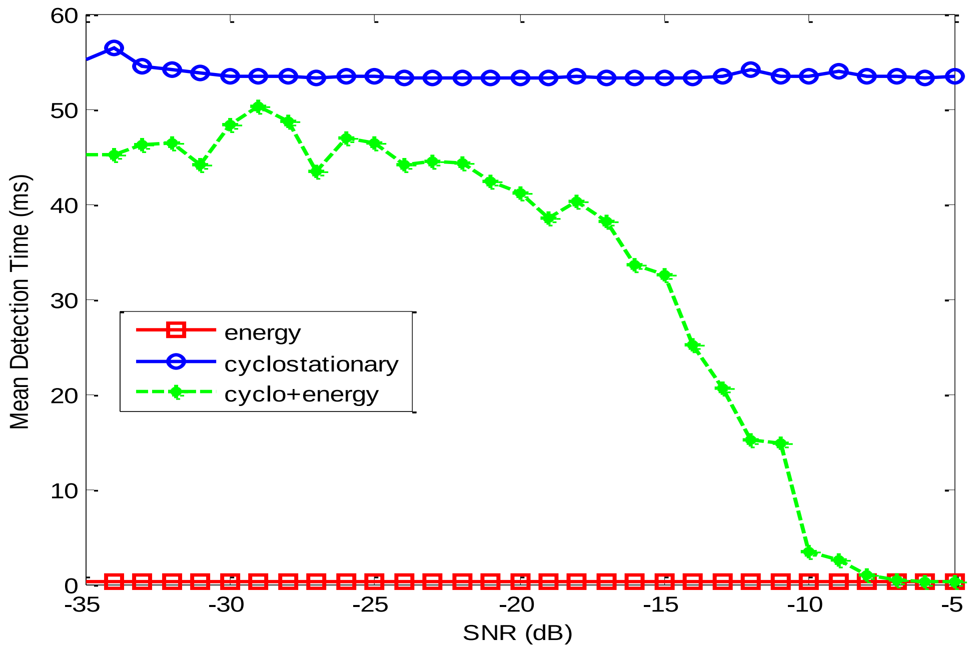



Fig 4-11 SNR Vs Mean detection time curve

Fig 4-11 shows that the mean detection time taken by the two-stage method is less than the cyclostationary method at low SNR and as SNR increases, the sensing time of two-stage method approaches to sensing time taken by the energy detection for $P(H_0) = 0$.

# 5

# CONCLUSION

The energy detection and cyclostationary detection method are two widely used methods for spectrum sensing in cognitive radio. The energy detection method is a less computational complex technique but performs poorly at low SNR conditions. The cyclostationary detection scheme is robust to noise and interference and thus performs well at low SNR, but is a high computational complex method. The two-stage spectrum sensing method incorporates both the detection schemes i.e. energy detection and cyclostationary detection. It overcomes the demerit of both the methods and uses their merit to achieve a better sensing performance.

In the two-stage spectrum sensing method, the received signals undergo energy detection. If the energy detection stage is unable to detect the presence of primary user signal then it is passed to cyclostationary detection stage. It performs better than the energy detection as well as cyclostationary detection method in terms of its detection capability at low SNR environment. Simulation results for wireless microphone signal and amplitude modulation signal verify that the two-stage method outperforms energy detection as well as cyclostationary detection scheme. It can be observed that at low SNR, its detection probability is greater than both the cyclostationary and energy detection technique. Also with the decrease in the observation samples the detection performance of the two-stage method deteriorates less in comparison to cyclostationary detection. Furthermore, we observed that the mean detection time taken by the two-stage detection scheme is much lower than the cyclostationary detection method at low SNR and approaches to the energy detection method as SNR increases.

So, the two-stage spectrum sensing method is a better detection scheme in comparison to both energy detection and cyclostationary detection method.

## 5.1 Future Work

The two-stage spectrum sensing method urge to achieve better spectrum sensing for cognitive radio at a cost of high computational complexity in low SNR environment. The future work can be derived from this demerit and the computational complexity of the two-stage spectrum sensing method can be reduced by applying some optimization techniques. The future works in the area of two-stage spectrum sensing can be described as follows

- Optimization techniques can be applied on the number of samples to be passed from first stage to second stage in order to obtain the desired detection results.
- Implementation of optimization technique to determine the number of samples to be used as input to the two-stage spectrum sensing method.

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