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ADDIS ABABA INSTITUTE OF TECHNOLOGY (AAiT) SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

Enhancement of Detection using Hybrid of Energy and Cyclostationary Detection Algorithm

By

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Enhancement of Detection using Hybrid of Energy and Cyclostationary Detection Algorithm in Cognitive Radio

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Abstract

The growing demand for bandwidth demanding wireless technologies has led to the problem of spectrum scarcity. However, a fixed spectrum assignment has led to underutilization of spectrum as a great portion of the licensed spectrum is not effectively utilized. Cognitive radio technology promises a solution to the problem by allowing unlicensed users, access to the licensed bands opportunistically. A prime component of cognitive radio technology is spectrum sensing. Many spectrum sensing techniques have been developed to sense the presence of a licensed user. Among them, energy detector is one of the known technique which uses the received signal energy and compare it to the threshold to identify weather the licensed user is using the channel or not but at a low SNR value, the performance is poor.

This thesis evaluates the performance of a hybrid of cyclostationary and energy spectrum sensing technique in noisy and fading environments. The performance of the energy detection technique was evaluated by use of Detection Probability Vs SNR value, Receiver Operating Characteristics (ROC), Complement Receiver Operating Curve (CROC), Detection Probability Vs False Alarm Probability curves over additive white Gaussian noise (AWGN) and fading (Rayleigh) channels.

The detection time for the proposed hybrid detector also analyzed.

Results show that using a hybrid detection technique performs better than the energy detection technique for all evaluation matrices in both AWGN and fading channel models. However, this will cost the detection time. The detection time increases as the probability of detection increases.

Keywords: Cognitive radio, primary user, secondary user, spectrum sensing, energy detector, cyclostationary detector, hybrid detection, detection time, performance matrices (receiver operating curve, complementary receiver operating curve, threshold value, false alarm and detection probability),

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List of Abbreviations

AWGN:	Additive white Gaussian noise.
ADC:	Analog to Digital Converter.
BPF:	Band Pass Filter.
CR:	Cognitive Radio.
CROC:	Complementary Receiver Operative Cure.
ETA:	Ethiopian telecommunication Agency
FCC:	Federal Communication commission of USA.
FFT:	Fast Fourier Transform.
LLR:	Likelihood Ratio.
MATLAB:	Matrix laboratory.
OSA:	Opportunistic Spectrum Access.
PDF:	Probability density function.
PU:	Primary User.
RF:	Radio Frequency.
ROC:	Receiver Operative Curve.
RX:	Receiver.
SNR:	Signal noise ratio.
SU:	Secondary User.
SCF:	Cyclic Spectral correlation function.
SIR:	Signal Interference Ratio.
TX:	Transmitter.
WLAN:	Wireless Local Area Network

LIST OF SYMBOLS

B:	Bandwidth of signal.
DB:	Decibel.
E:	Energy of a signal.
E [X]:	Average energy of the signal x.
fc:	Center frequency.
H_0:	Null hypothesis; the absences of PU signal.
H_1:	The presence of PU in the system.
$\Gamma(u)$:	Vth-order modified Bessel function of first kind
L:	length of the sampled signal.
N_0:	One side noise power spectral density
n(k):	System noise(AWGN)
nr(n):	Real component of noise.
nI(n):	Imaginary component of noise.
$P(H_0\|H_0)$:	Probability of correct non detection.
$P(H_1\|H_1)$:	Probability of correct detection= pd
$P(H_0\|H_1)$:	Probability of missed detection: =Pmd
$P(H_1\|H_0)$:	Probability of false alarm detection: =Pfa
r (t):	Received signal.
R_x:	Autocorrelation of the signal.
R_{xy}:	Cross correlation between signal x and y.
s(k):	Represents the signal to be detected.
S:	Complex signal.
S_x:	Power spectral value of the signal x.
SCF:	Spectral correlation function.
T:	Period of the signal
y (t):	Input signal
α:	Cyclic frequency.
σ^2:	Noise variance.
λ:	Threshold value.

τ:	Delay time.
Λ:	Likely hood function
γ:	Non-centrality parameters.
Γ (.):	Gamma function

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Chapter 1

1.1 Introduction

Spectrum is one of the most precious and scarce natural resource. It is tightly regulated resource due to its unique and important role in wireless communications. With the proliferation of wireless services, the demands for the RF spectrum are constantly increasing, leading to scarce spectrum resources. The radio frequency spectrum involves electromagnetic radiation with frequencies between 3000 Hz and 300 GHz. These full segments include VHF, UHF, and the low microwave frequencies from roughly 100 MHz to 4 GHz. That's where cell phones, broadcast TV, wireless local-area networks (LANs), and lots of popular short-range technologies like Bluetooth and Wi-Fi operate [1].

Wireless networks today follow a fixed spectrum assignment strategy, the use of which is licensed by government agencies. The usage of radio spectrum and the regulation of radio emissions are coordinated by both national and international regulatory bodies but each country is at liberty to manage spectrum as long as there are no interference risks to other countries. Spectrum among many other things is used for broadcast systems, personal communications systems, point to point directional systems, non-communication transmitter/receivers such as radar systems for air traffic control, weather forecast, and other national security purpose use, satellite systems and short range uses (E.g. Bluetooth and Wi-Fi).

The key purpose of spectrum management is to maximize the value that society gains from the radio spectrum by allowing as many efficient users as possible while ensuring that the interference between different users remains manageable [2].

Researchers have shown that most allocated spectrum sits idle at any given time. This results in a large portion of assigned spectrum being used only intermittently or not at all due to various factors such as amount of traffic load on licensed users or geographical variations specially the frequency spectrum usage in the band below 3 GHz has utilization efficiencies of 15% to 85% [3].

Figure 1-1 shows radio spectrum allocation for different application services, and the frequency spectrum range. As the technology moves from voice telephony to higher data rate, the existing scheme (FSA) does not accommodate and satisfy the user demand. However, study at FCC(Federal

Communication commission of USA) shows that the spectrum usage is higher on certain area and lesser in other. This shows significant amount of the spectrum remains underutilized [4]. It also depicts the spectrum utilization efficiencies is highest for wireless service, particularly the assignment is so congested in cellular network (GSM) and FM radio bands, TV bands and fixed radio system [4].

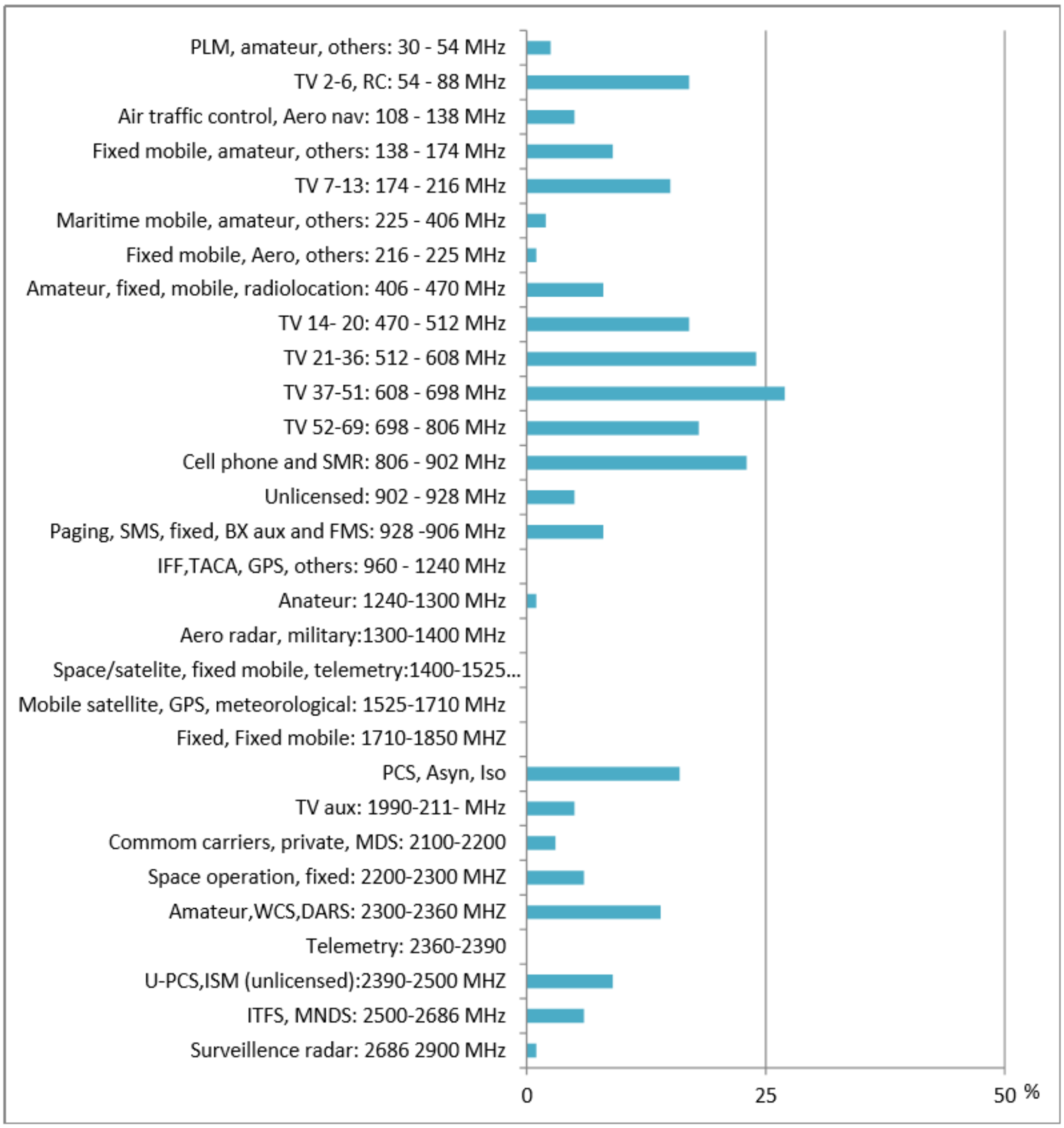


Figure 1-1: Spectrum Concentration [2].

In November 2002, FCC published a report prepared by the Spectrum-Policy Task Force, aimed at improving the way in which this precious resource is managed [3]. This necessitates a new communication paradigm to harness the underutilized wireless spectrum by accessing it opportunistically. This new communication technology is referred as Dynamic Spectrum Access (DSA) or Cognitive Radio (CR).

A cognitive radio is an intelligent wireless communication system that give opportunity to the secondary user (unlicensed or a user that don't have a privilege to use a channel) to use the frequency channel over temporarily unused spectral bands that are licensed to their primary users (a user that have a privilege to use the assigned channel). The FCC suggests that any radio having adaptive spectrum awareness should be referred to as cognitive radio [3].

The words cognitive have become buzzwords that are applied to many different networking and communications systems. From the oxford English dictionary, one of the most used definitions of cognitive is: "pertained to cognition or to the action or process of knowing" the word cognition means: "the mental process of getting knowledge through thought, experience and the senses." Thus, Term CR could be defined as a radio that is cognitive.

In the 1999 paper that first invented the term "cognitive radio", Mitola defines a cognitive radio as [5] "A radio that employs model based reasoning to achieve a specified level of competence in radio-related domains."

Six years after Mitola's first article on CR, Simon Haykin in his invited paper to IEEE Journal on Selected Areas in Communications, summarized the idea of CR as [6]: "An intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world),and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind:

- Highly reliable communications whenever and wherever needed;
- Efficient utilization of the radio spectrum.

Coming from a background where regulations focus on the operation of transmitters, the FCC has defined a cognitive radio as [3]: "An intelligent wireless communication system capable of changing its transceiver parameters based on interaction with the environment in which it operates."

By using only these common characteristics of all these definitions we reach at the definition of CR a radio system that can adaptively and dynamically allow user(s) to use the spectrum in the opportunistic way. Or Cognitive Radio is: “A radio system which dynamically and autonomously senses its operational electromagnetic environment. The word autonomously means exploiting unused spectrum to provide new path to spectrum access and adjust radio operating parameters such as maximizing system throughput, mitigate interference and facilitate access to secondary user [7].”

Cognitive radios possess the ability to observe their communication environment and adapt the parameters of their communication scheme to maximize the spectrum, while minimizing interference to the primary users [8]. To do so, [9], asserts that CRs must continuously sense the spectrum in use in order to detect re-appearance of a primary user.

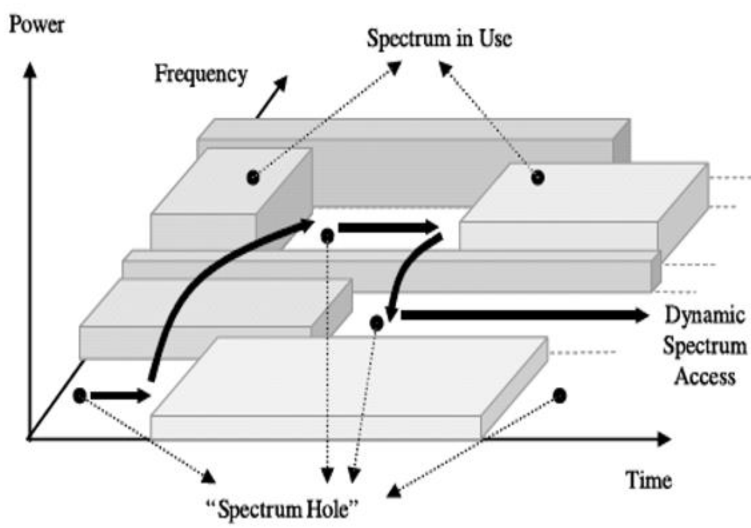


Figure 1.2: Illustration of the Spectrum Hole concept [10].

When implemented, the CR undergoes the various phases of the cognitive cycle. Thus specifying how the radio learns, as well as responds (adapts) to its operating environment [9]. From this cycle, the radio receives information (senses) it’s operating environment by performing direct observation; searching and identifying spectrum holes.

From this cycle, the radio receives information (senses) it’s operating environment by performing direct observation; searching and identifying spectrum holes. The information obtained is then analyzed to ascertain characteristics of the environment.

As seen from the figure1.3, the initial phase of the cognitive cycle consists of the sensing process. Hence, it is evident that reliable spectrum sensing is the most critical function of the cognitive radio process [11]. By sensing and adapting to the environment, a cognitive radio will possess the ability to fill in the spectrum holes and serve its users without causing harmful interference to the primary user. Ultimately, a spectrum sensing scheme should give a general picture of the medium over the entire radio spectrum. This allows the cognitive radio network to analyze all parameters (time, frequency and space) in order to ascertain spectrum usage [12].

From the aforesaid, it is essential that there should be efficient spectrum detection techniques that ensure secondary user transmissions, while safeguarding primary users. The challenge then is that one would want as few false detections and missed detections as possible.

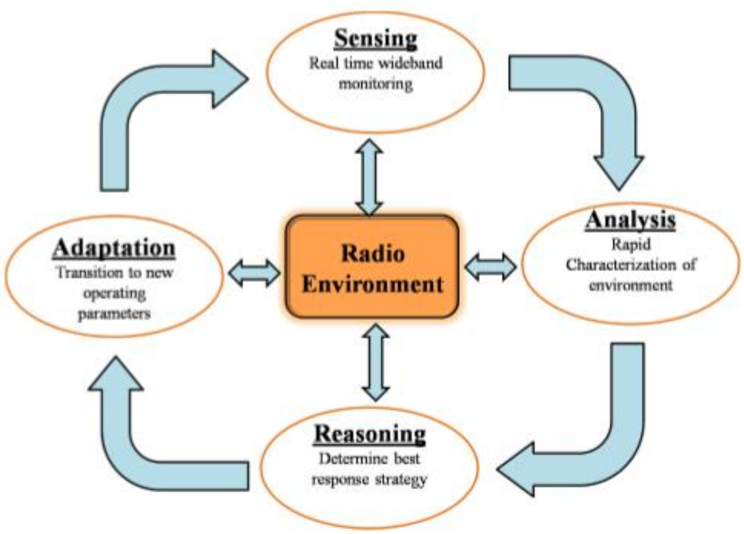


Figure 1.3: Cognitive Cycle [12]

Three well studied spectrum sensing (SS) techniques are the matched filter, cyclostationary detection and energy detection. Both the matched filter detection and the cyclostationary based detection concern prior knowledge of the primary signal and complex to implement but perform well under low SNR region were as energy detection does not require a priori knowledge of the primary signals and has lower complexity than the other two schemes but the performance under low SNR is poor compared with the other two.

From the characteristics of this detection techniques this thesis uses a combination of energy and cyclostationary detection to incorporate the advantage of each and to enhance the detection of a signal. The simulation result over AWGN and Rayleigh channel model is examined.

1.2. Statement of the problem

The increasing demand for spectrum in recent years due to the introduction of new wireless technology has put pressure on the spectrum. A number of measurement studies of spectrum utilization have indicated that the spectrum is rarely used in many geographical areas and times [3]. In order to meet the demand for spectrum, new solutions to efficiently utilize the limited resource are being developed. One of the technics is to sense an idle channel and assign it to the secondary user without causing interference to primary user. So this task requires correct information of the presence or absence of the primary user. If the system lacks this priory information, and the unlicensed user transmits information on the occupied channel, interference might occur in the system.

There are different spectrum sensing types and among them, energy detector is one of the spectrum sensing algorithms with low computational complexity and infrastructure cost. but its performance is poor when the received SNR of the signal is too low. This is due to the fact that, at low SNR, the signal is so corrupted and the received energy is below the energy detector threshold value and the system will face difficulty in distinguishing noise from the signal. Cyclostationary is another type of detection and due to its periodicity property it is insusceptible to noise at low SNR but its computational complexity and cost are high. In this thesis, we use a hybrid of Energy and Cyclostationary detector that will take the advantage of each and combine to get an enhanced SNR at the detection so better decision can be made. We also study the detection time and recommend accordingly. The simulation result of each detection will be separately examined and then a hybrid of energy and cyclostationary detector response will be evaluated and the results of the two will be compared and analyzed along with the detection time result.

1.3. Motivation

The challenge of spectrum scarcity and underutilization is the main driving force behind cognitive radio and adopting it can lead to a reduction of spectrum scarcity and better utilization of the spectrum resources. Spectrum sensing is the most crucial task for the establishment of cognitive radio-based communication.

There are a number of schemes for spectrum sensing like energy detector, cyclostationary detector, and matched filter detector. Energy detector functions properly for a higher signal to noise ratio (SNR) value whereas the cyclostationary detector complexity is very high and the matched filter requires prior knowledge of the primary user which is difficult to get. These constraints led to implementing a detector which performed well under low SNR conditions as well and with a complexity not as high as the matched filter.

Spectrum sensing becomes a main challenge in the cognitive process since it requires an advanced technique, knowledge of probability and stochastic, and finally the technique in signal detection and estimation. Due to these reasons, a detection technique that can be implemented with minimal complexity and with low cost that will give a better performance was the motivation for this thesis.

1.4 Literature Review

In 2015 Veena Gawde, Dr. B. K. Mishra, Rajesh Bansode [12] proposed hybrid spectrum sensing scheme which obtains reliable results with less sensing time. First, the scheme determines a better detection method by comparing the SNR of the signal for each detection method with a combination of energy and matched filter based detectors. In the combined energy and matched filter detector, the algorithm first applies an energy detector and the matched filter detector is applied only if a user is not detected by the energy detection method. Second, sensing is performed by a dedicated sensing receiver that is with the use of multiple antennas which reduces sensing time. To evaluate the scheme's performance, the results are compared with those where only energy detectors and matched filter detectors are performed. The performance metrics are the probability of detection, probability of false alarm, and sensing time. The proposed hybrid approach shows a better probability of detection compared to each detection alone in addition to that higher probability of detection is achieved for more than one antenna receiver.

In 2013, Chinky Sharma & Jatinder Saini [13] explored various sensing methods, their performance, applicability and effectiveness under different transmission conditions and advantages and disadvantages incorporated with each sensing method. In this paper, the first task is to identify the beam location of the primary user by applying a cyclostationary detection. If the primary user is absent further processing cannot be done but if its present, the second step is to calculate the primary signal and noise applying the spectral correlation function to identify the energy signal from the noise, if its only noise energy then no primary user but it's a combination of noise and some transmission signal then apply a beam-steering technique then obtain the RF signal then the relative phase is calculated and according to the phase the antenna direction is changed and they use the result to decide if the primary user is present or not. They have presented here the concept for combining these two techniques with beam steering which in return gives better results.

Benyam Hailegnaw [14] 2016 in his Thesis studied the performance of the energy detector when adaptive Weiner filter is inserted on the front end of conventional energy detector for AWGN and Rayleigh fading channel. To implement the adaptive Wiener filter, he uses the recursive least square algorithm. The performance matrices were the probability of detection, probability of false alarm, Probability of miss detection, the receiver operating characteristics curve (ROC), and the complementary receiver operating characteristics curve (CROC). The simulation result of energy detection and the enhanced one is compared and it is shown that there were an improvement in all measurements. The drawback of the energy detector which is poor performance under low SNR also improved by the insertion of an adaptive wiener filter at the front end.

James D. Gadze1, Oyibo, A. Michael, Ajobiewe, N. Damilola [15] tried to evaluates the performance of the energy detection based spectrum sensing technique in noisy and fading environments. They investigated on both single user detection and cooperative detection situation. Closed form solutions for the probabilities of detection and false alarm were derived. The analytical results were verified by numerical computations using Monte Carlo method with MATLAB. The performance of the energy detection technique was evaluated by use of Receiver Operating Characteristics (ROC) curves over additive white Gaussian noise (AWGN) and fading (Rayleigh & Nakagami-m) channels. Results show that for single user detection, the energy detection technique performs better in AWGN channel than in the fading channel models. The performance of cooperative detection is better than single user detection in fading environments.

A possible two-stage spectrum sensing approach was suggested by authors in [16] Wenjing Yue1, and Baoyu Zheng1. A very fast spectrum sensing algorithm based on the energy detection is introduced focusing on the coarse detection. A complementary fine spectrum sensing algorithm adopts one order cyclostationary properties of primary user's signals in time domain. This feature detection technique in time domain realizes simple and low computational complexity compared to spectral feature detection methods. Also, it drastically reduces hardware burdens and power consumption as opposed to two-order feature detection. The sensing performance of the proposed method is studied and the analytical performance results are given. The results indicate that better performance can be achieved in proposed two-stage sensing detection compared to the conventional energy detector.

In 2012 Yiming Zhou, Zheng Zhou and Shibo Zhang proposed energy autocorrelation based detection technique as a solution to overcome shortcoming of conventional energy detector by taking the advantage of statistical characteristics of Gaussian white noise statistical value of energy and autocorrelation of samples. In their work two statistics structured based energy and auto correlation of samples is considered. Without the prior information on noise and signal the proposed scheme can lead to stable and accurate result. The simulation test result showed that the energy auto correlation based detection is much better than energy based detection. Furthermore, the energy autocorrelation based detection methods shows similar performance result when the SNR> -12dB. And it has also shown that the improving probability of detection is limited by increasing the number of signal samples [17].

Therefore, this thesis proposes a hybrid method of energy and cyclostatinary detection to enhance the SNR of the receiver. The transmitted signal first goes through energy detection and whenever the signal is less than the threshold goes to cyclostationary detection and the result will be examined and compared to the energy detector and cyclostatinary detector for BPSK and QPSK modulation and in under different environment (AWGN and Rayleigh)

1.5. Methodology

For implementation of the proposed work first energy detector and cyclostationary feature detector applied separately then by combining these two to form a hybrid detector algorithm is applied and a comparison is done.

The signal which is sensed by the secondary user receiver undergoes to energy detection. The energy of the received signal compared with the threshold and if it's above the threshold that means a primary user is using a channel so the secondary user need to scan other channel but if the energy is less than the threshold it will go through cyclostationary detection to identify if the signal is not a noise signal and again a comparison between the correlated signal with a threshold is done and a decision is made either to use a channel or not.

1.6. General Objective

The general objective of this thesis is to enhance the received SNR by using a hybrid of energy and cyclostationary detection method.

1.6.1. Specific Objective

The specific objectives of this thesis are:

- To study and analyze different detection techniques (energy and cyclostationary detection in detail)
- To perform only energy detection and cyclostationary detection algorithm separately and see the result.
- To apply hybrid detection for AWGN and Rayleigh channel model
- To compare the result of the responses of the three detection methods.
- To analyze the detection time between the energy detector and hybrid detector

1.7. Thesis Outline

The outline of this thesis is organized as follows:

Chapter two is about the theoretical background of cognitive radio spectrum sensing techniques. Chapter three is about system modeling, performance metrics, energy detector test statistics, and cyclostationary detection test. Chapter four presents and discusses simulation results. In this section the matlab simulation results are obtained for energy and hybrid detector. Chapter five is about thesis conclusion and recommendation for future work.

Chapter 2

Theoretical Background

This chapter includes the summary of various approaches used to address the problem of spectrum sensing and the literature that have been conducted. The chapter encompasses the background work on spectrum sensing technique.

2.Cognitive Radio

The goal of cognitive radio (CR) technology is to improve the spectral efficiency through dynamic access by the unlicensed users [8] Opportunistic spectrum access (OSA) is one that facilitates use of local spectrum availability without major effect to the primary user [18]. The foundation on which the CR model is built is the OSA. With this model, devices would be capable of sensing the environment to find spectral holes and make use of frequency bands that are not occupied by primary users, without causing any interference system in the process. Basically, the secondary user identifies “gaps” in the spectrum, known as a spectrum holes or white spaces and puts them to use. These white spaces originate from partial or no occupations by the primary users (PU) (e.g. Digital TV broadcasters). The secondary communication can be executed once the white spaces are identified [19]. The function of spectrum sensing therefore, is to be aware of the environment by determining the frequencies occupied by the PU.

2.1 Spectrum Sensing

Detecting the presence of signals in the frequency spectrum is called spectrum sensing. An empty spot in frequency will be a candidate to allocate a new communication link. Under the definition of a primary and secondary user, this last one has to be able to detect or may be informed of an incoming primary user and move on to another vacant spot.

A number of methods have been proposed for identifying spectrum opportunities in a scanned frequency band. Typically, spectrum sensing is grouped within three main detection approaches, namely, transmitter based detection methods, cooperative detection methods and interference based method. Transmitter detection methods consist of matched filter, cyclostationary and energy detection [20].

These techniques are further classified as [21] coherent, semi-coherent or non-coherent; that is, either having complete, partial or no prior knowledge of the transmitter respectively. Schemes that are cooperative include centralized, distributed and cluster based sensing methods. Whereas transmitter and cooperative detection methods "perceive" spectrum to avoid interference to primary transmitters; interference based detection guarantees minimal primary receiver interference [22]. Figure 2.1 below describes in detail, classification of spectrum sensing techniques.

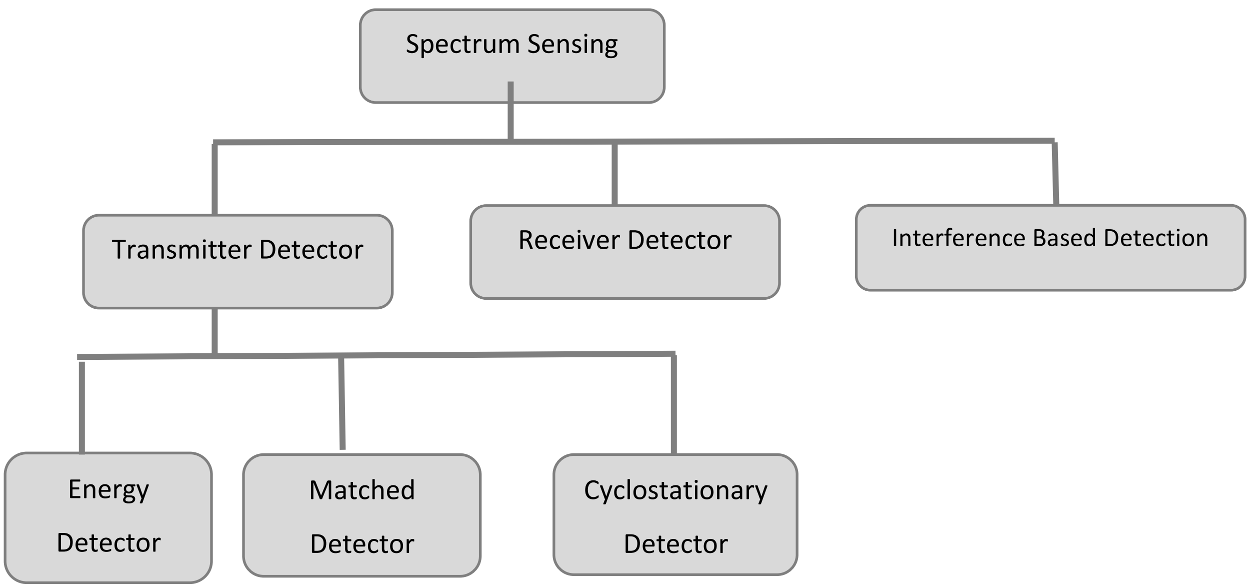


Fig 2.1: Spectrum Sensing Classification

2.2 Transmitter Detection Methods

An efficient approach to identify spectral opportunities with low infrastructure requirement is to detect the primary receiver within operative range of a secondary user (SU). Practically however, this is not feasible as the SU cannot locate a receiver since it is not intelligent enough. Hence, spectrum sensing methods rely on detecting the primary transmitter [20]. With this, a primary user transmitter is detected on the basis of the received signal at the secondary user end. The primary transmitter detection model represents analysis of the received signal at the secondary user. In its simple form, the idea is to find primary transmitters operating at a given time by using local measurements and observations. With these technique, the SU examines the signal strength generated from the PU to exploit the free space (whitespace) within the channel.

Analytically, when the decision on the availability of a primary user is to be made, it is reduced to an identification problem [12]. This is formalized as a hypothesis test as:

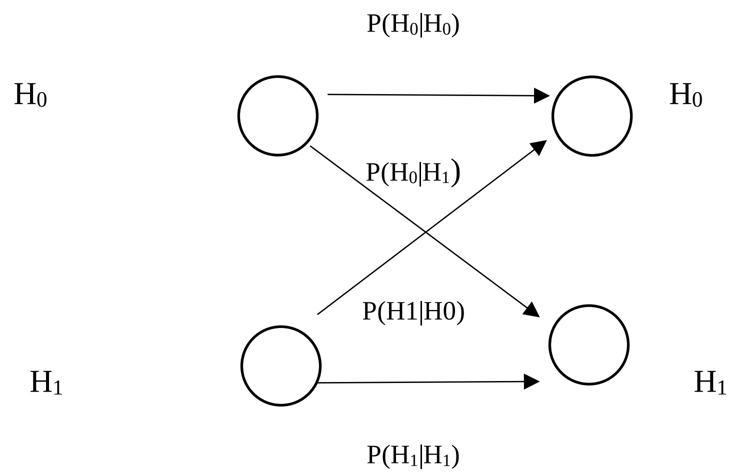


Figure 2.2: Hypothesis test with possible outcomes and their corresponding probabilities.

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

$$X(t) = n(t) \text{ .... Ho } \dots\dots\dots\dots\dots\dots\dots\dots \quad (2.1)$$

$$X(t) = hS(t) + n(t) \text{ .... } H_1 \dots\dots\dots\dots\dots\dots\dots\dots \quad (2.2)$$

Where $X(t)$is the signal received by CR, $S(t)$ is the transmitted signal of primary user $n(t)$ is additive white Gaussian noise (AWGN) and h is the amplitude gain of the channel. Ho is the null hypothesis

representing a sensed state with an absence of the licensed user signal. H_1 denotes the existence of a licensed user signal within the spectrum under consideration.

From Figure 2.2, four possible cases can be defined for the detected signal;

1. declaring H_0 when H_0 is true $(H_0|H_0)$;

2. declaring H_1 when H_1 is true $(H_1|H_1)$;

3. declaring H_0 when H_1 is true $(H_0|H_1)$;

4. declaring H_1 when H_0 is true $(H_1|H_0)$.

On the basis of this hypothesis model we generally use three transmitter detection techniques [4]: Matched filter detection, Energy detection and Cyclostationary detection.

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

2.2.1 Energy Detection(ED)

Energy detection (also called radiometry) is a non-coherent detection method that detects the presence of the primary signal based on the sensed energy level [23]. It uses the basic principle of signal detection method. The measured signal is always higher than that of the energy threshold value. To ensure whether the channel is idle or not, the energy detector uses the radio environment metric values such as frequency energy or received signal strength. This technique doesn't require a priori knowledge information of PU signals [23], [13]. If the prior knowledge of the PU signal is unknown, the energy detection technique becomes an optimum detecting method for any zero mean constellation signal [23].

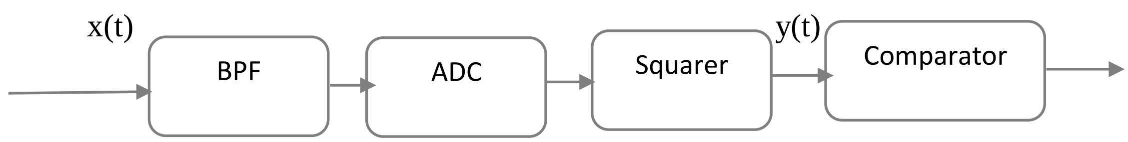


Fig 2.3 Block diagram of Energy detector [24]

As it can be depicted in figure 2-3 the input signal x(t) is filtered with a band pass filter to select the bandwidth of interest. The output signal is then passed to the ADC block, squared and integrated over the observation interval time T. At the front end the output of the integrator is compared to a predetermined threshold to check the presence of PU signal.

When the spectral signal is analyzed in frequency domain, the Fast Fourier transforms (FFT) based method is used. Specifically, the received signal of *x(t)* sampled in a time window, and converted into digital signal as discrete version. This signal passed through an FFT device to get the power spectrum.

$|X(f)|^2$. The peak of the power spectrum is then located. After windowing the peak of the spectrum, we get $|y(f)|^2$ as an output. The signal energy is then collected in the frequency domain.

Even though the energy detection method is simplest spectrum sensing technique, it has the following drawback [25], [26], [27].

- It became difficult to differentiate the interference from the other secondary user when they share same channels.
- The threshold value is depending on the noise variance value if the noise power is too small, it creates an estimation error which leads to poor performance.
- At low SNR it is too difficult to measure the noise variance accurately hence performance of energy detector is become poor.
- The sensing time taken to achieve a given probability of detection is high.
- The detection performance is subject to the uncertainty of noise power.
- Energy detection method cannot be used to detect the spread spectrum signal.

2.2.2 Matched Filter Detection

Unlike energy detection, a matched filter (MF) is a linear filter designed to maximize the output signal-to-noise ratio for a given input signal [28]. With this scheme, secondary users (SU) require complete knowledge of the PU transmitted signal. These information includes modulation format, carrier frequency, order, pulse shape, and packet format, are to be known to the secondary user beforehand [29]. These features are used to detect and implement a MF when primary users have pilots, preambles, synchronization words or spreading codes, leading to coherent detection. A matched-filtering process is equivalent to a correlation scheme; wherein a signal is convolved with a filter whose impulse response is a mirror and time shifted version of the reference signal [30]

Matched filter approach gives the best SNR since it matches a specific signal. The approach requires demodulation of the signal which means having in advance deep knowledge of primary user signal.

It could be impractical to implement a CR which could hold capabilities for all signal types. Although this information could be saved in the spectrum sensing device as a catalog of possible signals, it would come costly in terms of processing and memory.

The operation of matched filter is equivalent to the operation of a correlation in which the unknown signal is convolved with the filter whose impulse response is a mirror and a time shift version of the reference signals [31].

The operation of matched filter detection is expressed as [31]:

$$Y[n] = \sum_{k=-\infty}^{k=\infty} \mathrm{h}[\mathrm{n}-\mathrm{k}]\mathrm{x}[\mathrm{k}] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.3)$$

Where x and h are the unknown signal and the impulse response of matched filter respectively. k is the delay in discrete time analysis. Y[n] is the convolution result of sample delay of h with that of unknown signal x. The output of the matched filter is compared with the threshold value κ and decision is made whether primary user is present in the system or not.

An advantage of the MF is that it requires less time to achieve detection; however, false detection occurs when incorrect information concerning the transmitted signal is available at the SU end. A significant drawback of this technique is that an SU would require dedicated receivers for every primary user class. Another demerit of this scheme is the large amount of power consumed as several receiver algorithms relating to the various technology schemes are executed for detection [30].

2.2.3 Cyclostationary Detection

When signals exhibit statistical attributes (like mean, autocorrelation etc.) that change periodically with time, there are termed cyclostationary Features (CF) [33]. Usually, [19] wireless transmissions present cyclostationarity features depending on their data rate, modulation type, and carrier frequency. Most communication signals can be modelled as cyclostationary, since their exhibit underlying periodicities in their signal structures. Cyclostationary feature detection (CFD) is a method that applies cyclostationary features to detect a signal. The identification of a unique set of characteristics particular to a radio signal for a wireless access system can be used to detect the system based on its cyclostationarity features. These features have periodic statistics and spectral correlation not obtained with interference signals or stationary noise. Thus exploiting this periodicity in the received primary signal to identify the presence of primary users makes this method possess a high noise immunity compared to other spectrum in general, any modulated signal includes some periodicity by definition and some others added for synchronization or signaling purposes such as preambles, pilots, cyclic prefix, etc. It means that autocorrelation of the signal exhibit an observable grade of periodicity.

The cyclostationary detection uses the periodicity characteristics of primary signal to identify its presence or absent. The periodicity feature is commonly embedded in sinusoidal signal carriers, pulse train, spread code hopping sequence or cyclic prefixes of the primary user. This detection method uses cyclic spectral correlation function (SCF) to detect the presence of primary signal in the system [33]. The cyclostationary signals exhibits both the feature of periodic statistics and spectral correlation. From the definition of wide-sense cyclostationary time-series it is implied that for all t, τ mean E_X and the autocorrelation $R_x(t, \tau)$ of the signal exhibit periodic properties with time. Its periodicity can be expressed as

$$E[x(t+To)] = E[x(t)] \quad \text{...}(2.4)$$

$$R_x(t+To,\tau)] = R_x(t,\tau) \quad \text{...}(2.5)$$

where the autocorrelation function is defined as

$$R_x(t,\tau) = E[x(t+\tau)x(t)] \quad \text{...}(2.6)$$

Where *E [.]* is the expectation value or the mean of the signal. Since R_x is a periodic function it is possible to express in Fourier series as [33]:

$$R_x\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) = \Sigma_\alpha R_x^\alpha(\tau)e^{j2\pi\alpha t} \quad \text{..}(2.7)$$

where α includes the sum of overall integer multiple of the reciprocal of the fundamental period T_0 and is the cyclic auto correlation of the signal whose Fourier coefficient $R_x^{\alpha}(\tau)$ is given by [33]:

$$R_x^{\alpha}(\tau) = \frac{1}{To}\int_{-To/2}^{To/2} Rx\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) e^{-j2\pi\alpha t}dt \quad \text{...(2.8)}$$

Due to the periodicity nature the cyclostationary, the signal shows high correlation property between widely separated spectrum components. The spectral cyclic autocorrelation function in Eqn 2.7 has the Fourier transform [33]:

$$S_x(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau)e^{-j2\pi\alpha\tau}d\tau \quad \text{..(2.9)}$$

Given N samples of signal, the estimated spectral correlation function SCF $S_x^{\alpha}(\tau)$ (f) is given by [34]

$$S_x^{\alpha}(\tau) = \frac{1}{N}\sum_{n-1}^{N} Xl(n, K+\frac{K\sigma}{2})XL(n, K-\frac{K\sigma}{2}) \quad \text{...................................(2.10)}$$

Where

$$X_L(n,k) = \frac{1}{\sqrt{L}}\sum_{l=n-\frac{L}{2}}^{l=n+\frac{L}{2}-1} X(l)e^{-\frac{j2\pi kl}{L}} \quad \text{...(2.11)}$$

Equation 2.9 is an L point DFT at nth samples of the received signal and Kα =αL/Fs is the index frequency bin corresponding to cyclic frequency α and the SCF of the received signal. It is correlated with known priory signal and compared to the threshold value to test the presence of primary signal in the system. The block signal representation of cyclostationary detection system can be depicted in Figure 2-4

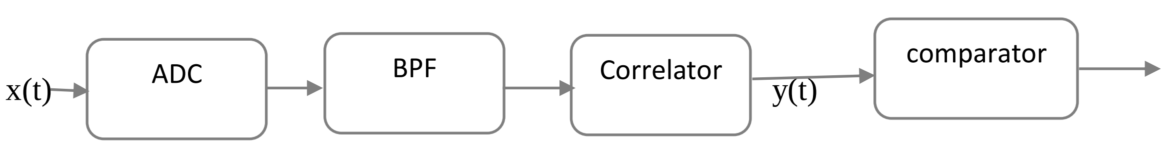


Fig 2.4: Block diagram of cyclostationary detector [33]

Generally speaking, the cyclostationary detection process can be summarized as:

- The cyclic autocorrelation function (CAF) of the observed signal x(t) calculated as {E$\{x(t+\tau)\ x^*(t-\tau)$ $e^{j\pi\alpha t}$} where E {.} denotes the statistical expectation operation and α is the cyclic frequency.
- The spectral correlation function (SCF) S (f, α) is obtained from the DFT of the CAF. The SCF is also called cyclic spectrum which is a two dimensional function in terms of frequency and cyclic frequency α.
- The detection is completed by searching for the unique cyclic frequency corresponding to the peak in the SCF plane.

However, the cyclostationary detection has the following drawback:

- Since the technique uses the spectral correlation, at high signal amplitude the spectral leakage is observed;
- The detection performance of the system become poor as the number of sample taken is too small because of poor estimate of the cyclic spectral density, and longer observation time is required,

2.3 Interference Based Detection

This theoretical method employs an interference temperature model; which is a measure of how well a radio operating within a particular modulation scheme and protocol can tolerate interference in its spectrum space [35]. This follows the fact that signal power received at a primary receiver reduces exponentially with distance; continuously till it reaches a level of the noise floor [22]. Though a primary transmitter still operates at this point, the receiver handles this process as noise and not transmission. This makes it possible for a secondary user to utilize the channel, since no interference is introduced to the primary users' communication (as the primary receiver is not in receiving mode).

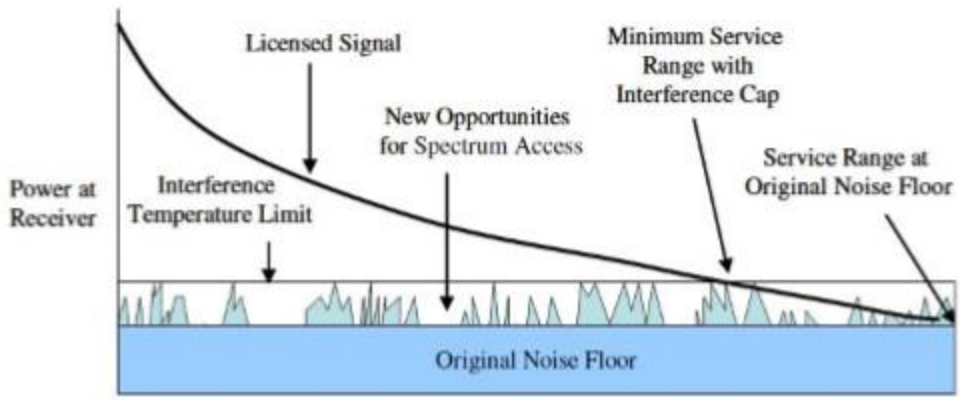


Figure 2.5: Interference temperature model [4].

Above the maximum noise level, an interference cap is introduced, below this threshold, the primary receiver will treat this transmission as noise. An illustration of the interference temperature model is shown in Figure 2.5 above. The SU may exploit the channel if the detected primary signal level is below the interference temperature limit. More so, if the power of transmission of an SU stays below the interference gap, it may utilize any frequency parameter of its choice. With this approach, it is hypothesized that the SUs will be allowed to transmit concurrently with the PU under stringent interference avoidance constraints; where in it is categorized as a spectrum underlay scheme. In this scheme it far more challenging; since the prime problem faced with an implementation of this technique will be in determining specific receiver interference temperature levels for the various communications.

2.4 Receiver Detection (Cooperative Detection)

In cooperative detection, multiple SUs collaborate in a centralized or decentralized manner to ascertain spectrum holes for opportunistic access. By cooperation, mean that the CR users can share their spectrum sensing information for making a combined decision more accurate than the individual decision. One of the most challenges in cognitive radio spectrum sensing technology is the problem of shadowing, multipath fading and the receiver uncertainty. These all, hinder the performance of spectrum sensing problem of the Cognitive radio

Figure 2.6 illustrated multipath fading, shadowing and receiver's uncertainty. As its shown from the figure CR1 and CR2 are placed inside the transmission range of the PU transmitter (PU T_X)

while CR3 is outside the range. Due to multiple attenuated copies of the PU signal and the blocking of a house, CR2 experiences multipath and shadow fading such that the PU's signal may not be correctly detected. Moreover, CR3 suffers from the receiver uncertainty problem because it is unaware of the PU's transmission and the existence of the primary receiver (PU R_X). As a result, the transmission from CR3 may interfere with the reception at PU R_X. If CR users, most of which observe a strong PU signal like CR1 in the figure, can cooperate and share the sensing results with other users, the combined cooperative decision derived from the spatially collected observations can overcome the deficiency of individual observations at each CR user [17], [35].

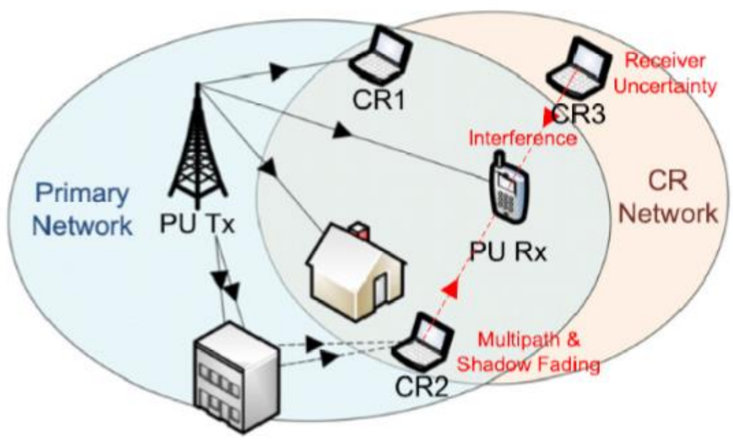


Figure 2.6: Receiver uncertainty and multipath/shadow fading [8].

There are broadly two approaches to cooperative spectrum sensing [35], [43] centralized and distributed approach we will see each in detail.

2.4.1. Centralized approach:

In this approach to CR cooperative spectrum sensing, there is a central CR called fusion center (FC) within the network that collects the sensing information from all the sense CRs within the network. For data cooperative, all CRs are tuned to a control channel where a physical point-to-point link between each cooperating CR and the FC for sending the sensing results is called a reporting channel as shown in Figure 2.6. FC then analyses the information and determines the bands that can and cannot be used.

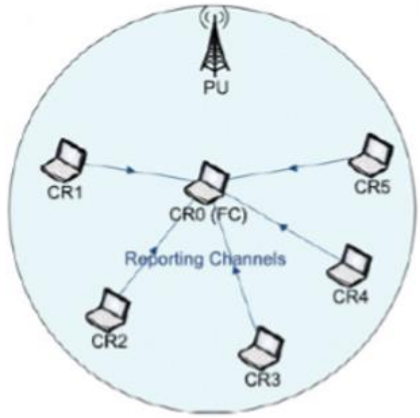


Figure 2.7: Cooperative sensing techniques: Centralized [8]

2.4.2. Distributed approach:

Unlike centralized approach, distributed cooperative sensing does not depend on a FC for making the cooperative decision. Using the distributed approach for CR cooperative spectrum sensing, no one CR takes control. Each CR sends its specific data of sensing to other CRs, merges its data with the received data of sensing, and decides whether or not the PU is present by using a local condition as shown in Figure 2.8. However, this approach requires for the individual CRs to have a much higher level of independence, and possibly setting themselves up as an ad-hoc network.

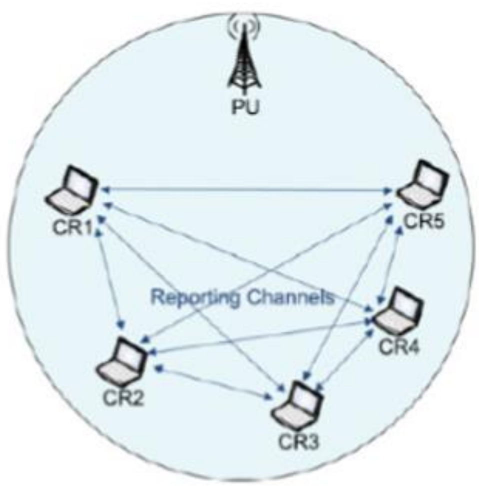


Figure 2.8: Cooperative sensing techniques: Distributed (decentralized) [8]

2.4.3 Other Methods

Waveform based, multi taper spectral estimation, radio identification, wavelet transform is some of the other different approaches found in the literature that are applied for spectrum sensing. Also it is common to find a combination of them to improve time response or save computation. Some solutions are more specific regarding the application and exploit some prior degree of knowledge about the sensing environment either as part of the sensing strategy or by definition of the approach.

2.5 Detection Time

A detection time is the duration that a required to identify weather the channel is occupied or free. For a given certain sampling frequency, detection time of energy detection is mainly determined by its sampling number [55].

Increasing the total number of samples increases the detection probability but also detection time. That means detection performance is a tradeoff between detection efficiency and detection probability).

Detection Type	Advantage	Disadvantage
Energy Detection	• Does not require a prior information • Low computational cost.	• Poor performance under low SNR
Cyclostatinary Detection	• Valid in low SNR region. • Robust against interference.	• Require the partial prior information • High computational cost.
Matched Filter Detection	• Optimal performance. • Low computational cost.	• Require the prior knowledge of the primary user information

Table2.1 summury of different detection method.

Chapter 3
System Model

This chapter presents the system model of energy and cyclostationary detection then explains the performance metrics. It also presented a mathematical derivations to support the analysis adopted for both the case of a AWGN and the case of Raylen channal.

Figure 3.1 shows the general model of the system the transimited signal s(n) received at the secondary user as x(n) then this signal pass through the detection process and the output of the detected signal y(n) will be analized and from the analisis a decision is done accordingly weather to use the channal or not.

3.1 Performance Metrics

The correctness of the spectral availability information is defined using sensing quality parameters. This feature makes up the performance metrics. Sensing the performance of the energy detector is specified by the following general metrics:

1. The probability of detection, P_d
2. The probability of false alarm, P_f
3. The probability of missed detection, P_m

In opportunistic spectrum sensing, the probability of detection specifies that a detector makes a correct decision that a channel is occupied (H_1). The (P_D) is an indicator of the level of interference protection provided to the primary user. Hence, a large P_D denotes to small chance(s) of interference.

A false alarm event occurs when the detector assumes H_1; when the right decision is H_0. The probability of this occurrence is specified as a probability of false alarm. When a false alarm event occurs, the SU will not use the free spectrum, thus missing a chance to utilize the free channel. P_{FA} should be kept as small as possible in order to prevent underutilization of transmission opportunities. The performance of the spectrum sensing technique is usually influenced by the probability of false alarm, since this is the most influential metric [37].

The probability of declaring the spectrum space vacant H_0, when it is indeed occupied H_1, is referred to as the probability of missed detection (P_M). A high P_M implies an increase in the chance of interference between the PU and the SU. If the detection fails, or a “miss detection” occurs, the SU initiates a transmission, resulting in interference with the PU signal; contravening the opportunistic access concept.

To summarized efficient spectrum sensing method should record a high probability of detection (low miss detection probability) and low probability of false alarm.

3.2 Performance Measurement

The receiver performance is quantified by showing the receiver operating characteristics (ROC) curves. This curves serve as a tool to select and study the performance of a sensing scheme. ROC graphs are preferred as a performance measure. ROC graphs are employed to show trade-offs between detection probability and false alarm rates, (i.e. P_D versus P_{FA}), thus allowing the determination of an optimal threshold. Complementary ROC curves depict plots of probability of miss-detection ($P_M = 1-P_D$) versus the probability of false-alarm (P_{FA}).

3.3 Energy Detection

The system model for digital energy detection that is used to identify the presence or absence of primary signal is shown in Fig 3.2(a).

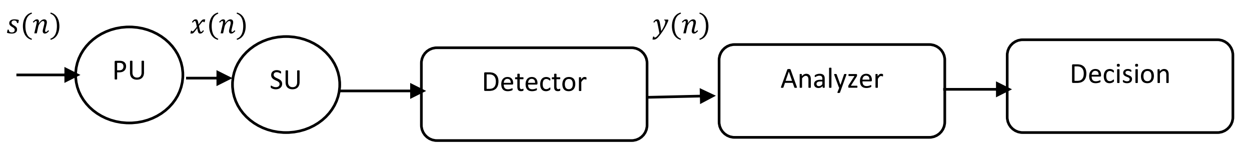
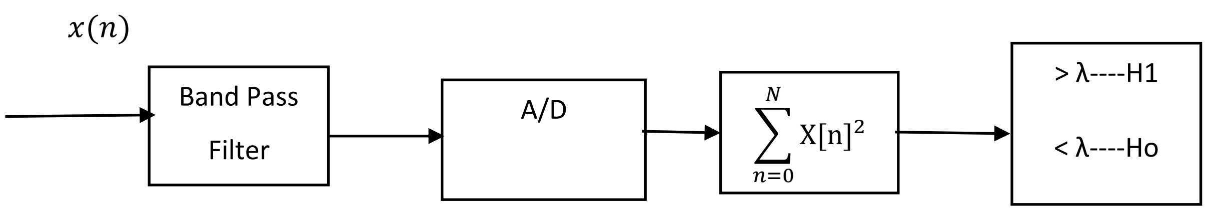


Figure 3.1: The general block diagram of the system

a)



b)

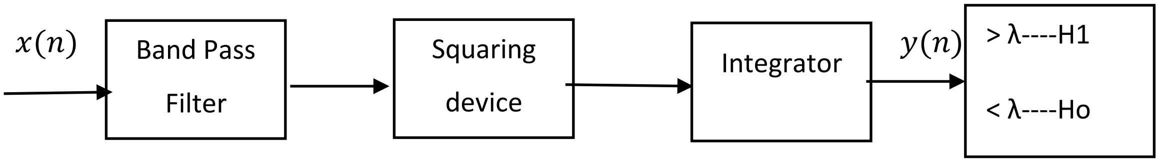


Figure 3.2: Energy Detecor (a) Digital, (b) Analog [36]

The received signal x(n), is filtered by a BPF, followed by a squaring device for measuring received energy, and an integrator that controls the observation interval, T. In order to decide whether the signal is present or not, the output of the integrator, y will act as a test statistic, and will be compared with a predetermined threshold, λ. The binary signal detection problem can be formulated as hypothesis test with H_0 (signal not present) or H_1 (signal present),

From figure 3.2(b) in the case of analog energy detector, the received signal x(n) pass through band pass filter that limits the noise and adjacent bandwidth signals then to an analog to digital converter (ADC) that converts continuous signals to discrete digital signal samples, and a square low device followed by an integrator.

When channel is either in idle or busy state, the detection of primary user in cognitive radio system can be modeled using binary hypothesis test. It is recalled that:

Hypothesis 0 (H0): the primary signal is absent.

Hypothesis 1 (H1): the primary signal is present

$$H0 : x(n) = w(n), \quad \text{.......} 3.1$$

$$H1 : x(n) = s(n) + w(n). \quad \text{.......} 3.2$$

where,

$x(n)$ is the sample to be analyzed at each instant n, $w(n)$ is additive noise; assumed to be white Gaussian noise (AWGN) (with samples having zero-mean and variance σ^2), $s(n)$ is the transmitted signal to be detected.

The goal is to observe the sample signal $x(n)$, then have some rule decide the correct hypothesis based on the test statistic being either greater or less than the threshold.

Characterizing the performance of such a decision rule is realized using some metrics.

3.3.1 Energy detector test statistics

Figure 3.2 shown the output of the analog/ digital integrator is called the test statistics of the system. The purpose of this test statistics is to compare the threshold value with that of the received signal SNR value and decide the presence/absence of primary signal in CR system. [37] When Nyman-Person Criterion applied one binary hypothesis model the probability density function of the given signal y can be expressed as log likelihood function and compared with the threshold value λ as: H is $f_y|H(x) : H(x) \in \{H_0, H_1\}$

Then the log likelihood function Λ_{LR} is given by[37]

$$\wedge_{LR} = \left(\frac{q(y|H_1)}{p(y|H_0)}\right)_{H0}^{H1} \gtrless \lambda \quad \text{......} \quad 3.3$$

Based on the above test statistics, the performance of energy detector is defined using the following metrics:

- False alarm probability (P_f): the probability of deciding the signal is present while H_0 is true, i.e., $P_f = \Pr[\wedge > \lambda | H_0]$ where λ is the detection threshold, and Pr[.] stands for an event probability[37]. In the context of cognitive radio networks, a false alarm yields undetected spectrum holes. So a large Pf contributes to poor spectrum usage by secondary users.
- Missed detection probability (P_{md}): the probability of deciding the signal is absent while H_1 is true, i.e., $P_{md} = \Pr[\wedge < \lambda | H_1]$, which is equivalent to identifying a spectrum hole where there is none. Consequently, large P_{md} introduces unexpected interference to primary users.
- Detection probability (P_d): the probability of deciding the signal is present when H1 is true, i.e., $P_d = \Pr[\wedge > \lambda | H1]$ and thus, $P_d = 1 - Pmd$. LLR characterize the statistical characteristic properties of the performance of an energy detector. To get the statistical properties, signal and noise models are essential. And the noise components, nr(n)and ni(n), are zero mean Gaussian,

Both reliability and efficiency are expected from the spectrum sensing technique built into the cognitive radio, i.e., a higher P_d (or lower P_{md}) and P_f are preferred.

3.3.2 Derivation of P_D and P_{FA}

The noise w(n) (from (3.1)) is considered a bandpass process consisting of two components; the in-phase noise component, wi(n) and quadrature phase component, wq(n), whose sample function is written as [38];

$$n(t) = n_i(t)\cos(nct) - n_q(t) sin(nct) \quad \text{..(3.4)}$$

where n_c is the angular frequency. If n(t) is restricted to bandwidth Bw, with power spectral density N_0, then $n_i(t)$and $n_q(t)$are considered to be two low pass processes with bandwidth less than Bw/2. The power spectral density of each is equal to $2N_0$. When a sample function has bandwidth B, duration T, it is described approximately by a set of values 2BwT or its degree of freedom is equal to 2BwT. Therefore, ni(t) and nq(t) each possess degrees of freedom d, equal to 2BwT [39]. Applying the approximation in [38], that;

$$\int_0^T \mathrm{n}(t)^2\, dt = \frac{1}{2}\int_0^T [\mathrm{ni}(t)^2 + \mathrm{nq}(t)^2] dt \quad \text{..(3.5)}$$

(since ni(t) and nq(t) are considered low-pass processes), and from the sampling theorem, the noise process is expressed as [40];

$$ni(t) = \sum_{\mathrm{j}=-\infty}^{\infty} \mathrm{C_{jk}} \sin c(Bwt - j) \quad \text{... (3.6)}$$

Where $sin(cx) = \frac{sin\pi x}{\pi x}$ and $\mathrm{C_{jk}} = n\frac{k}{Bw}$ are Gaussian random variables with zero mean and variance $\sigma^2{}_j = 2N_0Bw$ [43];

$$\int_{-\infty}^{\infty} \sin \mathrm{c}\,(\mathrm{B_w}t - j) \sin \mathrm{c}\,(\mathrm{B_w}t - m)dt = \begin{cases} \frac{1}{\mathrm{B_w}}, & j = \mathrm{m} \\ 0, & j \neq \mathrm{m} \end{cases} \quad \text{....................... (3.7)}$$

Thus, from (3.6) and (3.7) we obtain,

$$\int_{-\infty}^{\infty} \mathrm{n}_i(\mathrm{t})^2\, dt = \frac{1}{Bw}\sum_{\mathrm{j}=-\infty}^{\infty} \mathrm{C_{ij}2} \quad \text{...} \quad (3.8)$$

Since ni(t) has BwT degrees of freedom over the interval (0,T),

$$\int_0^{\mathrm{T}} \mathrm{n}_i(\mathrm{t})^2\, dt = \frac{1}{Bw}\sum_{\mathrm{j}=1}^{\mathrm{BwT}} \mathrm{C_{ij}2} \quad \text{and} \quad \int_0^{\mathrm{T}} \mathrm{n_q}(\mathrm{t})^2\, dt = \frac{1}{Bw}\sum_{\mathrm{j}=1}^{\mathrm{BwT}} \mathrm{C_{qj}2} \quad \text{............}(3.9)$$

Substituting $\frac{\mathrm{C_{ij}}}{\sqrt{2\mathrm{BwNo}}} = \mathrm{d_{ij}}$ and $\frac{\mathrm{C_{qj}}}{\sqrt{2\mathrm{BwNo}}} = \mathrm{d_{qj}}$ in (3.8) and (3.9), and using (3.3),

$$\int_0^{\mathrm{T}} \mathrm{n}(\mathrm{t})^2\, dt = [\sum_{\mathrm{j}=1}^{\mathrm{BwT}} \mathrm{d_{ij}2} + \sum_{\mathrm{j}=1}^{\mathrm{BwT}} \mathrm{d_{qj}2}].\mathrm{No} \quad \text{..................................}(3.10)$$

In the same manner, considering the transmitted signal s(t), as a band-pass process,

we have that: $\int_0^{\mathrm{T}} \mathrm{s}(\mathrm{t})^2\, dt = [\sum_{\mathrm{j}=1}^{\mathrm{BwT}} \mathrm{b_{ij}2} + \sum_{\mathrm{j}=1}^{\mathrm{BwT}} \mathrm{b_{qj}2}].\mathrm{No}$ ....(3.11)

where $\frac{\mathrm{S_{ij}}}{\sqrt{2\mathrm{BwNo}}} = \mathrm{b_{ij}}$ and $\frac{\mathrm{S_{qj}}}{\sqrt{2\mathrm{BwNo}}} = \mathrm{b_{qj}}$ and $Es = \int_0^{\mathrm{T}} \mathrm{s}^2(\mathrm{t})dt$ is the energy of the signal.

The output of this filter is then squared and integrated over a time interval T to yield a measure of the energy of the received waveform $i.e\ Y = \frac{1}{T}\int_0^{\mathrm{T}} \mathrm{x}^2(\mathrm{t})dt$.

The output of the integrator, denoted Y , is the test statistic (testing the hypotheses H_0 and H_1) [23, 25];

$$Y = \frac{1}{No}\int_0^{\mathrm{T}} \mathrm{x}^2(\mathrm{t})dt \quad \text{..}(3.12)$$

Under Hypothesis H_0 (with the primary signal absent), the received signal is only noise,

i.e. x(t) = n(t). Applying (3.10), the test statistic Y , is written as:

$$Y = \sum_{j=1}^{BwT} (a_{ij}2 + b_{ij}2) \quad \text{..} \quad (3.13)$$

The test statistic under H_0 is said to be chi-square distributed with 2BwT=(2d) degrees of freedom, i.e. $Y \sim \chi^2{}_{2d}$ [23]. The chi-squared distribution is used to test for significant difference between the expected and observed result under the null hypothesis.

Under hypothesis H_1, the received signal is a sum of the signal and noise, i.e. x(t) = s(t) + n(t). Therefore, using equations (3.2) - (3.11) we get;
The test statistics in equation under the condition H_1 is non-central Chi-square distribution with 2BwT freedom. The non-central chi-square distribution offers a statistical test value that uses to determine how far the estimation is from the null hypothesis. d(BwT), is the time bandwidth product at the node and γ is the non-centrality parameters equal to the signal noise ratio. γ can be written as: $\gamma = \frac{Es}{N} = \frac{Es}{2No}$ .... (3.14)

Therefore the decision statistics under hypothesis H_0 and H_1 are

$$Y \sim \begin{cases} \chi^2_{2d}\,(\gamma) \ldots\ldots\ldots\ldots\ldots\ldots\ldots Ho \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.15) \\ \chi^2_{2d}\,(2\gamma) \ldots\ldots\ldots\ldots\ldots\ldots H1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.16) \end{cases}$$

The probability density function (PDF) for a chi-squared distribution for Y is (from [24]);

$$f_Y\,(y) = \begin{cases} \frac{1}{2^d\Gamma(d)} y^{d-1} e^{\frac{-y}{2}} \ldots\ldots\ldots\ldots\ldots\ldots \quad Ho \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.17) \\ \frac{1}{2}\left(\frac{y}{\gamma}\right)\frac{d-1}{2} e^{\frac{-(2\gamma+y)}{2}} \; I_{d-1}\left(\sqrt{2\gamma y}\,\right) \ldots\ldots \quad H1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\,3.18) \end{cases}$$

where Γ(.) is the modified gamma function and Iv(.) is the vth-order modified Bessel function of the first kind. (its definition is given in Appendix A).

Using the above equations we can derive the probability of detection and false alarm for different channel models specifically AWGN and Rayleigh channel.

3.3.3 Probability of Detection for AWGN Channel

Additive white Gaussian noise (AWGN) is a type of noise which exists in the communication channels generally. In a AWGN channel model, we always assume that there's no any other distortion or effects from other sources. Additive white Gaussian noise is a model for the thermal noise generated by random electron movement in the receiver [42].

We know that Pd is the probability that H_1 is selected when the primary signal is present and P_f is probability of false alarm when H_1 selected when the prmary user is not present.

$$P_f = P(Y > \lambda \mid H_0) \quad \text{...} \quad (3.19)$$

$$P_d = P(Y > \lambda \mid H_1) \quad \text{...} \quad (3.20)$$

Where λ is the decision threshold then from their PDF, it is possible to express Pfa as:[43]

$$P_f = f_Y(y)dy \quad \text{...} \quad (3.21)$$

Inserting the value of f_y from Eqn 3.16 into Eqn 3.20:

$$P_f = \int_{\lambda}^{\infty} \frac{1}{2^d \Gamma(d)} y^{d-1} e^{\frac{-y}{2}} dy \quad \text{...} \quad (3.22)$$

substituting $\frac{y}{2} = t\,, \frac{dy}{2} = dt$ and changing the limits of (3.21);

$$P_f = \frac{1}{2^d \Gamma(d)} \int_{\lambda/2}^{\infty} t^{d-1}\, e^{-t} dy \quad \text{...} \quad (3.23)$$

or

$$P_f = \frac{\Gamma\left(d, \frac{\lambda}{2}\right)}{\Gamma(d)} \quad \text{.. (3.24)}$$

Γ(a,x) is the incomplete gamma function, defined by Γ(d,x) = $\left[\int_{-\infty}^{\infty} e^{-t} t^{(d-1)} dt\right]$ and d is the time bandwidth [44].

Since the signal power is unknown, the false alarm probability P_{FA} is set to a constant applying (3.23), the detection threshold λ can be determined.

The value of λ in real communication systems is influenced by the system requirements. Research efforts like [45] choose a threshold λ in a way the P_{FA} is bounded by a target value. From (3.24), P_{FA} depends on two parameters: time bandwidth product d and the threshold λ. Thus the value of λ is not related to SNR (γ).

From (3.17), the probability of detection is obtained by the cumulative distribution function (CDF);

$$P_d = 1 - F_Y(y) \quad \text{.. (3.25)}$$

The CDF of Y is obtained (for an even number of degrees of freedom- 2d in this case) as

$$F_Y(y) = 1 - (Q_d(\sqrt{2\gamma}, \sqrt{\lambda}) \quad \text{.. (3.26)}$$

Thus, from (3.24), the probability of detection, Pd for an AWGN channel is ;

$$P_d = Q_d(\sqrt{2\gamma}, \sqrt{\lambda}) \quad \text{.. (3.27)}$$

Where Q_b (a,b) is the generalized Marcum Q-function. Using eqns 3.24 and 3.27 which are expressions for the P_f and P_d respectively, Receiver Operating Characteristics curves can be drawn. Using eqn 3.27 for varous SNR value, SNR vs Pd graph can also be drawn.

3.3.4 Probability of Detection for Rayleigh Fading Channels

Because signals take more than a path between a transmitter and receiver, they are generally modelled by fading distributions that account for uncertainties encountered in the channel. Among these Rayleigh, Nakagami and Rician fading are the known models. These channel models serve as a tool for studying both multipath and path loss features of a typical environment. In this thesis we are going to see the Rayleigh model channal.

For Rayleigh fading, the signal is not received on a line-of-sight path; directly from the transmitting antenna [46]. This fading model considers urban multipath features, including effects of the ionosphere and troposphere. More so, it describes the statistical time varying nature of the received envelope of a flat fading signal or the envelope of an individual multipath component [47]. When this model is employed, attenuation of the signal is Rayleigh distributed, making the SNR at every node exponentially distributed [48]. By averaging the conditional P_D in the AWGN case, (as given in (3.26)) over the SNR fading distribution, closed form expression for the P_D in Rayleigh fading channels is expressed [25]. It is noteworthy that the P_{FA} of (3.23) will remain unchanged under any fading channel, since the P_{FA} is independent of SNR.

If the signal amplitude follows a Rayleigh distribution, the SNR γ, follows an exponential PDF [25].

$$f(\gamma) = \frac{1}{\gamma}\exp\left(-\frac{\gamma}{\bar{\gamma}}\right) \quad \ldots\ldots\ldots \quad \gamma \geq 0 \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.28)$$

To obtain the Probability of Detection for of Energey Detection for Rayleigh channels, (3.26) is averaged over (3.27) i.e.;

$$\mathrm{P}_{dERay=} \int_0^{\infty} Pd\, f(\gamma) d\gamma \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (3.29)$$

from (3.27),

$$\mathrm{P}_{dERay=} \ \frac{1}{\gamma}\int_0^{\infty} \mathrm{Q}_d(\sqrt{2\gamma}, \sqrt{\lambda}) \ \exp\left(-\frac{\gamma}{\bar{\gamma}}\right) d\gamma \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (3.30)$$

Substituting $\sqrt{\gamma} = x$; $\Rightarrow d\gamma = 2xdx$ above, yields;

$$\mathrm{P}_{dERay=} \ \frac{2}{\gamma}\int_0^{\infty} x.\ \mathrm{Q}_d(\sqrt{2x}, \sqrt{\lambda}) \ \exp\left(-\frac{x^2}{\bar{\gamma}}\right) dx \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.31)$$

From the solution in Appendix A.1 [49], substituting $p^2 = \frac{2}{\bar{\gamma}}, a = \sqrt{2}, b = \sqrt{\lambda}$ and M = d

yields the Probability of detection in Rayleigh channel as:

$$\mathrm{P}_{dRay} = e^{-\frac{\lambda}{2}} \sum_{\mathrm{n}=0}^{\mathrm{d}-2} \frac{1}{n!} \left(\frac{\lambda}{2}\right)^n + \frac{(1+\bar{\gamma})^{\mathrm{d}-1}}{\bar{\gamma}} \left[e^{-\left(\frac{\lambda}{2(1+\bar{\gamma})}\right)} - e^{-\frac{\lambda}{2}} \sum_{\mathrm{n}=0}^{\mathrm{d}-2} \frac{1}{n!} \left(\frac{\lambda\bar{\gamma}}{2(1+\bar{\gamma})}\right)\right] \ldots\ldots (3.32)$$

$d = TBw \ and \ n = \mathrm{d}/2$

3.4 Cyclostationary Detection

The received signal x(t), is filtered by a BPF, followed by a correlator device for measuring received energy, and an integrator that controls the observation interval, T. In order to decide whether the signal is present or not, the output of the integrator, y will act as a test statistic, and will be compared with a predetermined threshold, λ.

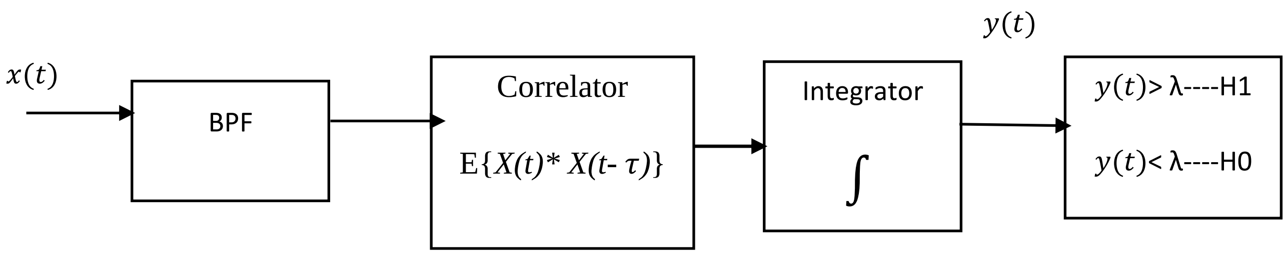


Fig3.3 Block diagram of cyclostationary detection [10]

The analysis of sensing performance is done by correlation process. The correlation can be calculated by multiplying the received signal x(t) and the corresponding delayed signal x(t- τ). The sum of correlations is compared with a predetermined sensing threshold to decide whether PU is present or absent. If the sum of correlation is greater than the predetermined threshold then PU is assumed to be present otherwise it is absent. The decision statistics at the output using the correlation characteristics can be expressed as equation 3.33 to 3.37.

The following conditions are essential to be filled by a process for it to be wide sense cyclostationary[50].

$$E\{x(t-\tau) = E\{x(t)\} \quad \text{......} (3.33)$$

$$R_{xx}(t, t-\tau) = Rx(t,\tau) \quad \text{......} (3.34)$$

$$R_{xx}(t, t-\tau) = E\{x(t)x^*(t-\tau)\} \quad \text{......} (3.35)$$

$$R_{xx}(t, t-\tau) = \sum_{\alpha} R_{xx}^{\alpha}(\tau)\, e^{j2\pi\alpha t} \quad \text{......} (3.36)$$

$$R_{xx}^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T}\int_{-T/2}^{T/2} Rxx(t, t-\tau)\, e^{-j2\pi\alpha t} dt \quad \text{......} (3.37)$$

The cyclic spectral density (CSD) representing the time averaged correlation between two spectral components of a process which are separated in frequencies by ‘α’ is given as:

$$s(f,\alpha) = \int_{\tau=-\infty}^{\infty} R_{xx}^{\alpha}(\tau)\, e^{-j2\pi f t} dt \quad \text{...} \quad (3.38)$$

In order to reduce complexity and delay, single cycle detector measures the signal power only for one specific cyclic frequency [52]

$$Y = R_{xx}^{\alpha}(\tau = 0) \quad \text{...} (3.39)$$

3.4.1 Probability of Detection of Cyclostationary Detection for AWGN Channels

In this section, the detection probability Pd and false alarm probability Pfa of the detector in AWGN channel are derived. The cyclic autocorrelation function is [33][53]

$$R_{xx}^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(\,t+\tau/2)x*(t-\tau/2)\, e^{-j2\pi\alpha t} dt \quad \text{...........................} (3.40)$$

Assuming t = mΔt (where Δt is the sampling period), T = NsΔt (where Ns is the number of received samples) and Tc = MΔt (where Tc is the chip (or bit) time interval), from (3.41) and (3.42), the discrete-time counterpart of sufficient statistic of cyclostatinary detector is given by

$$Y = \frac{1}{Ns} \sum_{m=1}^{Ns} |x[m]|^2 e^{-j2\pi\alpha t} \text{...………..} \ (3.41)$$

where α = k/ M . Hence, the sufficient statistics in different hypotheses (H_0 and H_1) in AWGN channel according to the binary hypotheses test (1) can be represented [54].

$$H_0 : Y = \frac{1}{Ns} \sum_{m=1}^{Ns} |n[m]|^2 e^{-j2\pi\alpha t m} \quad \text{...} \ (3.42)$$

$$H_1 : Y = \frac{1}{Ns} \sum_{m=1}^{Ns} |s[m] + n[m]|^2 e^{-j2\pi\alpha t m} \text{......................................} \ (3.43)$$

where $n[m] = n_r[m] + jn_q[m]$ is a complex AWGN sample with zero mean and variance σ^2, s[m] is a primary-user signal sample, and Ns = NcM where Nc is the number of chips (or bits) and M is the number of samples in each chip (or bit) time interval. The structure of the detector can be defined as

$$T_{SC} = |Y|^2 \gtrless \lambda \quad \text{..} \quad (3.44)$$

where λ denotes detection threshold and T_{SC} is the test stastics.

$$P_f = P(T_{SC} > \lambda \mid H_0) \quad \text{...} \ (3.45)$$

$$P_d = P(T_{SC} > \lambda \mid H_1 \text{...} \ (3.46)$$

The dervation for Pf and Pd can be derived from the central limit theorem for large Ns, Y is approximatly Gaussian. Ns = NcM, $E\{|n[m]|^2\} = \sigma^2$ and var $\{|n[m]|^2\} = \sigma^4$ and

for $\alpha = \frac{k}{m}, = \frac{1}{Ns}\sum_{m=1} e^{\ -j2\pi\alpha tm} = 1$,[54]

$$\text{var}\{\ Y>\lambda \mid H_0\} = \frac{1}{Ns}\sum_{m=1} \text{var}\{\ |\, n[m]|^2\}e^{-j2\pi\alpha tm} = \frac{\sigma^4}{Ns} \quad \text{.................................... (3.47)}$$

$\{\ Y>\lambda \mid H_0\} = Y^r{}_0+jY_0{}^i$ is a complex gaussian random variable, it follows that

$$(Tsc|Ho) = |Y|H_0|^2 = (Y_o{}^r)^2 + (Y_o{}^i)^2$$

is a central chi-square distribution with two degrees of freedom i.e $P(\lambda\, |Ho) = \frac{1}{2\sigma_0^2}e^{\frac{-\lambda}{2\sigma_0^2}}$, and the false alarm probablity[52].

$$P_f = \int_{-\gamma}^{\infty} \frac{1}{2\sigma_0^2}e^{\frac{-\lambda}{2\sigma_0^2}}\, d\lambda = e^{-\frac{\gamma}{2\sigma_0^2}} \quad \text{.. (3.48)}$$

Where, $\sigma_0^2 = \frac{\sigma^4}{Ns}$

Similarly, var$\{|s[m] + n[m]|^2\}$

$$\text{var}\ \{Y|H_1\} = \frac{1}{Ns}\sum_{m=1} e^{-j2\pi\alpha tm}\ \text{var}\ \{|\, s[m] + n[m]|^2\}, \quad \text{........... (3.49)}$$

Where, $\frac{1}{Ns}\sum_{m=1} e^{\ -j2\pi\alpha tm} = 1$

$$P(Tsc|H_1) = \frac{1}{2\sigma_1^2}e^{-\frac{(\gamma^2+\lambda)}{2\sigma_1^2}}\, Io(\sqrt{\lambda}\frac{\gamma}{\sigma_1^2}) \quad \text{... (3.50)}$$

$$Pd = \int_{-\gamma}^{\infty} \frac{1}{2\sigma_1^2}e^{-\frac{(\gamma^2+\lambda)}{2\sigma_1^2}}\, Io(\sqrt{\lambda}\frac{\gamma}{\sigma_1^2})\, d\lambda, \quad \text{.. (3.51)}$$

where I(a) is

$$Pd = Q(\gamma/\sigma_1, \sqrt{\lambda}/\sigma_1) \quad \text{.. (3.52)}$$

Where, $Q_1(a,b)$ is the first degree Marcum Q funtion, $\sigma_1 = \frac{(2\gamma^2\sigma^2+1)\sigma^4}{Ns}$ and γ is the SNR.

3.4.2 Probability of Detection of Cyclostationary Detector for Rayleigh Fading Channels

As its been explained above for a Rayleigh distribution, the SNR γ, follows an exponential PDF from equation 3.27

$$f(\gamma) = \frac{1}{\gamma} \exp\left(-\frac{\gamma}{\bar{\gamma}}\right) \quad \ldots\ldots\ldots\ldots \geq 0 \quad \ldots\ldots\ldots\ldots (3.53)$$

From equation 3.28, the probablity of detection for cyclostationary detection can be calculated as

$$P_{dCRay=} \int_0^\infty Pd\, f(\gamma) d\gamma \quad \ldots\ldots\ldots\ldots (3.54)$$

$$P_{dCRay=} \ \frac{1}{\gamma} \int_0^\infty Qd\left(\frac{\gamma}{\sigma_1}, \frac{\sqrt{\lambda}}{\sigma_1}\right) \exp\left(-\frac{\gamma}{\bar{\gamma}}\right) d\gamma \quad \ldots\ldots\ldots\ldots (3.55)$$

which is unsolvable intgration so we use a differernt approch to simulate for fading enviroment. In order to inspect the cyclostionary of the received faded signal, we characterise the impact of Rayleigh fading impairments on the received CAF(Cyclic Autocorrelation Function). In fact the received CAF is directly proportinal to the autocorrelation of the channel fading process. [54]

$$R_{yy}^{\alpha}(\tau) = \mathrm{R}_h\,(\tau) R_{xx}^{\alpha}(\tau) \quad \ldots\ldots\ldots\ldots (3.56)$$

Where, $\mathrm{R}_h\,(\tau)$ is the Rayleigh channel fading coefficent and $R_{xx}^{\alpha}(\tau)$ is the Cyclic Autocorrelation Function.

Comparing the CAF(Cyclic Autocorrelation function) with a given threshold will give us the probablity of detection.

3.3. Hybrid Detector

To optimize the detection probability, a hybrid detector is proposed which is a combination of energy detector and cyclostationary detector. We know that energy detector is simpler as compared to cyclostationary detector. So the output of PU transmitter first passes from energy detector to verify whether the PU is present or not. If energy detector is not sure about the presence of PU, then a cyclostationary detector is applied. The flow chart of proposed hybrid detector is shown in Figure 3. 3

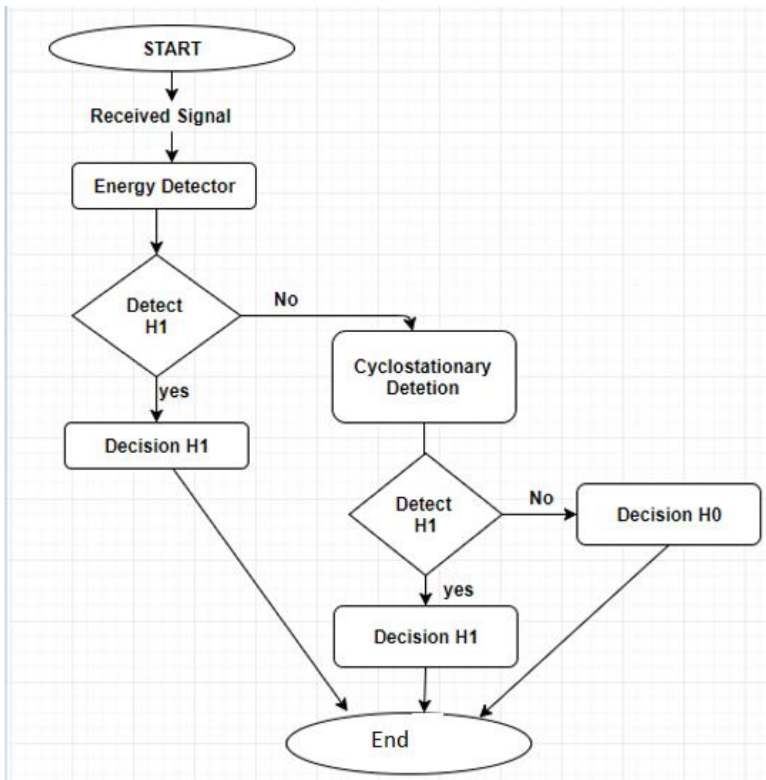


Figure 3.4 Conceptual work flow

Whenever there is a missed detection by energy detector, cyclostationary detection is applied. The probability of undergoing cyclostationary detection (P_{cyclo}) in hybrid scheme over AWGN can be expressed as:

$$P_{mEd} = 1 - P_{DEd} \quad \text{..........} \quad (3.57)$$

Where P_{mEd}: probability of miss detection for energy detector and P_{DEd} probability of detection for energy detection

$$P_{cyclo} = P_{mEd} \quad \text{.......} \quad (3.58)$$

P_{cyclo}: probability that it goes to cyclostatinary detection

So the detection probability ($P_{Dhybrid}$) of a hybrid detection scheme under AWGN channel can be expressed as,

$$P_{Dhybrid} = 1\text{-}(1 - P_{DEd})(1\text{-} P_{Dcyclo}) \quad \text{.......} \quad (3.59)$$

Where P_{Dcyclo} is probability of detection for cyclostatinary detector.

Then the missed detection probability ($P_{mhybrid}$) of hybrid scheme is given as:

$$P_{mhybrid} = 1 - P_{Dhybrid} \quad \text{.......} \quad (3.60)$$

Similarly the false alarm probability ($P_{fhybrid}$) is given as

$$P_{fhybrid} = 1\text{-}(1 - P_{fEd})(1\text{-} P_{fcyclo}) \quad \text{.......} \quad (3.61)$$

3.4 Detection Time

To calculate the detection time, since the time required for calculation is negligible, it is mainly determined by the sampling number:

$$Td = \frac{N}{fs} \quad \text{.......} \quad (3.62)$$

where fS is the sampling frequency. In the rest of this paper, we will discuss the sampling number N instead of the detection time Td for simplicity.

The proposed scheme chooses N-point sampling. Let $P0$ and $P1$ represent the prior probabilities of hypotheses *H0* and *H1* , respectively. Then the average sampling number of Hybrid Detector can be expressed as [55]:

$$\overline{N} = N(P0 * Pf + P1 * Pd)$$

$$+2N(P0 * (1 - Pf) + P1 * (1 - Pd)) \quad \text{.......} \quad (3.63)$$

Without loss of generality, assume $P0$ = $P1$ = 0.5 in this paper. Then we have

$$\overline{N} = \frac{N}{2}(4 - Pf - Pd) \quad \text{...}(3.64)$$

Since $0 < Pf + Pd < 1$, [56] the bounds of average sampling number in Hybrid detector given by

$$1.5N < \overline{N} < 2N \quad \text{...} \quad (3.65)$$

Note that, Energy detection uses N-point sampling, the Hybrid detector requires more samples, between *1.5N* and *2N*. which is about 50% higher than of energy detector.

Chapter 4

Simulation Results and Discussions

In the previous chapter, the system model was introduced with mathematical expression to present a theoretical description of the standard energy detection as well as cyclostationary, and hybrid detection of a signal in a spectrum. In this chapter, the simulation results for AWGN and Rayleigh channel models simulations by applying a combination of energy and cyclostationary detection scheme. Results of the analysis performed are presented along with a discussion of interpretations.

Simulation parameters	Type and Value
Cognitive User	Single user
Transmitted Signal	BPSK,QPSK
Detection Type	Energy Detector, Cyclostationary Detector
Transmitted SNR	4dB
Probability of False alarm	0.01
Channel	AWGN and Rayleigh
Sampling Number	200

Table 4.1 simulation parameters

4.1 Simulation for AWGN channel

4.1.1 Simulation results and discussions of Energy Detection for AWGN channel

Figure 4-1 is the energy detector response based on the parameters listed in Table 4.1. The plot is generated when 200 sampled signals are transmitted, for BPSK modulation. the IEEE 802.22 standard suggests both probabilities of false alarm and missing be less than 0.1[57]. Here in, as stricter requirement that setting the value of false alarm probability equal to 0.01. Figure 4.1 plots the relationship between the detection of probabilities Vs signal SNR values. The detection probability (P_d) for different values of SNR are generated. As the SNR value increase from -30dB to -20dB with a step increment of 0.5dB, so does the detection probability but then the increment is small. Though the detection values at lower SNR is too low, specifically for SNR values below -20dB, it reached around 0.3 when the signal SNR is equal to -18dB. For SNR values greater than

-15dB, it is shows a high increment on Pd and become 100% at 0dB. To summarize, it is observed that when the SNR value is below -20 dB the probability of detection is in the range of 0.27 to 0.30, a slow increment on the probability of detection. For the SNR value on the range of -20dB to -1dB the probability of detection increment is fast, in the range of 0.3 to 0.99 and at 0dB SNR, the probability detection becomes high and attains its maximum value.

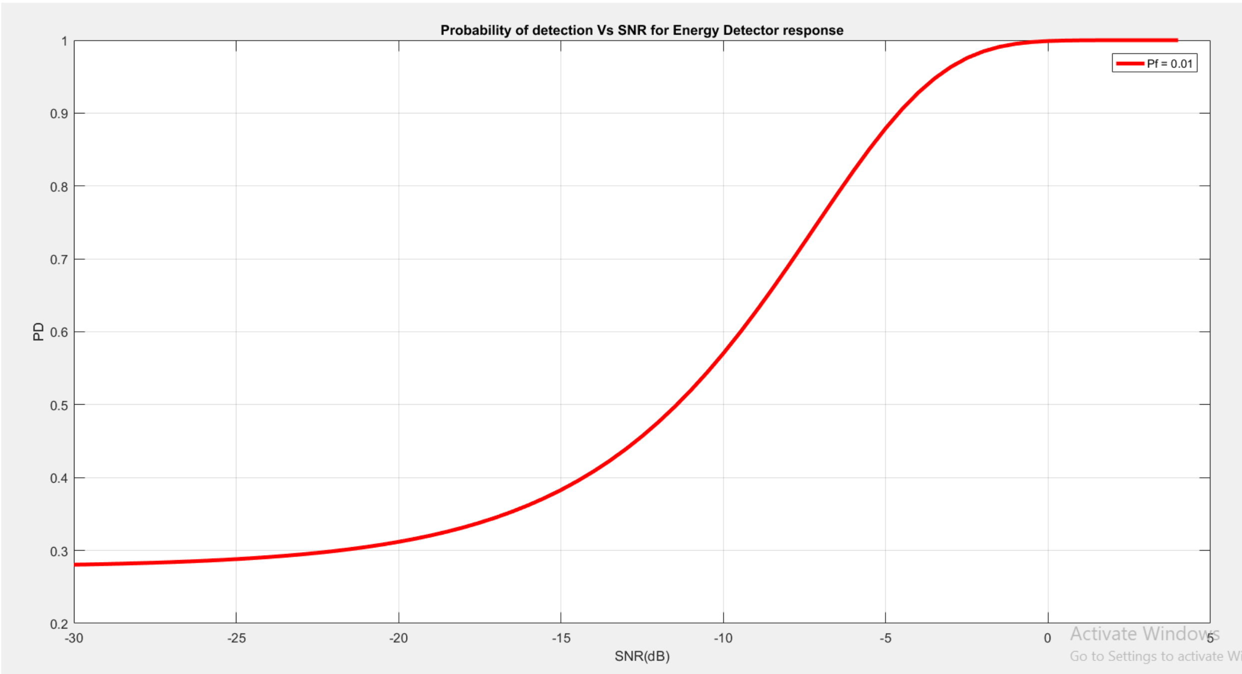


Figure 4.1. Probability of detection Vs SNR for Energy Detector response

SNR_DB	-30	-29.5	-29	-28.5	-28	-27.5	-27
P_{ED}	0.274663	0.275093	0.275575	0.276116	0.276723	0.277403	0.278166
SNR_DB	-26.5	-26	-25.5	-25	-24.5	-24	-23.5
P_{ED}	0.279021	0.27998	0.281055	0.282259	0.283608	0.28512	0.286814
SNR_DB	-23	-22.5	-22	-21.5	-21	-20.5	-20
P_{ED}	0.288711	0.290835	0.293213	0.295874	0.29885	0.30218	0.305901
SNR_DB	-19.5	-19	-18.5	-18	-17.5	-17	-16.5
P_{ED}	0.310059	0.314703	0.319886	0.325667	0.332109	0.339283	0.347263
SNR_DB	-16	-15.5	-15	-14.5	-14	-13.5	-13
P_{ED}	0.35613	0.36597	0.376873	0.388935	0.402252	0.416924	0.433048
SNR_DB	-12.5	-12	-11.5	-11	-10.5	-10	-9.5
P_{ED}	0.450717	0.470015	0.491012	0.51376	0.53828	0.564559	0.592537
SNR_DB	-9	-8.5	-8	-7.5	-7	-6.5	-6
P_{ED}	0.622095	0.65305	0.685137	0.718011	0.75124	0.784308	0.816633
SNR_DB	-5.5	-5	-4.5	-4	-3.5	-3	-2.5
P_{ED}	0.847588	0.876538	0.902889	0.926141	0.94594	0.962128	0.974761
SNR_DB	-2	-1.5	-1	-0.5	0	0.5	1
P_{ED}	0.984112	0.990627	0.994864	0.997413	0.998815	0.999513	0.999823
SNR_DB	1.5	2	2.5	3	3.5	4	
P_{ED}	0.999942	0.999984	0.999996	0.999999	1	1	

Table 4.2 Simulation Result of SNR Vs Probability of detection for Energy Detection

4.1.2 Simulation results and discussions of Energy Detection for various values of Pf for AWGN channel

Next, the effect of increased probability of false alarm (P_f) on detection performance is explored. For this case, P_f is increased from 0.01 to 0.05 then to 0.1 respectively, as shown in Figure 4.2. for the various value of false alarm there is an increases on the probability detection. If we see the increment property, as P_f increase from 0.01 to 0.05, P_d increment from 0. 34 to 0.56 which is about 39%. When P_f increase from 0.05 to 0.1 the value of Pd is almost the same. Even though P_f and P_d have directly proportional we cannot fully improve the detection probability by just increasing P_f value.

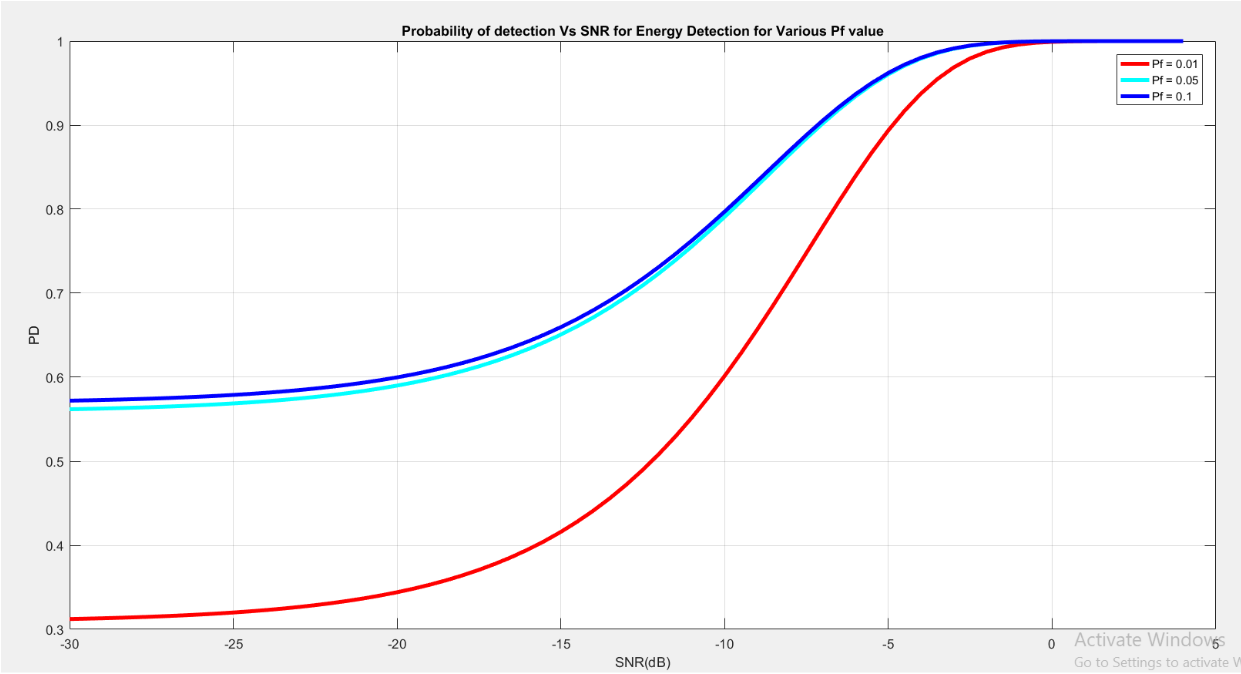


Figure 4.2. Probability of detection Vs SNR for Energy Detection for Various Pf value

4.1.3 Simulation results and discussions of Hybrid Detection for various values of P_f for AWGN channel

Figure 4.3 plots the relation between P_f and P_d for a hybrid detector for various false alarm values as the value of P_f increase from 0.01 to 0.05. It is observed that the P_d also increases, which is from 0.75 to 0.76 about 0.01 step increment. The result agrees with the theoretical description, when the probability of false alarm increase so does probability of detection.

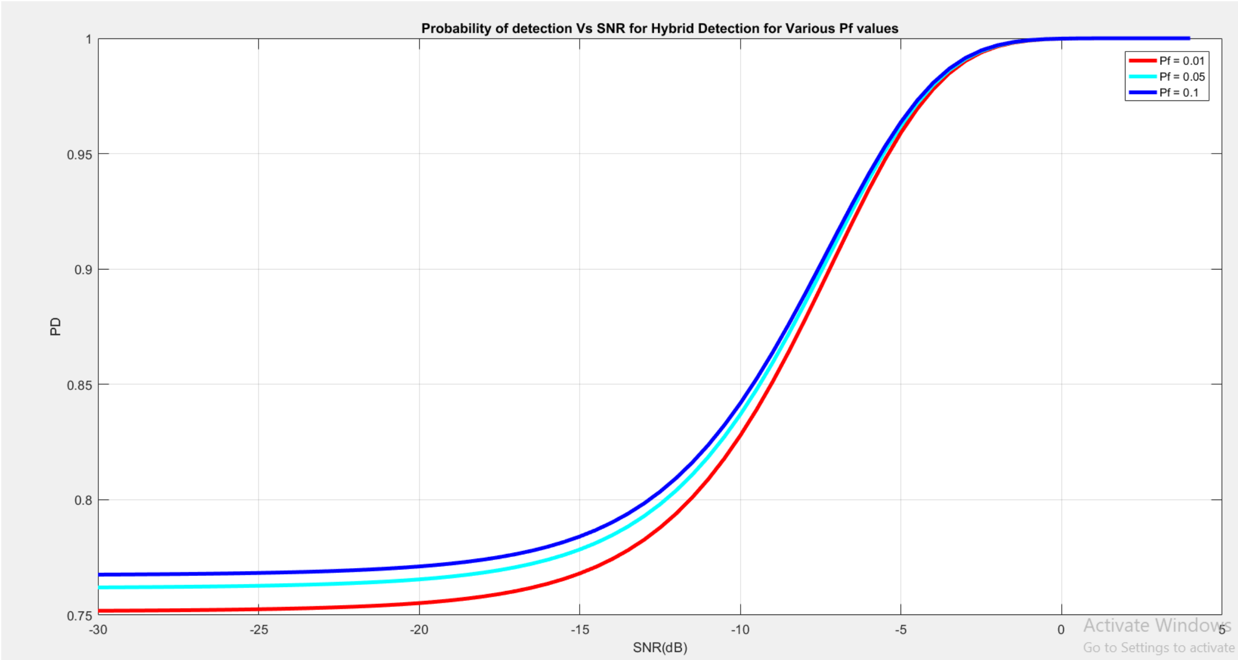


Figure 4.3. Probability of detection Vs SNR for Hybrid Detection for Various Pf values

4.1.4. Simulation results and discussions of Hybrid Detection for AWGN channel

Figure 4.4 is the enhanced simulation plot when the Hybrid detection method is applied. It generated the value of detection probability for corresponding SNR values. Setting the value of false alarm probability equal to 0.01 the hybrid detection response generated, the detail response for each SNR value with the increment of 0.5 is found on in table 4.3, according to the output it can be analyzed three groups:

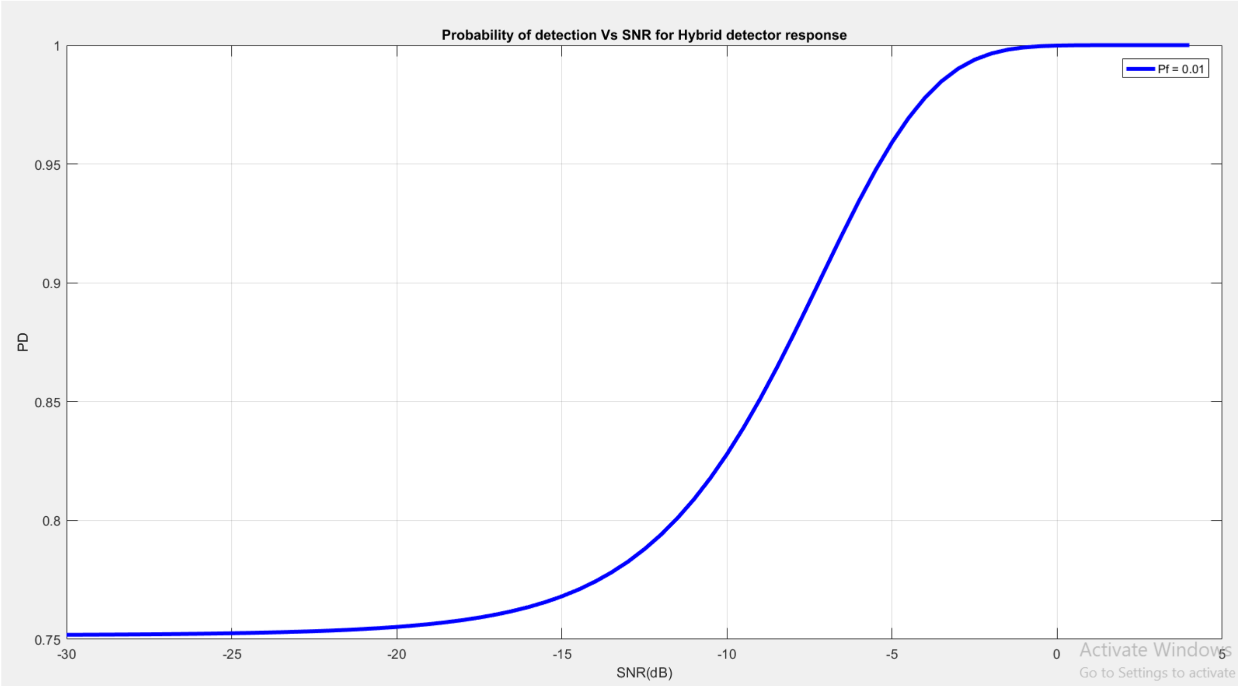


Figure 4.4. Probability of detection Vs SNR for Hybrid detector response

Group1: {-30≤ SNR ≤ -20dB}, Group 2: {-20dB≤ SNR ≤ -5dB} and Group 3: {-5dB≤ SNR ≤ 5dB} Comparing the detection probability values in table 4.2-Energy detector with that of table 4.3-hybrid detector response, Table 4-3 showed the detection probabilities in Group 1 which are low SNR values recorded, has higher(enhanced) value than that of table 4.2. for example, for -30 dB, there is a 0.31 step increment on the hybrid detector. Thus using a hybrid detector improved the performance of the system at a low value of SNR specifically in the value between -30≤ SNR ≤ -20dB.

SNR_DB	-30	-29.5	-29	-28.5	-28	-27.5	-27	-26.5
P_{HD}	0.7519	0.7519	0.7519	0.752	0.752	0.7521	0.7522	0.7522
SNR_DB	-26	-25.5	-25	-24.5	-24	-23.5	-23	-22.5
P_{HD}	0.7523	0.7524	0.7525	0.7527	0.7528	0.753	0.7532	0.7534
SNR_DB	-22	-21.5	-21	-20.5	-20	-19.5	-19	-18.5
P_{HD}	0.7537	0.754	0.7543	0.7547	0.7552	0.7558	0.7564	0.7572
SNR_DB	-18	-17.5	-17	-16.5	-16	-15.5	-15	-14.5
P_{HD}	0.7581	0.7591	0.7604	0.7619	0.7636	0.7657	0.7681	0.7709
SNR_DB	-14	-13.5	-13	-12.5	-12	-11.5	-11	-10.5
P_{HD}	0.7742	0.7781	0.7827	0.7879	0.794	0.801	0.8089	0.8179
SNR_DB	-10	-9.5	-9	-8.5	-8	-7.5	-7	-6.5
P_{HD}	0.8279	0.839	0.8511	0.8641	0.8778	0.892	0.9064	0.9207
SNR_DB	-6	-5.5	-5	-4.5	-4	-3.5	-3	-2.5
P_{HD}	0.9345	0.9474	0.9592	0.9694	0.978	0.9849	0.9901	0.9939
SNR_DB	-2	-1.5	-1	-0.5	0	0.5	1	1.5
P_{HD}	0.9965	0.9981	0.9991	0.9996	0.9998	0.9999	1	1
SNR_DB	2	2.5	3	3.5	4			
P_{HD}	1	1	1	1	1			

Table 4.3 Simulation Result of SNR Vs Probability of detection for Hybrid Detection for AWGN

4.1.5 Simulation Result for the Energy, Cyclostationary and Hybrid Detection for AWGN

Figure 4.5 depicts energy, cyclostationary, and hybrid energy detector simulation plots together. It is observed that for energy detector, much higher SNR is required to obtain comparable result with cyclostatinary detector. If we take SNR value = -28dB there is a 72% improvement on using the hybrid one. To attend the maximum detection value 100%, as much of 5dB is required. A hybrid detector performs well for low SNR compare with energy detector however, the disadvantage is it required higher detection time.

The cyclostationary detector also perform very well but, cyclostationary feature detection algorithm is complex as compared to other detection techniques.

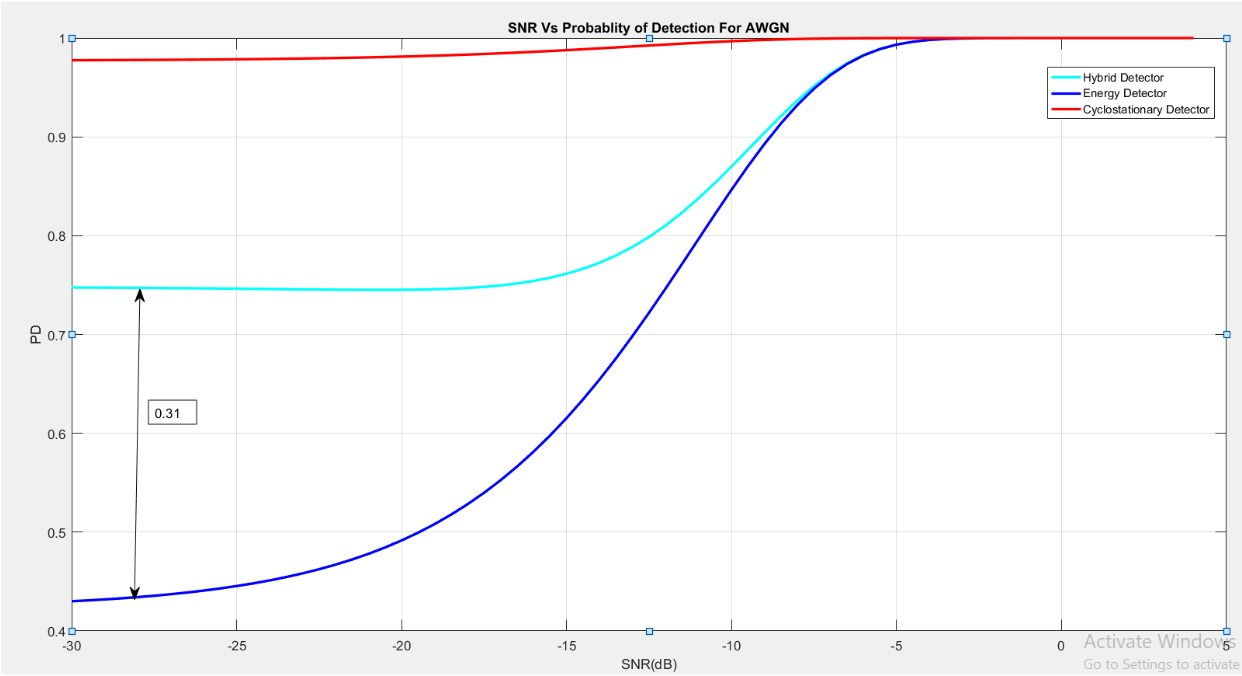


Figure 4.5. Probability of detection Vs SNR for Energy, Cyclostationary and Hybrid detector response for AWGN

4.1.6 Probability of detection Vs SNR for Cyclostationary detector response for AWGN

Figure 4.6 shows the probability of primary detection as a function of SNR for a cyclostationary detection. It is observed that we can attend above 98% of detection at SNR value -30dB.and become almost 100% when the SNR is above -15dB. Cyclostationary detection perform well for low SNR value, however the disadvantage is it required higher detection time to detect the occupancy detection. Further, cyclostationary feature detection algorithm is complex as compared to other detection techniques.

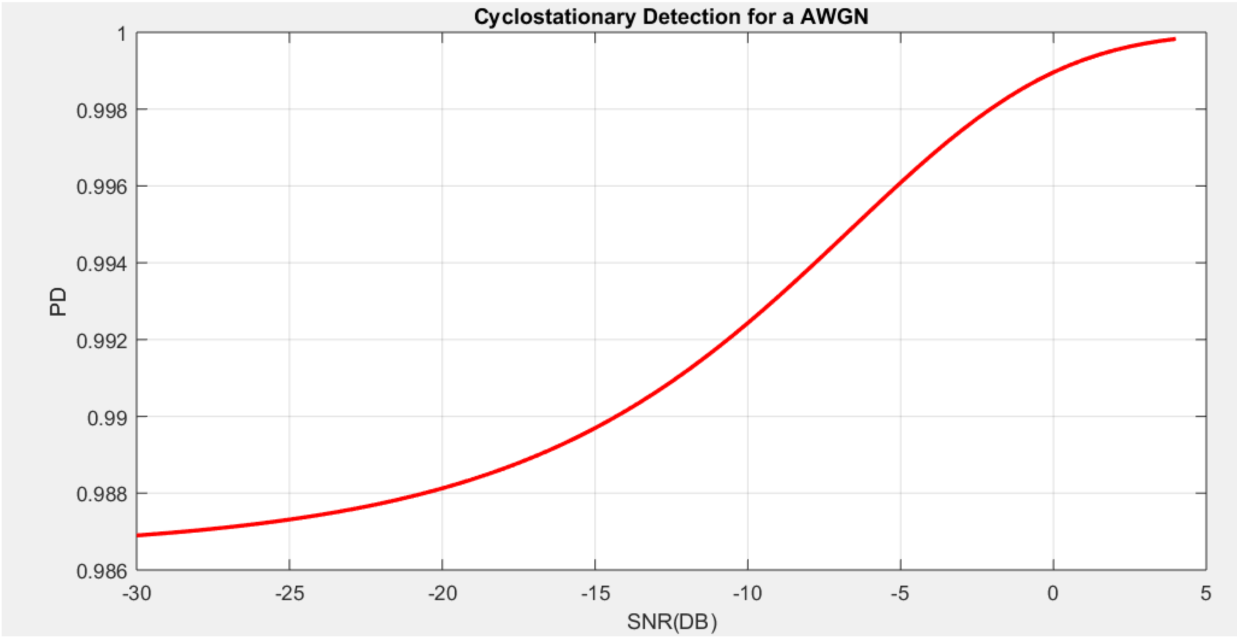


Figure 4.6. Probability of detection Vs SNR for Cyclostationary detector response for AWGN

4.1.7 Energy, Cyclostationary and Hybrid detector response for QPSK Modulation for a AWGN.

On QPSK Modulation we can also do the same analysis as BPSK and there is also a visible improvement using a hybrid detector. From figure 4.7 for the various values of SNR especially if the SNR value is less than -15dB the enhancement is high compared to the improvement in the region between -15dB and to -10dB. If we take the two-points, P1(-20,0.59) and P2(-20, 0.75) there is a 16% improvement by using a hybrid detector instead of using just an energy detector. For SNR > -10dB the probability of detection for the Hybrid and Energy detector becomes the same and approach 1.

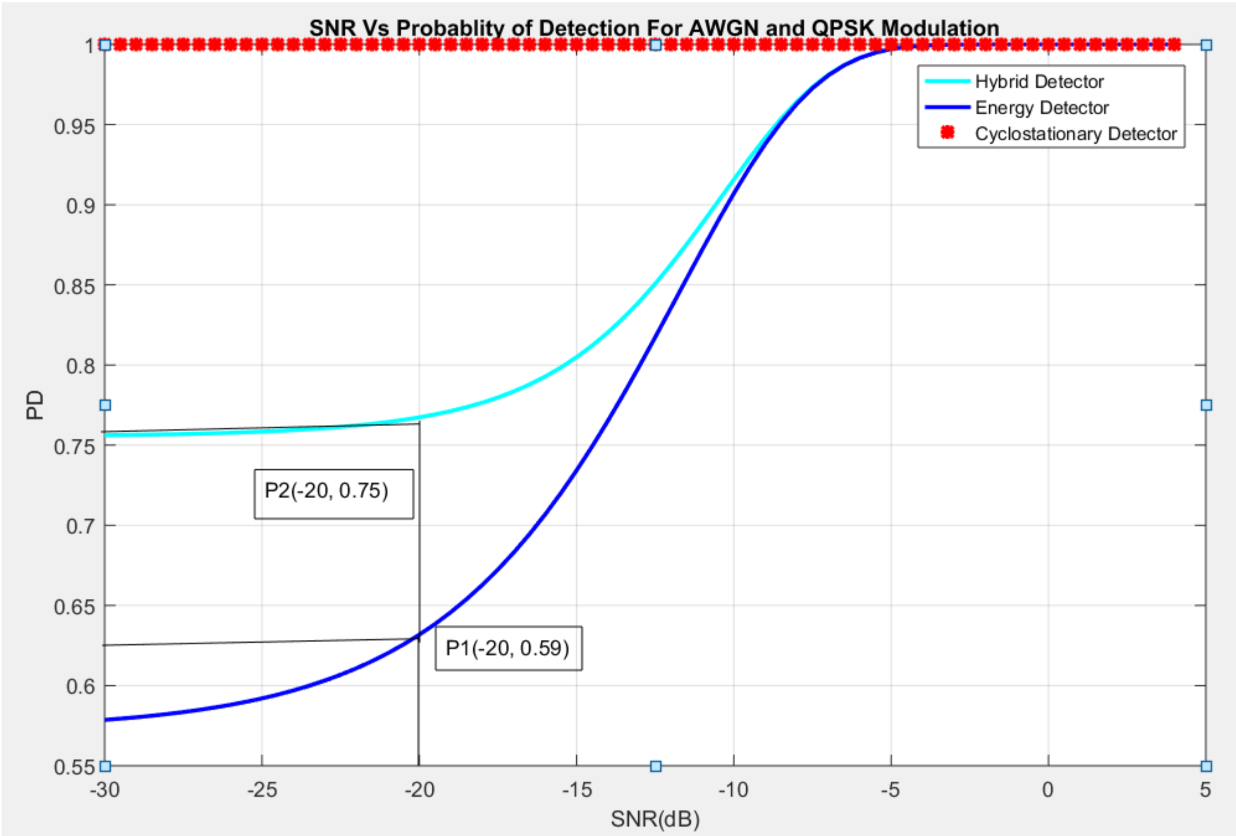


Figure 4.7 Probability of detection Vs SNR for Energy, Cyclostatinary and Hybrid detector response for AWGN and QPSK Modulation.

SNR_DB	-30	-29.5	-29	-28.5	-28	-27.5	-27	-26.5	-26
P_{ED}	0.5786	0.5794	0.5802	0.5812	0.5823	0.5835	0.5848	0.5863	0.5880
P_{HD}	0.7562	0.7563	0.7564	0.7566	0.7568	0.7570	0.7572	0.7575	0.7577
SNR_DB	-25.5	-25	-24.5	-24	-23.5	-23	-22.5	-22	-21.5
P_{ED}	0.5899	0.5920	0.5944	0.5970	0.5999	0.6031	0.6068	0.6108	0.6153
P_{HD}	0.7581	0.7585	0.7589	0.7594	0.7600	0.7606	0.7614	0.7623	0.7633
SNR_DB	-21	-20.5	-20	-19.5	-19	-18.5	-18	-17.5	-17
P_{ED}	0.6202	0.6257	0.6317	0.6384	0.6458	0.6539	0.6627	0.6724	0.6830
P_{HD}	0.7644	0.7658	0.7674	0.7692	0.7713	0.7737	0.7765	0.7797	0.7835
SNR_DB	-16.5	-16	-15.5	-15	-14.5	-14	-13.5	-13	-12.5
P_{ED}	0.6944	0.7068	0.7200	0.7343	0.7494	0.7653	0.7821	0.7995	0.8174
P_{HD}	0.7878	0.7927	0.7984	0.8049	0.8122	0.8204	0.8296	0.8397	0.8507
SNR_DB	-12	-11.5	-11	-10.5	-10	-9.5	-9	-8.5	-8
P_{ED}	0.8356	0.8540	0.8722	0.8900	0.9071	0.9232	0.9380	0.9513	0.9629
P_{HD}	0.8626	0.8753	0.8885	0.9021	0.9157	0.9291	0.9419	0.9537	0.9643
SNR_DB	-7.5	-7	-6.5	-6	-5.5	-5	-4.5	-4	-3.5
P_{ED}	0.9727	0.9807	0.9869	0.9916	0.9949	0.9971	0.9985	0.9992	0.9997
P_{HD}	0.9735	0.9811	0.9871	0.9917	0.9949	0.9971	0.9985	0.9992	0.9997
SNR_DB	-3	-2.5	-2	-1.5	-1	-0.5	0	0.5	1
P_{ED}	0.9999	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
P_{HD}	0.9999	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
SNR_DB	1.5	2	2.5	3	3.5	4			
P_{ED}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000			
P_{HD}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000			

Table 4.4 Simulation Result of SNR Vs Probability of detection for Hybrid and Energy Detection for QPSK modulation and AWGN.

4.1.8 Simulation results and discussions of ROC for Energy, Cyclostationary and Hybrid detection for AWGN channel.

Figure 4.8 shows the receiver operating curve (ROC) over a nonfading (AWGN) channel for energy, hybrid and cyclostationary detection methods respectively. For the various probability of false alarm values, -4dB average SNR, time-bandwidth product d = 4, and sample size N = 200 respectively.

It is observed that for P_f value less than 0.5, the hybrid detector performance is higher (improved) then the energy detector. Let's consider two points of P_f (0.04 and 0.1) For the first point (Pf=0.04) the probability of detection for energy and hybrid detector is shown as S1(0.04, 0.0.57) and S2(0.04, 0.75) respectively and there is a 24% improvement on the hybrid detector. If we again consider the second point, P_f =0.1, P1(0.1, 0.72) and P2(0.1, 0.80) for energy and hybrid respectively we can see a 10% improvement. It is further seen as P_f and P_d have direct relationship, we get a higher value of probability of primary user detection with the cost of higher false alarm probability.

Thus from the above analysis even though primary detector performance increase with the cost of higher false alarm the hybrid detector able to achieve improved detection compared with the energy detector. Cyclostatinary detector perform very well for low P_f than both energy and hybrid detector.

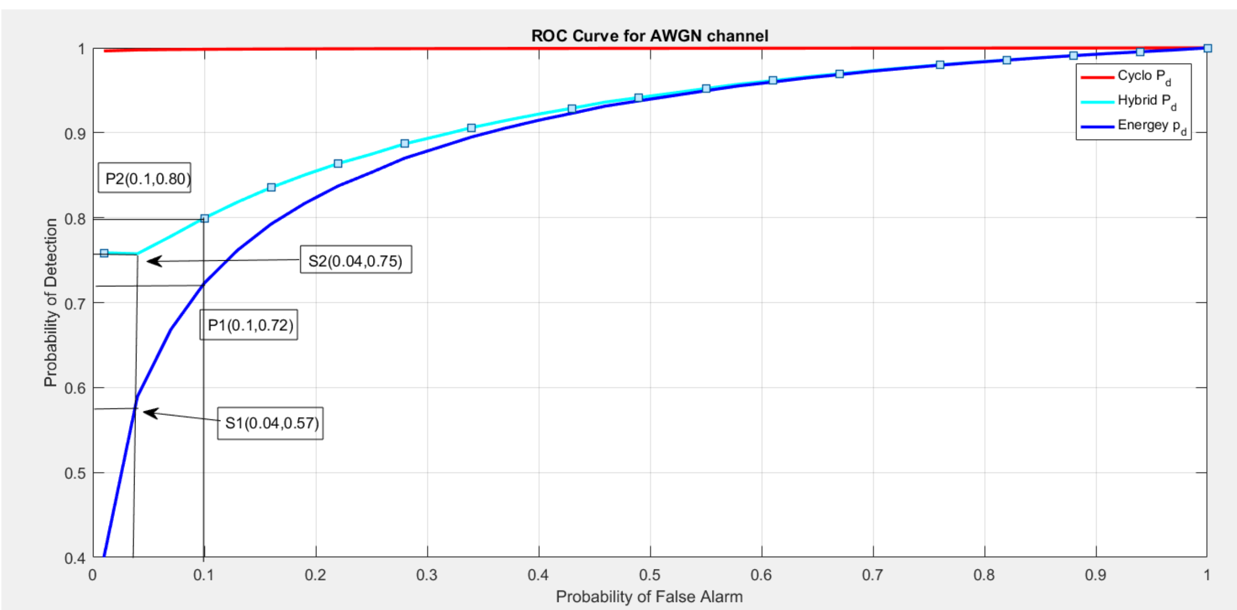


Figure 4.8: Energy, Cyclostationary and Hybrid Detector of ROC (Probability of detection Vs Probability of False Alarm).

P_f	0.01	0.04	0.07	0.1	0.13	0.16	0.19	0.22
P_{ED}	0.405189	0.574876	0.6690956	0.723478	0.762112	0.791814	0.816538	0.83918
P_{HD}	0.7577	0.756787	0.7783731	0.799811	0.818616	0.835096	0.850154	0.865014
P_f	0.25	0.28	0.31	0.34	0.37	0.4	0.43	0.46
P_{ED}	0.853644	0.869308	0.8823349	0.8941	0.904846	0.914028	0.92238	0.931152
P_{HD}	0.875041	0.886371	0.8961674	0.905305	0.913893	0.921414	0.928401	0.935889
P_f	0.49	0.52	0.55	0.58	0.61	0.64	0.67	0.7
P_{ED}	0.937843	0.943847	0.9494112	0.955569	0.959966	0.964463	0.968687	0.972521
P_{HD}	0.941704	0.946999	0.9519691	0.957542	0.961568	0.965726	0.969667	0.973276
P_f	0.73	0.76	0.79	0.82	0.85	0.88	0.91	0.94
P_{ED}	0.976144	0.979268	0.9827094	0.985394	0.988506	0.990912	0.993142	0.995308
P_{HD}	0.976713	0.979698	0.9830083	0.985607	0.988638	0.990994	0.993189	0.99533
P_f	0.97	1						
P_{ED}	0.997434	0.999967						
P_{HD}	0.997441	0.999967						

Table 4.5 Simulation Result of Probability of false alarm Vs Probability of detection for Hybrid and Energy Detection for AWGN.

Figure 4.9 show the primary user detection performance is not significantly affected by false alarm probability. For Pf value from 0.01 to 1 we attend the maximum detection probability, 100%.

Further the plot also shows a direct relation between P_f and P_d which agree with the theoretical explanation.

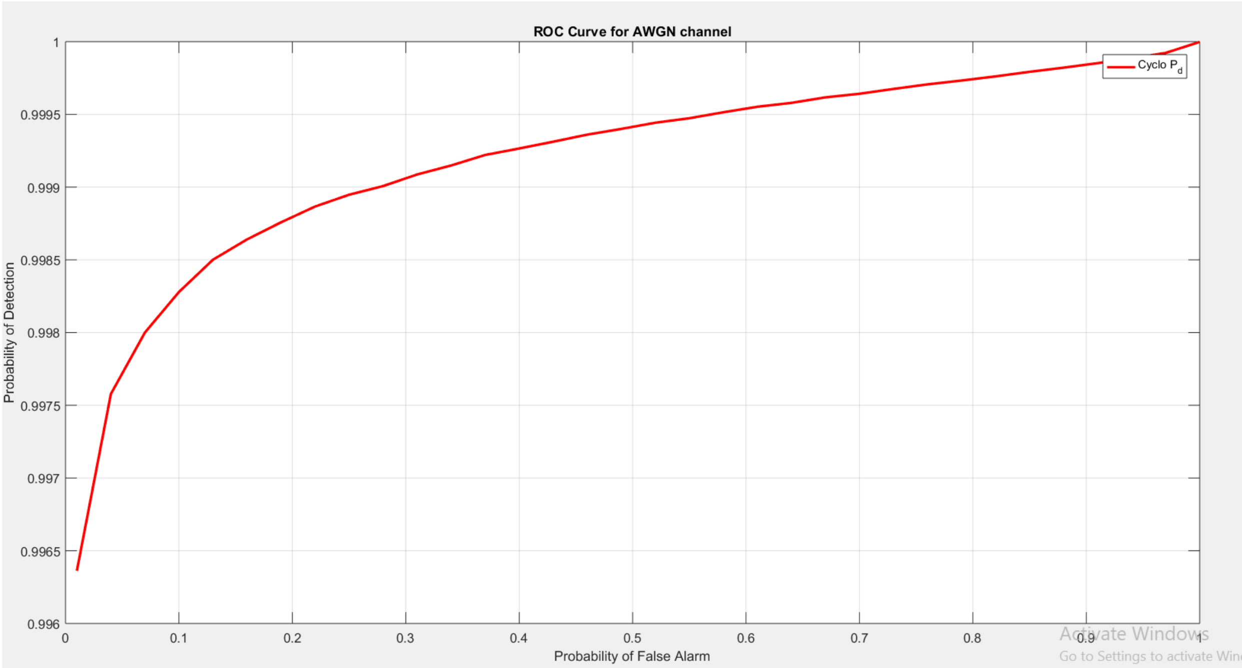


Figure 4.9: ROC for Cyclostationary Detector of ROC.

4.2 Simulation for Rayleigh channel

4.2.1 Simulation and discussion result of ROC for Energy Detection over Rayleigh channel

Figure 4-10 depicts the simulation result of the ROC curve of AWGN and the Rayleigh channel model. The plot shows the relationship between the false alarm values P_f with that of the corresponding detection probabilities P_d value for average SNR = 4dB. Considering points P1(0.2, 0.64) and P2 (0.2, 0.824). AWGN shows higher P_d than the Rayleigh channel which is expected because the fading effect is more on Rayleigh.

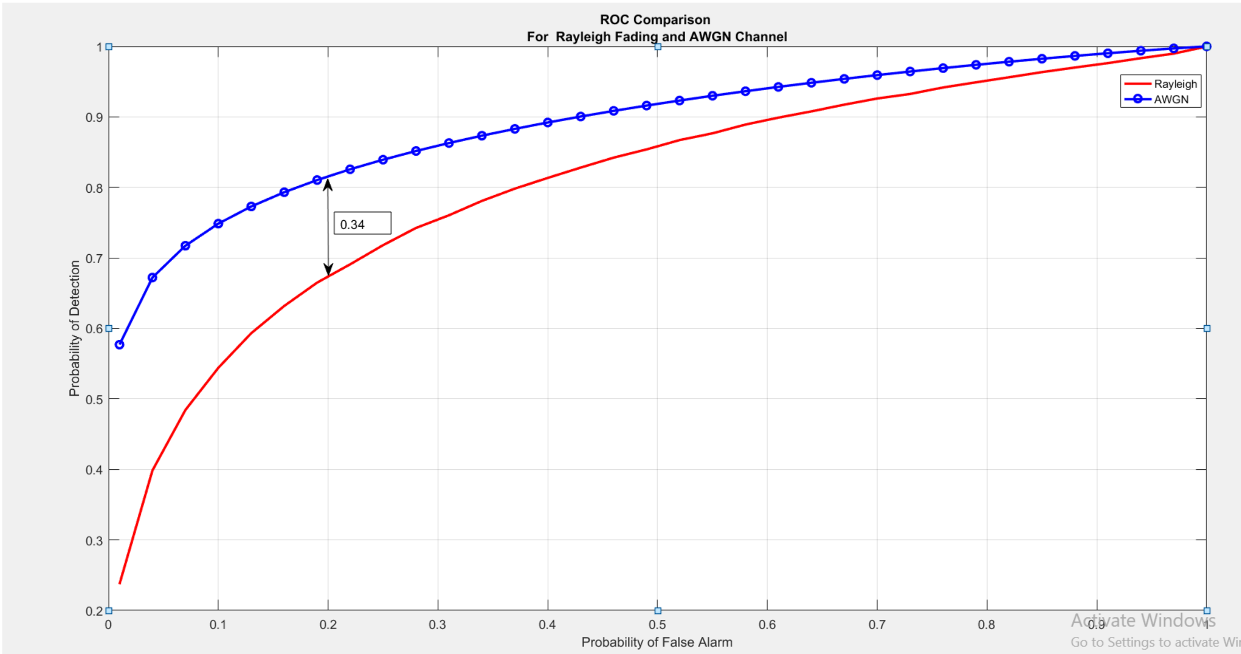


Figure 4.10: ROC for Energy Detection for AWGN and Rayleigh channel

4.2.2 ROC Curve for Energy, Hybrid and Cyclostationary Detection for Rayleigh channel

To evaluate the cyclostationary detection, a number of Monte Carlo simulations were carried out. receiver operating characteristics (ROCs) were computed by randomly generating a random signal and inserting cyclostationary signatures. Subcarriers were modulated using the Binary Phase shift key (BPSK). The data was propagated through a channel model and noise with an SNR of 4dB was added. Detection was then carried out using a signal recorded for a duration of N = 200 symbols. Finally, probabilities of detection and false alarm, P_d and P_f, were estimated by averaging 10,000 runs.

Figure 4-9 shows an enhanced ROC curve under Rayleigh fading channel model. If we see for various P_f values, P1(0.01,0.57) and P2(0.01,0.75) there is a 32% increment at the hybrid detector, at P_f =0.05, S2 (0.1,0.74) and S2(0.1,0.81) there is a 9% improvement on the hybrid detector. after P_f = 0.5, the probability detector is almost the same and attended its maximum. The cyclostationary detector performance is almost 100% even for low P_f value

To summarize, it is observed that a hybrid detector improves the probability of detector for various P_f values, as the value of P_f his low the improvement is higher.

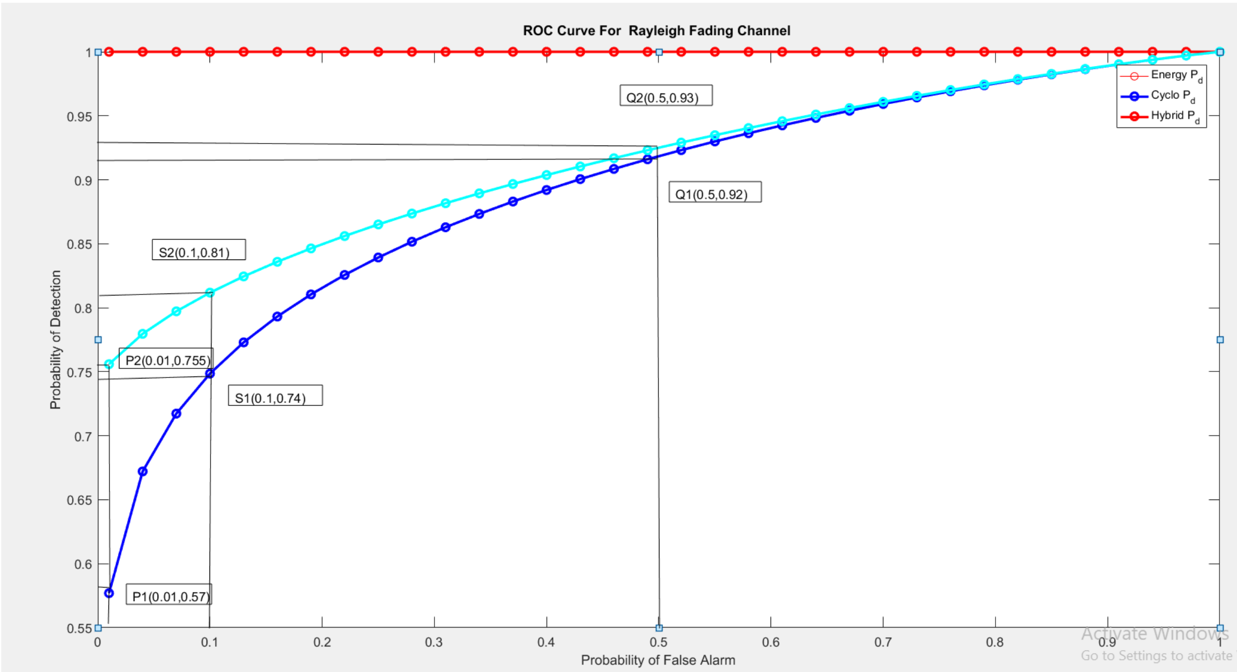


Figure 4.11: ROC Curve for Energy, Hybrid and Cyclostationary Detection for Rayleigh channel

P_{FD}	0.01	0.04	0.07	0.1	0.13	0.16	0.19	0.22
P_{ED}	0.576979	0.67211	0.717283	0.748566	0.772948	0.793123	0.810433	0.82565
P_{HD}	0.755926	0.779622	0.797212	0.811785	0.824501	0.835921	0.846369	0.856048
P_{FD}	0.25	0.28	0.31	0.34	0.37	0.4	0.43	0.46
P_{ED}	0.839263	0.851599	0.862892	0.873313	0.882993	0.892031	0.900507	0.908487
P_{HD}	0.865099	0.873622	0.881691	0.889363	0.896683	0.903688	0.910406	0.916862
P_{FD}	0.49	0.52	0.55	0.58	0.61	0.64	0.67	0.7
P_{ED}	0.916023	0.923158	0.929929	0.936365	0.942494	0.948337	0.953911	0.959234
P_{HD}	0.923075	0.929063	0.934839	0.940415	0.945801	0.951006	0.956035	0.960896
P_{FD}	0.73	0.76	0.79	0.82	0.85	0.88	0.91	0.94
P_{ED}	0.964318	0.969173	0.973809	0.97823	0.982441	0.986442	0.990227	0.993785
P_{HD}	0.965591	0.970123	0.974495	0.978704	0.98275	0.986626	0.990323	0.993824
P_{FD}	0.97	1						
P_{ED}	0.997083	1						
P_{HD}	0.997092	1						

Table 4. 6 probability of detection for Energy, Hybrid and Cyclostationary for various value of probability of false alarm.

4.2.3 Complementary ROC Curve for Relying channel

The complementary ROC curves over the Rayleigh channel for average SNR (γ) values of 4dB, time-bandwidth product d = 4, sample size N = 200 is as shown in Figure 4.12. when we analyze the complementary ROC curve it is the lower probability of miss detection (P_m) the better the method.

Figure 4.12 plots P_f vs P_m, If we compare energy and hybrid detection method, as the value of P_f increase from 0 to 1, P_m converges to 0 more quickly for the hybrid detector. Let's take two points and compare at P_f =0.2, the value of P_m is reduced by 26% for the hybrid detector as it compared with energy detector.

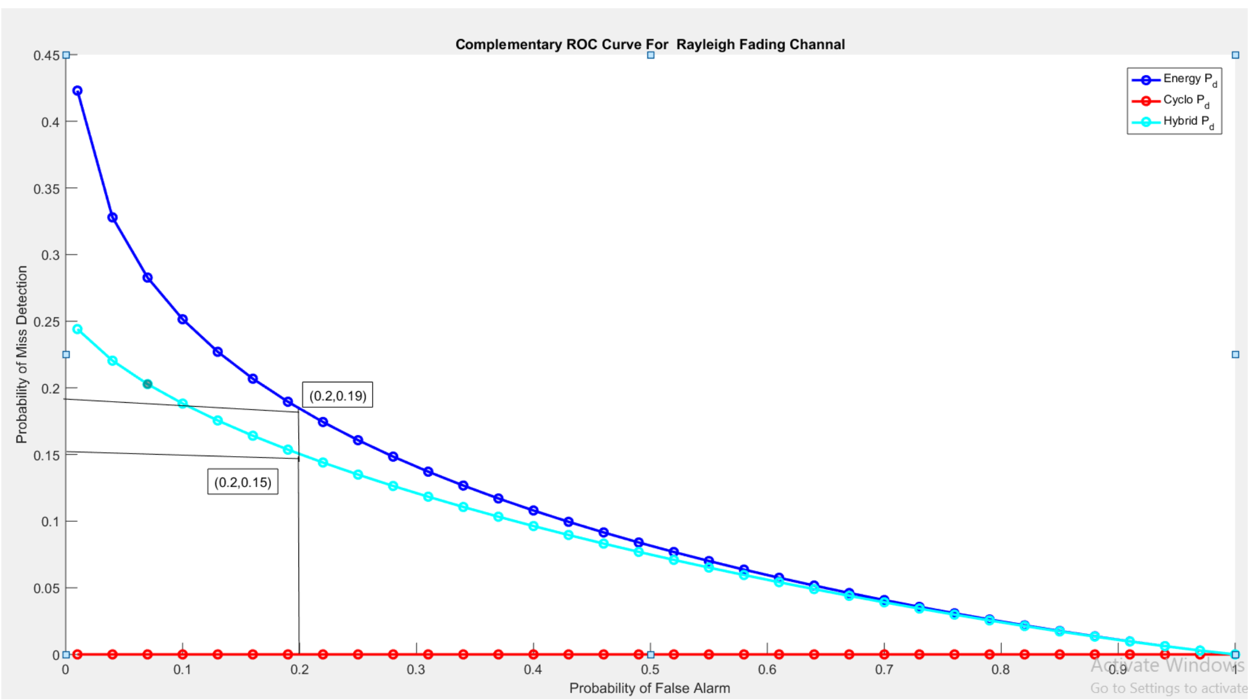


Figure 4.12 shows the complementary ROC curve for Energy, Hybrid and Cyclostationary detection for Rayleigh channel

Pf	0.01	0.04	0.07	0.1	0.13	0.16	0.19	0.22
Pm-Energy	0.423021	0.32789	0.282717	0.251434	0.227052	0.206877	0.189567	0.17435
Pm-Hybrid	0.244074	0.220378	0.202788	0.188215	0.175499	0.164079	0.153631	0.143952
Pf	0.25	0.28	0.31	0.34	0.37	0.4	0.43	0.46
Pm-Energy	0.160737	0.148401	0.137108	0.126687	0.117007	0.107969	0.099493	0.091513
Pm-Hybrid	0.134901	0.126378	0.118309	0.110637	0.103317	0.096312	0.089594	0.083138
Pf	0.49	0.52	0.55	0.58	0.61	0.64	0.67	0.7
Pm-Energy	0.083977	0.076842	0.070071	0.063635	0.057506	0.051663	0.046089	0.040766
Pm-Hybrid	0.076925	0.070937	0.065161	0.059585	0.054199	0.048994	0.043965	0.039104
Pf	0.73	0.76	0.79	0.82	0.85	0.88	0.91	0.94
Pm-Energy	0.035682	0.030827	0.026191	0.02177	0.017559	0.013558	0.009773	0.006215
Pm-Hybrid	0.034409	0.029877	0.025505	0.021296	0.01725	0.013374	0.009677	0.006176
Pf	0.97	1						
Pm-Energy	0.002917	0						
Pm-Hybrid	0.002908	0						

Table 4. 7 CROC Simulation Result of probability of miss detection of Energy and Hybrid detections for various values of probability of false alarm.

4.3 Simulation for Detection Time

In order to evaluate the detection time between energy and hybrid detector, Figure 4.13 plots Sampling numbers versus SNR for various SNR values (-30 dB to 5dB). From the plot, if we compare point P1(-25,200) and P2(-25,367) the detection time on the hybrid detector is about 1.8 times that of energy detection. As the value of SNR increases to -5dB the detection time decreases rapidly and at point S1(-5,200) and S2(-5,300) the detection time reduce to 1.5 times energy detector sampling time (detection time). For a higher SNR the sampling time reduce by 22%.

To summarized in spite of the fact that a hybrid detector method significantly improves the probability of detection as shown in the above graph figure (4.7) it is by the cost of the sampling time.

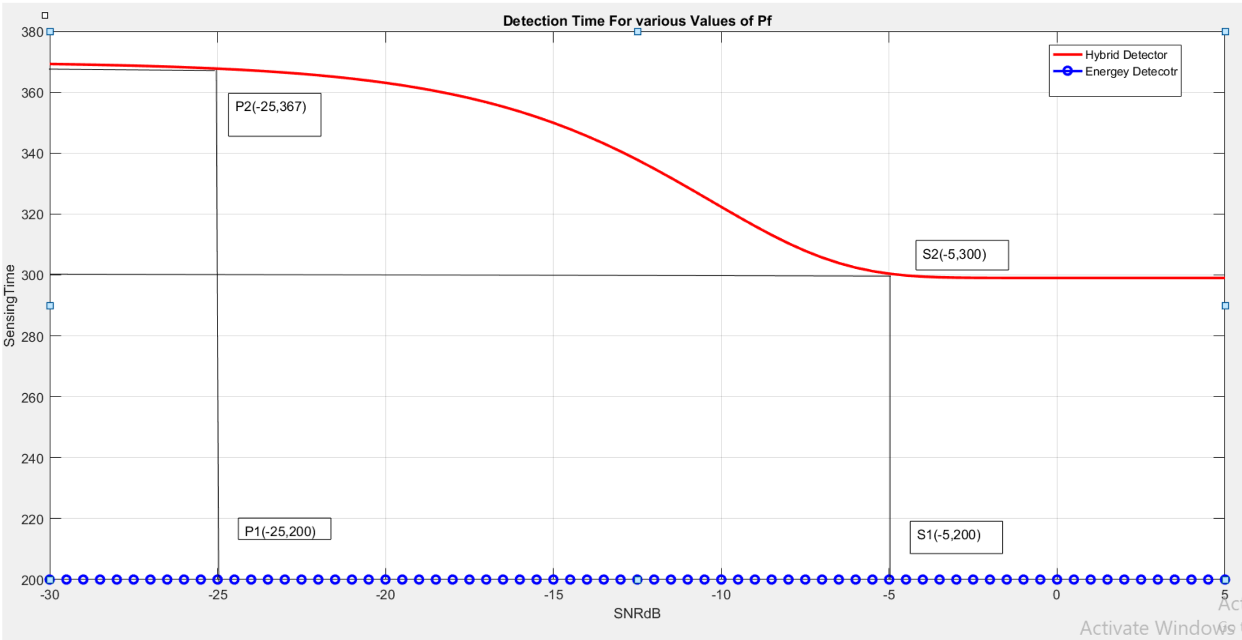


Figure 4.13 shows Detection time for Energy and Hybrid detector

Figure 4.14 shows detection time under different false alarm constraints P_f = 0.1, 0.05, 0.01 with $P0$ = 0.5 and N = 200. As the value of false alarm increases the detection time decreases as expected.

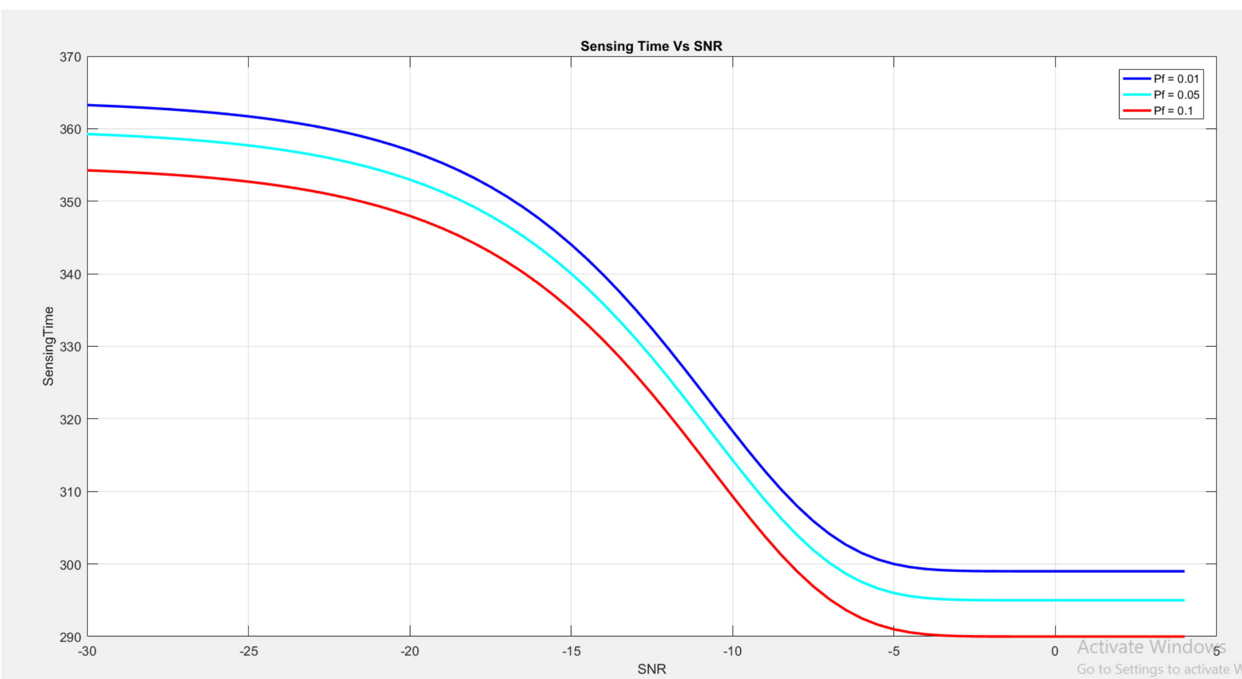


Figure 4.14 shows Detection time for Various Pf for Hybrid detector

Chapter 5

Conclusion and Recommendation

5.1. Conclusion

In this thesis, the hybrid detection method is used to enhance the detection probability for various SNR values. The mathematical formulas of the probability of detection and probability of false alarm for AWGN and Rayleigh fading channel models were incorporated. Each primary user signal is given to the energy detection method and if its PU is not detected then cyclostationary detection will apply. Based on these, various simulation plots were presented and analyzed for AWGN and Rayleigh fading channels. The results are simulated using Matlab.

For SNR vs Probability of detection plot the cyclostationary detection performs very well compare to energy detection due to the primary information is known at the receiver and the test statics calculation is the second order of the output. At the low SNR region, the energy detector performance was low. To overcome this a hybrid detector is used which improves the performance significantly. However, this improvement is not without any cost, it is observed that as the detection time increases and required more sampling number.

The Receiver operating characteristic curve has also been plotted for energy detection and cyclostationary detection. Cyclostationary detection provides a higher probability of detection of primary users for less probability of false alarms as compared to energy-based detection. But energy detection does not need prior information of the user so it is the simplest method of detection. The proposed hybrid approach of sensing uses a combination of both methods a higher probability of detection is achieved.

To summarize the simulation results, it is observed that a hybrid detector outperforms energy detector and specifically at low SNR regions, that means it improves performance over energy detector but avoids the complexity of using full cyclostationary detection at all cognitive radio system with the cost of detection time.

Based on the simulation results, the following conclusion can be drawn:

- Hybrid or combining the two known detector which is energy and cyclostationary detector improved all the performance metrics indicator considered in this thesis.
- Whenever there is a miss detection on energy detector, applying cyclostationary detection method specially at low value of signal SNR, improve the performance significantly.
- The detection time for hybrid detector is higher than that of Energy detector.

5.2. Recommendation for Future work

Some of the recommendation for further works are listed below.

- The research is done only for energy and cyclostationary detection method, so incorporating other detection method could also be investigated.
- The simulation result was limited to AWGN and Rayleigh channels model, response of Nakagami and Rican fading channel can be a good research area.
- Though various techniques have been proposed in literature, practical implementation has remained elusive. In this regard, small scale experiments need to be conducted to ascertain the reliability of this approach in real world scenarios.
- The simulation result was limited to enhance the detection probability, study on improving the detection time could be a good research area.

6. Reference

[1] Nisha Yadav, Suman Rathi, "Spectrum Sensing Techniques: Research Challenge and Limitations, IJECT Vol. 2, Issue 4, Oct - Dec. 2011.

[2] S. D. Tanuja and S. Dina. "*Spectrum sensing algorithm for cognitive radio networks for dynamic spectrum access for ieee 802.11 af standard*". InternationalJournal of Research and Reviews in Wireless Sensor Networks (IJRRWSN),2(1):77 – 84, 2012.

[3] FCC. Et docket no. 03-322. *"Notice of Proposed Rule Making and Order"*, Dec. 2003.

[4] Tevifik Yucek,Hu Seyin Arslan, "A Survey of Spectrum Sensing Algorithim for Cognitive Radio Application," IEEE Communications Survey &Tutorial, vol. 11, no. 1, pp. 116-130, Firist Quarter 2009.

[5] J. Mitola III and G. Q. Maguire, Jr., "Cognitive radio: Making software radios more personal," IEEE Personal Commuicatios Magazine, vol. 6, no. 4, pp. 13-18, Aug. 1999. DOI: 10.1109/98.788210.

[6] Simon Haykin, David J. Thomson, Jeffrey H. Reed, "*Spectrum Sensing for Cognitive Radio*," IEEE Proceeding, vol. 97, no. 5, pp. 849-877, 2009.

[7] Saman Atapattu, Chintha Tellambura and Hai Jiang,*" Energy Detection for Spectrum Sensing in Cognitive Radio"*Book, Springer New York Heidelberg Dordrecht London,2014

[8] I. F. Akyildiz, F. L. Brandon, and R. Balakrishnan. Cooperative spectrum sensing in cognitive radio networks: A survey. Physical Communication,4:40–62, 2010.

[9] D. Cabric, S. M. Mishra, and R. W. Brodersen. Implementation issues in spectrum sensing for cognitive radios. In Signals, Systems and Computers, 2004. Conference Record of the Thirty-Eighth Asilomar Conference on, volume 1, pages 772–776 Vol.1, 2004.

[10] Joseph Mitola III. Cognitive Radio-An Integrated Agent Architecture for Software Defined Radio. PhD thesis, PhD Dissertation Royal Institute of Technology (KTH) Stockholm, 2000.

[11] O. Olabiyi and A. Annamalai. Analysis of detection performance of modified periodogram over fading channels. In Consumer Communications and Networking Conference (CCNC), 2012 IEEE, pages 449–453, 2012.

[12] Veena Gawde, Dr. B. K. Mishra, Rajesh Bansode*," A Novel Hybrid Approach for Spectrum Sensing in Cognitive Radio"* International Journal of Scientific & Engineering Research, Volume 6, Issue 11, November-2015.

[13] Chinky Sharma & Jatinder Saini "*Performance Evaluation of Cyclostationary based spectrum sensing in cognitive radio network*", Automation, Computing, Communication, Control and Compressed Sensing (iMac4s), pp 90 – 97, 2013.

[14] Benyam Hailegnaw, *"SNR Enhancement of Energy Detector Algorithm using Adaptive Wiener Filter in Cognitive Radio*" Master of Communication Engineering Thesis, Addis Ababa University Institute of Technology Addis Ababa, 2016.

[15] James D. Gadze1, Oyibo, A. Michael2, Ajobiewe, N. Damilola, *"A Performance Study of Energy Detection Based Spectrum Sensing for Cognitive Radio Networks"* Department of Electrical/Electronics Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana, April 2014.

[16] Wenjing Yue1, and Baoyu Zheng1," *A Two-Stage Spectrum Sensing Technique in Cognitive Radio Systems Based on Combining Energy Detection and One-Order Cyclostationary Feature Detection*" Institute of Signal Processing and Transmission, Nanjing University of Posts and Telecommunications, Nanjing, China. May, 2009.

[17] Yiming Zhou ,Zheng Zhou ,Shibo Zhang, " An Improved Spectrum Sensing Method Energy Autocorrelation Based Detection Technology," Circuit System Signal Processing, pp. 273282, 2013.

[18] IEEE. Standard definitons and concepts for dynamic spectrum access terminology relating to emerging wireless networks, system functionality, and spectrum management, 2008.

[19] G. Baldini, R. Giuliani, D. Capriglione, and K. Sithamparanathan. A practical demonstration of spectrum sensing for wimax based on cyclostationary features. In S Cheng, editor, Foundation of Cognitive Radio Systems, pages 34–39. InTech, Croatia, 2012.

[20] R. Umar and A.U.H. Sheikh. A comparative study of spectrum awareness techniques for cognitive radio oriented wireless networks. Physical Communication, pages 1–23, July 2012.

[21] A. A. Tabassam, M. U. Suleman, S. Kalsait, and S. Khan. Building cognitive radios in matlab simulink; a step towards future wireless technology. In Wireless Advanced (WiAd), 2011, pages 15–20, 2011.

[22] L. N. T. Perera and H. M. V. R. Herath. Review of spectrum sensing in cognitive radio. In Industrial and Information Systems (ICIIS), 2011 6th IEEE International Conference on, pages 7–12, 2011.

[23] Xin Liu,Chengwen ,Xuezhi Tan, "Double Threshold Cooperative Detection For Cognitive radio Based on Weighing," Wireless Communication and Mobile Computing , pp. 12311243, 2014.

[24] Saman Atapattu, Chintha Tellambura and Hai Jiang*," Energy Detection for Spectrum Sensing in Cognitive Radio"*Book, Springer New York Heidelberg Dordrecht London,2014

[25] Omar Altrad ,Sami Muhidat, "A New Mathematical Analysis of the Probability of Detection in Cognitive Radio over Fading Channels," EURASIP Journal on wireless communication and Networking, vol. 159, 2013.

[26] H. Wang,G Noh D. Kim,S. Kim, D. Hong, "Advanced Sensing Techniques of Energy Detection in Cognitive Radios.," Journal of Communication Networks, vol. 12, no. 1, pp. 19-29, 2010.

[27] Prof.AbhijeetA.Chincholkar, Ms.Chaitali H.Thakare Yavatmal, "Matlab implementation of Spectrum Sensing Methods in Cognitive Radio," Global Journal of Engineering Science and Research Management Chin holkar, vol. 1, no. 2, pp. 2349-4506, 2014.

[28] W. Ejaz, N. Hasan, S. Lee, and H.S. Kim. I3s: Intelligent spectrum sensing scheme for cognitive radio networks. EURASIP Journal on Wireless Communications and Networking, (1):26, 2013.

[29] M. Subhedar and G. Birajdar. Spectrum sensing techniques in cognitive radio networks: A survey. International Journal of Next Generation Networks (IJNGN), 3(2):37 – 51, 2011.

[30] S. A. Ghauri, I.M. Qureshi, M. F. Sohail, S. Alam, and M. A. Ashraf. Spectrum sensing for cognitive radio networks over fading channels. International Journal of Computer and Electronics Research, 2(1):24–27, 2013.

[31] Pradeep Kumar Vermal, Mr. Sachin Taluja, Prof. Rajeshwar Lal Dua, "Performance Analysis of Energy Detection, Matched filter detection & Cyclo stationary feature detection Spectrum Sensing Techniques," Intrnational Journal of Computational Energy Research, vol. 2, no. 5, 2011.

[32] W. Gardner and C. Spooner, , " Advantages of Cyclic-feature Detectors and Signal Performance interception," IEEE Transactions on Communications, vol. 40, no. 1, pp. 149159, 1992.

[33] W. A. Gardner and C. M. Spooner. Signal interception: performance advantages of cyclic-feature detectors. Communications, IEEE Transactions on,40(1):149–159, 1992.

[34] P. S. Aparna and M. Jayasheela. Cyclostationary feature detection in cognitive radio using different modulation schemes. International Journal of Computer Applications (0975-8887), 47(21):12–16, 2012.

[35] J. T. MacDonald and D. R. Ucci. Interference temperature limits of ieee 802.11 protocol radio channels. In Electro/Information Technology, 2007 IEEE International Conference on, pages 64–69, 2007

[36] Mohamood A. Abdulasattar, Zahir A.Hussien, "Energy Detection Technique for Spectrum Sensining in Cognitive Radio : A Survey," International Journal Of Computer Networks & Communication(IJCNC), vol. 4, no. 5, 2012.

[37] L.S. Cardoso, M. Debbah, S. Lasaulce, K. Mari, and J. Palicot. Spectrum sensing in cognitive radio networks. Cognitive Radio Networks: Architectures, Protocols and Standards, 2009.

[38] W.C.V. Etten. Introduction to Random signals and Noise. John Wiley & Sons, 1st edition, 2005

[39] D. He, Y. Lin, C. Hen, and L. Jiang. Novel spectrum-sensing technique in cognitive radio based on stochastic resonance. IEEE Transactions on Vehicular Technology, 59(4):1680–1688, 2010.

[40] J. G. Proakis and S. Masoud. Digital Communications. McGraw Hill Higher Education, Boston, 5th edition, 2008.

[41] F. F. Digham, M. S. Alouini, and M. K. Simon. On the energy detection of unknown signals over fading channels. In Communications, 2003. ICC ’03. IEEE International Conference on, volume 5, pages 3575–3579 vol.5, 2003.

[42] H. Tang, “Some physical layer issues of wide-band cognitive radio system,” DySPAN, pp. 151159, Nov. 2005.)

[43] H.Urkoitz, "Energy Detection of Unknown Deterministic Signals," Proceedings Of IEE, vol. 55, no. 4, pp. 523-531, 1967.

[44] I. S. Gradshteyn and I. M. Ryzhik. Table of Integrals, Series, and Products. Academic Press, New York, 7th edition, 2007.

[45] J. Ma, G. Y. Li, and B. H. Juang. Signal processing in cognitive radio. Proceedings of the IEEE, 97(5):805–823, 2009.

[46] M. S. Alouini and A. J. Goldsmith. Capacity of rayleigh fading channels under different adaptive transmission and diversity combining techniques. IEEE Transactions on Vehicular Technology, 48(4):1165–1181, July 1999.

[47] T. Rappaport. Wireless Communications: Principle and Practice. Prentice Hall, 2nd edition, 2002.

[48] D. Horgan and Murphy C. C. Performance limits of cooperative energy detection in fading environments. In F. Simone and M. Nicola, editors, 4th International Conference on Cognitive Radio and Advanced Spectrum Management (CogART), Barcelona, Spain, 26-29 October 2011. ACM.

[49] A. H. Nuttall. Some integrals involving the q-m function. IEEE Transactions on Information Theory, 21(1):95–96, 1975.

[50] Yue, Wen-jing, Bao-yu Zheng, and Qing-min Meng, "Cyclostationary property based spectrum sensing algorithms for primary detection in cognitive radio systems", Journal of Shanghai Jiaotong University (Science) , vol. 14, no. 6, pp.676680, 2009.

[51] H.S. Chen, W. Gao, and D. Daut, "Spectrum sensing for DMBT systems using PN frame headers", IEEE International Conference (ICC), pp. 4889–4893, May 2008.

[52] M. Derakhshani, M. Nasiri-Kenari, and T. Le-Ngoc, "Cooperative cyclostationary spectrum sensing in cognitive radios at low snr regimes," in Communications (ICC), 2010 IEEE International Conference on, 2010, pp. 1–5.

[53] G. K. Yeung and W. A. Gardner, "Search-efficient methods of detection of cyclostationary signals," IEEE Trans. Signal Processing, vol. 44, no. 5, pp. 1214–1223, May 1996

[54] Dandawate, A.V., Gjannakis, G.B, "Statistical tests for presence of cyclostationary," IEEE Trans. Signal Process, 1994, 42, (9), pp. 2355–2369

[55] S. Peng, X. Yang, S. Shu, P. Zhu, and X. Cao, "Adaptive sequential cooperative energy detection scheme for primary user detection in cognitive radio," IEICE Transactions on Communications, vol. 94, no. 10, pp. 2896–2899, 2011.

[56] S.-L. Peng, X. Yang, S. Shu, and X. Cao, "Exploitation of temporal persistence for accuracy improvement in primary user detection," IET Communications, vol. 4, no. 15, pp. 1855–1864, 2010.

[57] Cordeiro, C., Challapali, K., and Ghosh, M. 2006. Cognitive phy and mac layers for dynamic spectrum access and sharing of tv bands. In Proceeding of the first international workshop on Technology and policy for accessing spectrum, ACM.

Appendix A

Definition of Functions

$$\int_{e}^{\infty} dx.x.\exp\left(\frac{-p^2x^2}{2}\right)QM(ax,b) =$$

$$\frac{1}{p^2}\exp\left(\frac{b^2}{2}\right).\{\left(\frac{p^2+a^2}{a^2}\right)^{M-1}[\exp\left(\frac{b^2}{2}.\frac{a^2}{p^2+a^2}\right)-\sum_{n=0}^{M-2}\frac{1}{n!}\left(\frac{b^2}{2}.\frac{a^2}{p^2+a^2}\right)^n]+\sum_{n=0}^{M-2}\frac{1}{n!}\left(\frac{b^2}{2}\right)^n\} \qquad (A.1)$$

$$P_d = e^{-\frac{k}{2}}\sum_{n=0}^{d-2}\frac{1}{n!}\left(\frac{k}{2}\right)^n + \frac{(1+\overline{\gamma})^{d-1}}{\overline{\gamma}}\left[e^{-\left(\frac{k}{2(1+\overline{\gamma})}\right)} - e^{-\frac{k}{2}}\sum_{n=0}^{d-2}\frac{1}{n!}\left(\frac{k\overline{\gamma}}{2(1+\overline{\gamma})}\right)\right]$$

$$\Gamma(x,a) = \int_{-\infty}^{\infty} e^{-t}e^{-(x-1)}dt \qquad (A.2)$$

$$I_a(y) = \left(\frac{y}{2}\right)^a\sum_{j=1}^{\infty}\frac{\left(\frac{y^2}{4}\right)^j}{j!\Gamma(a+j+1)} \qquad (A.3)$$

$$\Gamma(u) = \int_0^{\infty} e^{u-1}e^{-t}dt$$

Matlab code

Probability of Detection for Energy, Cyclostationary and Hybrid Detection.

```
clc
close

%% Initialize key variables.
d=0;
T_bit = 5;                % 1/T_bit is the bit rate
num_bits = 20;             % Desired number of bits in generated signal
iter = T_bit*num_bits;
fc = 0.05;                 % Desired carrier frequency (normalized units)
N0_dB = -10.0;             % Noise spectral density(average noise power)
Power_dB = 0.0;            % Signal power in decibels
N_psd = 128;               % Number of frequencies to use in PSD estimate
pf =0.01;                  % Probability of False Alarm
t =(qfuncinv(pf)+sqrt(L));
thresh = (qfuncinv(pf)./sqrt(L))+ 1;
tn = t/10;
snrdb = -30:0.5:4;
snr = 10.^(snrdb./10);
pdcm = [];
pd=[];

%% Create the baseband signal.

% Create bit sequence.

bit_seq = randi([0 1], [1 num_bits]);

% Create symbol sequence from bit sequence.

sym_seq = 2*bit_seq - 1;
zero_mat = zeros((T_bit - 1), num_bits);
sym_seq = [sym_seq ; zero_mat];
sym_seq = reshape(sym_seq, 1, T_bit*num_bits)

% Create pulse function.

p_of_t = ones(1, T_bit);

% Convolve bit sequence with pulse function.
for k = 1: length(sym_seq)
s_of_t = filter(p_of_t, [1], sym_seq)
y = (s_of_t).^2;
v = var(y);
end
for s = 1:length(snr)

    sigmab(s) = ((2*snr(s)+1)*v.^4)/(2*num_bits);
     pdcm(s) = marcumq(sqrt((num_bits*snr(s))/v.^2),sqrt(tn)/1*sigmab(s));
     pd(s) =   marcumq(sqrt(num_bits*snr(s)),sqrt(tn));
     pdm(s) = 1-(pd(s));
```

```
     pdcnew(s) = pdm(s)*pdcm(s);
     pdhf(s) = 1-(pdm(s)*(1- pdcnew(s)));



%% Frequency-shift the baseband signal and add noise.

% Apply the carrier frequency.

e_vec = exp(sqrt(-1)*2*pi*fc*[1:length(s_of_t)]);
x_of_t = s_of_t .* e_vec;

% Add noise.

n_of_t = randn(size(x_of_t)) + sqrt(-1)*randn(size(x_of_t));
noise_power = var(n_of_t);
N0_linear = 10^(N0_dB/10);
pow_factor = sqrt(N0_linear / noise_power);
n_of_t = n_of_t * pow_factor;
for i = 1:length(snr)
y_of_t1 = x_of_t + n_of_t;
end
y2 = abs((y_of_t1).^2);
energeyfinal = y2';
enerdesc = sort(energeyfinal, 'descend')';
thresh = enerdesc(ceil(pf*T_bit*num_bits));
energy = mean(y2);

%% Applying the Hybrid Detector.


    if energy < thresh
    pdh(s) = pdhf(s);
    else
    pdh(s) = pd(s);
    end
 end

hpd = plot(snrdb, pdh,'c*');
set(hpd, 'linewidth', 2);
hold on
hp = plot(snrdb,pd,'b');
set(hp, 'linewidth', 2);
hold on
hpd = plot(snrdb, pdcm,'r');
set(hpd, 'linewidth', 2);
 grid on;
xlabel('SNR(dB)');
ylabel('PD');
title('SNR to Probablity of Detection For AWGN');
legend ('Hybrid Detector','Energy Detector','Cyclostationary Detector')
```

For Various value of Pf probability of Detection Vs SNR for AWGN channel

```
 clc
 close

%% Initialize key variables.
d=0;
T_bit = 5;                % 1/T_bit is the bit rate
num_bits = 20;             % Desired number of bits in generated signal
iter = T_bit*num_bits;
fc = 0.05;                 % Desired carrier frequency(normalized units)
L = T_bit*num_bits;
N0_dB = -10.0;             % Noise spectral density(average noise power)
Power_dB = 0.0;            % Signal power in decibels
N_psd = 128;               % Number of frequencies to use in PSD estimate
pf =0.01;                  % Probability of False Alarm
pf1 =0.05;
pf2 =0.1;
t =(qfuncinv(pf)+sqrt(L));
thresh = (qfuncinv(pf)./sqrt(L))+ 1;
tn = t/10;
snrdb = -30:0.5:4;
snr = 10.^(snrdb./10);
pdcm = [];
pd=[];

%% Create the baseband signal.
% Create bit sequence.

bit_seq = randi([0 1], [1 num_bits]);

% Create symbol sequence from bit sequence.

sym_seq = 2*bit_seq - 1;
zero_mat = zeros((T_bit - 1), num_bits);
sym_seq = [sym_seq ; zero_mat];
sym_seq = reshape(sym_seq, 1, T_bit*num_bits)

% Create pulse function.

p_of_t = ones(1, T_bit);

% Convolve bit sequence with pulse function.
for k = 1: length(sym_seq)
s_of_t = filter(p_of_t, [1], sym_seq);
y = (s_of_t).^2;
v = var(y);

end

%% Frequency-shift the baseband signal and add noise.

% Apply the carrier frequency.

e_vec = exp(sqrt(-1)*2*pi*fc*[1:length(s_of_t)]);
```

```
x_of_t = s_of_t .* e_vec;
% Add noise.
n_of_t = randn(size(x_of_t)) + sqrt(-1)*randn(size(x_of_t));
noise_power = var(n_of_t);
N0_linear = 10^(N0_dB/10);
pow_factor = sqrt(N0_linear / noise_power);
n_of_t = n_of_t * pow_factor;
for i = 1:length(snr)
y_of_t1 = x_of_t + n_of_t;
end
y2 = abs((y_of_t1).^2);
energeyfinal = y2';
enerdesc = sort(energeyfinal, 'descend')';
threshh = enerdesc(ceil(pf*T_bit*num_bits));
threshh1 = enerdesc(ceil(pf1*T_bit*num_bits));
threshh2 = enerdesc(ceil(pf2*T_bit*num_bits));
energy = mean(y2);
%% detection calculation
for s = 1:length(snr)
     sigmab(s) = ((2*snr(s)+1)*v.^4)/(2*num_bits);
     pdcm(s) = marcumq(sqrt((num_bits*snr(s))/v.^2),sqrt(tn)/1*sigmab(s));
     pd(s) =   marcumq(sqrt(num_bits*snr(s)),sqrt(threshh));
     pd1(s) =   marcumq(sqrt(num_bits*snr(s)),sqrt(threshh1));
     pd2(s) =   marcumq(sqrt(num_bits*snr(s)),sqrt(threshh2));
     pdm(s) = 1-(pd(s));
     pdm1(s) = 1-(pd1(s));
     pdm2(s) = 1-(pd2(s));
     pdcnew(s) = pdm(s)*pdcm(s);
     pdhf(s) = 1-(pdm(s)*(1- pdcnew(s)));
     pdhf1(s) = 1-(pdm1(s)*(1- pdcnew(s)));
     pdhf2(s) = 1-(pdm2(s)*(1- pdcnew(s)));

%% Hybrid.
    if energy < thresh
    pdh(s) = pdhf(s);
    pdh1(s) = pdhf1(s);
    pdh2(s) = pdhf2(s);
    else
    pdh(s) = pd(s);
    end
 end
hpd = plot(snrdb, pd,'r');
set(hpd, 'linewidth', 2);
hold on
hpd = plot(snrdb, pd1,'c');
set(hpd, 'linewidth', 2);
hold on
hp = plot(snrdb,pd2,'b');
set(hp, 'linewidth', 2);
hold on
grid on;
xlabel('SNR(dB)');
ylabel('PD');
title('SNR to Probablity of Detection For Various Pf');
legend ('Pf = 0.01','Pf = 0.05','Pf = 0.1')
```

ROC Curve

```
clc
close all
clear all
L = 10; % Number of sensing samples
iter =10^5; % Number of iterations for Monte Carlo Simulation
Pf =0.01:0.03:1; % Probability of False Alarm
snr_db = 0; % Signal-to-noise ratio (SNR) in dB
snr = 10.^(snr_db./10); % SNR in linear scale
for tt = 1:length(Pf) % Calculating threshold for each value of Pf
 energy_fin = []; % Initialization
 n = [];
 y = [];
 energy = [];
 energy_fin = [];

 n=randn(iter,L); % Gaussian noise, mean 0, variance 1
 y = n; % Received signal at the secondary user under the hypothesis H0
 energy = abs(y).^2; % Energy of received signal over L sensing samples under
the hypothesis H0
for kk=1:iter % Start simulation loop to calculate the threhsold
 energy_fin(kk,:) =sum(energy(kk,:)); % Test Statistic of the energy
detection
end
energy_fin = energy_fin'; % Taking transpose to arrage values in descending
order
energy_desc = sort(energy_fin,'descend')'; % Arrange values in descending
order
thresh_sim(tt) = energy_desc(ceil(Pf(tt)*iter)); % Threshold obtained by
simulations; the first 'Pf' fraction of values lie above the threshold
end

%% Simulated probability of detection for Rayleigh channel

for tt = 1:length(Pf)

    s = []; % Initializtion
    h = []; % Initializtion


    mes = randi([0 1],iter,L); % Generating 0 and 1 with equal probability
for BPSK
    s = (2.*(mes)-1); % BPSK modulation
    h1 = (randn(iter,1)+j*randn(iter,1))./(sqrt(2)); % Generating Rayleigh
channel coefficient
    h = repmat(h1,1,L); % Slow-fading is considered, i.e., the channel
remains the same during the senisng process.
    y = sqrt(snr).*s + n; % Received signal y at the secondary user, abs(h)
is the Rayleigh channel gain.
    energy = (abs(y).^2);  % Received energy under the hypotheis H1
    v = sum(var(y))/L;
    sigma = ((2*snr+1)*v.^4)/2*L+1;

for kk=1:iter % Number of Monte Carlo Simulations
```

```
    energy_fin(kk) =sum(energy(kk,:)); % Test Statistic for the energy
detection undet the hypothesis H1
end
c=sqrt(2*L*snr);
d(tt) = sqrt(thresh_sim(tt));
Pde(tt)=marcumq(sqrt(2*L*snr),sqrt(thresh_sim(tt)));
a = sqrt((2*snr)/v.^2);
b(tt) = thresh_sim(tt)/sigma;
Pdc(tt)=marcumq(sqrt((2*snr)/v.^2),thresh_sim(tt)/sigma);
pc(tt) = 1-(Pde(tt));
pdcnew(tt) = pc(tt)*Pdc(tt);
pdhf(tt) = 1-pc(tt)*(1- pdcnew(tt));
if (energy_fin >= thresh_sim(tt)); % Checking whether the received energy
above the threshold
    pdh(tt) = Pde(tt);
else
    pdh(tt) = pdhf(tt);
end
end
hc = plot(Pf,Pdc,'r')
set(hc,'linewidth',2)
hold on
hh = plot(Pf,pdh,'c')
set(hh,'linewidth',2)
hold on
hd = plot(Pf,Pde,'b')
set(hd,'linewidth',2)
grid on
title('ROC Curve for AWGN Cyclostationary Detection')
title('ROC Curve for AWGN channel')
legend('Cyclo P_d','Hybrid P_d','Energey p_d')
xlabel('Probability of False Alarm')
ylabel('Probability of Detection')
hold on
```

QPSK Pd vs SNR for the Energy, Cyclostatinary and Hybrid detector

```
clc
close

%% Initialize key variables.
d=0;
T_bit = 5;                % 1/T_bit is the bit rate
num_bits = 20;             % Desired number of bits in generated signal
iter = T_bit*num_bits;
fc = 0.00005;                % Desired carrier frequency(normalized units)
L = T_bit*num_bits;
N0_dB = -10.0;             % Noise spectral density(average noise power)
Power_dB = 0.0;            % Signal power in decibels
N_psd = 128;               % Number of frequencies to use in PSD estimate
pf =0.01;                  % Probability of False Alarm
% thresh = (qfuncinv(pf)./(sqrt(L))+ 1);
t=0:.01:.99;
```

```
snrdb = -13:1:10;
snr = 10.^(snrdb./10);
pdcm = [];
pd=[];
c=cos(2*pi*10*t);
%% Create the baseband signal.

% Create bit sequence.

bit_seq = randi([0 1], [1 num_bits]);

% Create symbol sequence from bit sequence.

sym_seq = 2*bit_seq - 1;
zero_mat = zeros((T_bit - 1), num_bits);
sym_seq = [sym_seq ; zero_mat];
sym_seq = reshape(sym_seq, 1, T_bit*num_bits);

% Create pulse function.

p_of_t = ones(1, T_bit);

% Convolve bit sequence with pulse function.
for k = 1: length(sym_seq)
s_of_t = filter(p_of_t, [1], sym_seq);
qpsk=[];

for i = 1:2:100
    if s_of_t(i)==1 &&  s_of_t(i+1)==-1
        qpsk=[qpsk cos(2*pi*10*t+(pi/4))];
        else if s_of_t(i)==0 && s_of_t(i+1)==-1
        qpsk=[qpsk cos(2*pi*10*t+(3*pi/4))];
        else if s_of_t(i)==-1 && s_of_t(i+1)==1
        qpsk=[qpsk cos(2*pi*10*t+(5*pi/4))];
        else if s_of_t(i)==1 && s_of_t(i+1)==1
        qpsk=[qpsk cos(2*pi*10*t+(7*pi/4))];
                end;
            end;
        end;
    end;
end;
modsig=[];
for l=1:1:10

    for j=1:10
        k = (l+j);
          p=qpsk(i+j);
          modsig=[modsig p];
    end;
end;
y = (s_of_t).^2;
v = 1;
thres =gaminv(pf,L/2,2/L);

 end
for s = 1:length(snr)
```

```
     sigmab(s) = ((2*snr(s)+1)*v.^4)/(2*num_bits);
     pdcm(s) = marcumq(sqrt((num_bits*snr(s))/v.^2),(thres)/1*sigmab(s));
     pd(s) =   marcumq(sqrt(num_bits*snr(s)),sqrt(thres));
     pdm(s) = 1-(pd(s));
     pdcnew(s) = pdm(s)*pdcm(s);
     pdhf(s) = 1-(pdm(s)*(1- pdcnew(s)));


%% Frequency-shift the baseband signal and add noise.

% Apply the carrier frequency.
c=cos(2*pi*10*t)

e_vec = exp(sqrt(-1)*2*pi*fc*[1:length(s_of_t)]);

x_of_t = s_of_t .* e_vec;

% Add noise.

n_of_t = randn(size(x_of_t)) + sqrt(-1)*randn(size(x_of_t));
noise_power = var(n_of_t);
N0_linear = 10^(N0_dB/10);
pow_factor = sqrt(N0_linear / noise_power);
n_of_t = n_of_t * pow_factor;
for i = 1:length(snr)
y_of_t1 = modsig + n_of_t;
end
y2 = abs((y_of_t1).^2);
energeyfinal = y2';
enerdesc = sort(energeyfinal, 'descend')';
energy = snr*mean(y2);
%% Estimate PSD and plot.

num_blocks = floor(length(y_of_t1) / N_psd);
S = y_of_t1(1, 1:(N_psd*num_blocks));
S = reshape(S,  N_psd, num_blocks);
I = fft(S);
I = I.* conj(I);
I = sum(I.');
I = fftshift(I);
I = I /(num_blocks * N_psd);
Iave = mean(I);

freq_vec = [0:(N_psd-1)]/N_psd - 0.5;
for d = 1:length(snrdb)
    if energy(s) < thres
   pdh(s) = pdhf(s);
    else
     pdh(s) = pd(s);
    end
 end
end
hpd = plot(snrdb, pdcm,'r');
set(hpd, 'linewidth', 2);
hold on
hpd = plot(snrdb, pdh,'c-o');
```

```
set(hpd, 'linewidth', 2);
hold on
hp = plot(snrdb,pd,'b-o');
set(hp, 'linewidth', 2);
hold on
grid on;
xlabel('SNRDB');
ylabel('PD');
title('QPSK SNR to Probablity of Detection For AWGN');
legend ('PDenergy','PDhybrid','PDcyclostationary')
```

ROC CURVE for Rayleigh Fading

```
clc
close all
clear all

%% Initialize key variables.

T_bit = 10;              % 1/T_bit is the bit rate
num_bits = 40;         % Desired number of bits in generated signal
iter = 10^5;
fc = 0.05;               % Desired carrier frequency (normalized units)
N0_dB = -10.0;           % Noise spectral density(average noise power)
Power_dB = 0.0;          % Signal power in decibels
N_psd = 500;             % Number of frequencies to use in PSD estimate
bit_seq = randi([0 1], [1 num_bits]);
Pf =0.01:0.03:1; % Probability of False Alarm
thresh_theory = 2*gammaincinv(1-Pf,T_bit/2);
snr_db = 4; % Signal-to-noise ratio (SNR) in dB
snr = 10.^(snr_db./10); % SNR in linear scale

% Create symbol sequence from bit sequence.

sym_seq = 2*bit_seq - 1;
zero_mat = zeros((T_bit - 1), num_bits);
sym_seq = [sym_seq ; zero_mat];
sym_seq = reshape(sym_seq, 1, T_bit*num_bits);

% Create pulse function.

p_of_t = ones(1, T_bit);
% Convolve bit sequence with pulse function.
s_of_t = filter(p_of_t, [1], sym_seq);


% Apply the carrier frequency.

e_vec = exp(sqrt(-1)*2*pi*fc*[1:length(s_of_t)]);
x_of_t = s_of_t .* e_vec;

% Add noise.
n_of_t = randn(size(x_of_t)) + sqrt(-1)*randn(size(x_of_t));
noise_power = var(n_of_t);
```

```
N0_linear = 10^(N0_dB/10);
pow_factor = sqrt(N0_linear / noise_power);
n_of_t = n_of_t*pow_factor;

%%raylign
 h1 = randn(size(x_of_t)) + sqrt(-1)*randn(size(x_of_t))./(sqrt(2)); %
Generating Rayleigh channel coefficient
 h = repmat(h1,1,1); % Slow-fading is considered, i.e., the channel remains
the same during the senisng process.
y_of_t = abs(h).*x_of_t
plot(y_of_t);
 y_of_t = x_of_t + n_of_t;

 %% Estimate PSD and plot.
for tt = 1:length(Pf)
num_blocks = floor(length(y_of_t) / N_psd);
S = y_of_t(1, 1:(N_psd*num_blocks));
S = reshape(S,  N_psd, num_blocks);
I = fft(S);
I = I .* conj(I);
I = sum(I.');
I = fftshift(I);
I = I /(num_blocks * N_psd);
meas_pow = sum(I) *(1.0/N_psd);
plot(S);
for kk=1:N_psd % Number of Monte Carlo Simulations
   Ss(kk) =sum(S(kk,:)); % Test Statistic for the energy detection undet the
hypothesis H1
Sfinal = abs(Ss);
end
Sfinal = Sfinal'; % Taking transpose to arrage values in descending order
S_desc = sort(Sfinal,'descend')'; % Arrange values in descending order
thresh_sim(tt) = S_desc(ceil(Pf(tt)*N_psd)); % Threshold obtained by
simulations; the first 'Pf' fraction of values lie above the threshold

upper = (Sfinal >= thresh_sim(tt)); % Checking whether the received energy
above the threshold
    i = sum(upper); % Count how many times out of 'iter', the received energy
is above the threshold.
     Pd_cyclo(tt) = i/kk; % Calculation of the probability of detection
(simulated)
end
plot(Pf,Pd_cyclo,'r-o')
hold on

%% Probability of detection: Rayleigh Fading
thresh_theory = 2*gammaincinv(1-Pf,T_bit/2);% Theory threhsold, from the
formula of Pf = gammainc(thresh_theory./(2), L/2,'upper')
temp1 = snr*T_bit/2;
Pd_enery  = [];
A = temp1./(1 + temp1);
u = T_bit./2; % Time-Bandwidth product
for pp = 1:length(Pf)
    n = 0:1:u-2;
    term_sum1 = sum((1./factorial(n)).*(thresh_theory(pp)./2).^(n));
    term_sum2 = sum((1./factorial(n)).*(((thresh_theory(pp)./2).*(A)).^(n)));
```

```
    Pd_enery(pp) = exp(-thresh_theory(pp)./2).*term_sum1 + (1./A).^(u-
1).*(exp(-thresh_theory(pp)./(2.*(1+temp1))) - exp(-
thresh_theory(pp)./2).*term_sum2); %---------(2) Theory Probability of
detection for Rayleigh
end
pcyco = 1-Pd_enery % probablity of going to cyclostatinary detection
phcyclo = pcyco.*Pd_cyclo % probablity of cyclostationary after the second
trial
pd_hybrid = 1-pcyco.*(1-phcyclo) % probablity of detection for hybrid
algorithm
if (Sfinal <= thresh_sim(tt))
    pd_final =pd_hybrid
else
    pd_final = Pd_enery
end
%% ploting the graph

hpd = plot(Pf,Pd_enery,'b-o');
set(hpd, 'linewidth', 2);
hold on
hc =plot(Pf,Pd_cyclo,'r-o');
set(hc,'linewidth',2);
hold on
hh =plot(Pf, pd_final, 'c-o');
set(hh,'linewidth',2);
title('ROC Curve For  Rayleigh Fading Channel')
 legend('Energy P_d','Cyclo P_d', 'Hybrid P_d')
 xlabel('Probability of False Alarm')
 ylabel('Probability of Detection')
```

complementary ROC CURVE for Rayleigh Fading

```
clc
close all
clear all

%% Initialize key variables.

T_bit = 10;              % 1/T_bit is the bit rate
num_bits = 40;           % Desired number of bits in generated signal
iter = 10^5;
fc = 0.05;                % Desired carrier frequency(normalized units)
N0_dB = -10.0;           % Noise spectral density(average noise power)
Power_dB = 0.0;           % Signal power in decibels
N_psd = 500;             % Number of frequencies to use in PSD estimate
bit_seq = randi([0 1], [1 num_bits]);
Pf =0.01:0.03:1; % Probability of False Alarm
thresh_theory = 2*gammaincinv(1-Pf,T_bit/2);
snr_db = 4; % Signal-to-noise ratio (SNR) in dB
snr = 10.^(snr_db./10); % SNR in linear scale

% Create symbol sequence from bit sequence.

sym_seq = 2*bit_seq - 1;
zero_mat = zeros((T_bit - 1), num_bits);
```

```
sym_seq = [sym_seq ; zero_mat];
sym_seq = reshape(sym_seq, 1, T_bit*num_bits);

% Create pulse function.

p_of_t = ones(1, T_bit);
% Convolve bit sequence with pulse function.
s_of_t = filter(p_of_t, [1], sym_seq);


% Apply the carrier frequency.

e_vec = exp(sqrt(-1)*2*pi*fc*[1:length(s_of_t)]);
x_of_t = s_of_t .* e_vec;

% Add noise.
n_of_t = randn(size(x_of_t)) + sqrt(-1)*randn(size(x_of_t));
noise_power = var(n_of_t);
N0_linear = 10^(N0_dB/10);
pow_factor = sqrt(N0_linear / noise_power);
n_of_t = n_of_t*pow_factor;

%% Rayleigh
 h1 = randn(size(x_of_t)) + sqrt(-1)*randn(size(x_of_t))./(sqrt(2)); %
Generating Rayleigh channel coefficient
 h = repmat(h1,1,1); % Slow-fading is considered, i.e., the channel remains
the same during the senisng process.
y_of_t = abs(h).*x_of_t
y_of_t1 = y_of_t + n_of_t;

 %% Estimate PSD and plot.
for tt = 1:length(Pf)
num_blocks = floor(length(y_of_t) / N_psd);
S = y_of_t1(1, 1:(N_psd*num_blocks));
S = reshape(S,  N_psd, num_blocks);
I = fft(S);
I = I .* conj(I);
I = sum(I.');
I = fftshift(I);
I = I /(num_blocks * N_psd);
meas_pow = sum(I) *(1.0/N_psd);
for kk=1:N_psd % Number of Monte Carlo Simulations
   Ss(kk) =sum(S(kk,:)); % Test Statistic for the energy detection undet the
hypothesis H1
Sfinal = abs(Ss);
end
Sfinal = Sfinal'; % Taking transpose to arrage values in descending order
S_desc = sort(Sfinal,'descend')'; % Arrange values in descending order
thresh_sim(tt) = S_desc(ceil(Pf(tt)*N_psd)); % Threshold obtained by
simulations; the first 'Pf' fraction of values lie above the threshold

    upper = (Sfinal >= thresh_sim(tt)); % Checking whether the received
energy above the threshold
    i = sum(upper); % Count how many times out of 'iter', the received energy
is above the threshold.
```

```
    Pd_cyclo(tt) = i/kk; % Calculation of the probability of detection
(simulated)
    Pm_cyclo(tt) = 1- Pd_cyclo(tt);

end
hold on

%% Probability of detection Rayleigh Fading
thresh_theory = 2*gammaincinv(1-Pf,T_bit/2);% Theory threhsold, from the
formula of Pf = gammainc(thresh_theory./(2), L/2,'upper')
temp1 = snr*T_bit/2;
Pd_enery  = [];
A = temp1./(1 + temp1);
u = T_bit./2; % Time-Bandwidth product
for pp = 1:length(Pf)
    n = 0:1:u-2;
    term_sum1 = sum((1./factorial(n)).*(thresh_theory(pp)./2).^(n));
    term_sum2 = sum((1./factorial(n)).*(((thresh_theory(pp)./2).*(A)).^(n)));
    Pd_enery(pp) = exp(-thresh_theory(pp)./2).*term_sum1 + (1./A).^(u-
1).*(exp(-thresh_theory(pp)./(2.*(1+temp1))) - exp(-
thresh_theory(pp)./2).*term_sum2); %---------(2) Theory Probability of
detection for Rayleigh
    Pm_energey(pp) = 1- Pd_enery(pp);
end
pcyco = 1-Pd_enery % probablity of going to cyclostatinary detection
phcyclo = pcyco.*Pd_cyclo % probablity of cyclostationary after the second
trial
pd_hybrid = 1-pcyco.*(1-phcyclo) % probablity of detection for hybrid
algorithm
pm_hybrid  = 1- pd_hybrid
if (Sfinal <= thresh_sim(tt))
    pm_final =pm_hybrid
else
    pm_final = Pm_energey
end
%% ploting the graph

hpd = plot(Pf,Pm_energey,'b-o');
set(hpd, 'linewidth', 2);
hold on
hc =plot(Pf,Pm_cyclo,'r-o');
set(hc,'linewidth',2);
hold on
hh =plot(Pf,pm_final,'c-o');
set(hh,'linewidth',2);
title('Complementary ROC Curve For  Rayleigh Fading Channal')
 legend('Energy P_d','Cyclo P_d','Hybrid P_d')
 xlabel('Probability of False Alarm')
 ylabel('Probability of Miss Detection')
```

Detection Time

```
clc
close

Pf = 0.05;
Pf2 = 0.1;
Pf3 = 0.01;
N=200;
T_bit = 5;
num_bits = 20;
Pd2 = 0.8;
tr = 0.7;
SNRdb = -30:0.5:4;
SNR = 10.^(SNRdb./10);
threshh = enerdesc(ceil(Pf*T_bit*num_bits));
for s = 1:length(SNRdb)
  pd(s) =   marcumq(sqrt(2*num_bits*SNR(s)),sqrt(threshh));
NHyb(s) = N/2*(4-Pf-pd(s));
NHyb2(s) = N/2*(4-Pf2-pd(s));
NHyb3(s) = N/2*(4-Pf3-pd(s));

end


hpd = plot (SNRdb, NHyb3,'b');
set(AvED, 'linewidth', 2);
hold on
hpd = plot(SNRdb, NHyb,'c');
set(hpd, 'linewidth', 2);
hold on
hpd = plot(SNRdb, NHyb2,'r');
set(hpd, 'linewidth', 2);
grid on;
xlabel('SNR');
ylabel('SensingTime');
title('Sensing Time Vs SNR');
legend ('Pf = 0.01','Pf = 0.05','Pf = 0.1')
```