

PERFORMANCE ANALYSIS OF NARROW BAND SPECTRUM SENSING OVER DIFFERENT FADING CHANNELS IN COGNITIVE RADIO

by

Md. Rasheduzzaman Rashed
ID No. 1409556

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Department of Electronics and Communication Engineering
Khulna University of Engineering and Technology
Khulna- 9203, Bangladesh.

Declaration

This is to certify that the thesis work entitle “Performance Analysis of Narrow Band Spectrum Sensing over Different Fading Channels in Cognitive Radio” has been carried by Md. Rasheduzzaman Rashed in the Department of Electronics and Communication Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh. The above thesis work or any part of this work has not been submitted anywhere for the award of any degree or diploma.

Dr. Sk. Shariful Alam
Associate Professor
Dept of E.C.E, KUET
Thesis Supervisor

Md. Rasheduzzaman Rashed
Student, M.Sc. Engineering
Roll No. 1409556

Approval

This is to certify that the thesis work submitted by Md. Rasheduzzaman Rashed entitled Performance Analysis of Narrow Band Spectrum Sensing over Different Fading Channels in Cognitive Radio” has been approved by the board of examiners for the partial fulfillment of the requirements for the degree of M. Sc. Eng in the department of Electronics and Communication Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh in August 2016.

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Head of the Department
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ABSTRACT

Due to rapid advancements in wireless communication the scarcity of radio spectrums are decreasing day by day. To ensure the future efficient wireless communication services, the radio spectrum management is a very important factor. To cope up with this demand, cognitive radio (CR) is a solution of huge prospect for spectrum sensing in order to detect and utilize empty spaces in the spectrum without creating interference to the primary users (PUs). The CR is referred to an intelligent and reconfigurable radio which enables efficient usages of unused spectrum while avoiding any kind of interference. Spectrum sensing is the key element in CR network for identifying the opportunity and to avoid the interference of PUs. The sensing methodology of spectrum depends upon its band of interest, surrounding environments, knowledge of pattern of PUs, required accuracy, required time of detection, power consumption and complexity & cost of the device.

This work focus on the formulation of mathematical system model for classical narrow band transmitter based detection which includes energy detector (ED) based sensing techniques, cyclostationary features detection and matched filtering and the simulation and performance analysis of their characteristics curve by MATLAB software. Finally, the work has recommended the best techniques for optimum performance of narrow band spectrum sensing over different fading environments.

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LIST OF ACRONYMS

CR	Cognitive Radio
CRN	Cognitive Radio Network
FCC	Federal Communication Commission
SDR	software Defined Radio
RF	Radio Frequency
FSA	Fixed Spectrum Access
PU	Primary Users
SU	Secondary Users
QoS	Quality of Service
ADC	Analog to Digital Converter
CSMA	Carrier Sense Multiple Accessing
DSA	Dynamic Spectrum Sensing
PDA	Personal Digital Assistance
AWGN	Additive White Gaussian Noise
BPF	Bandpass Filter
SNR	Signal to Noise Ratio
ROC	Receiver Operating Characteristics
CS	Compressive Sensing
$r(t)$	Received Signal
$s(t)$	Primary Signal
T	Observation Time
λ_E	Fixed Threshold
Y	Decision Metric
P_D	Probability of Detection
γ	SNR
P_F	Probability of False Alarm
$Q_m(a,b)$	Generalized Marcum Q-function
$\Gamma(a, b)$	Incomplete Gamma Function
$f_y(x)$	Probability Distribution Function (PDF) of SNR
LoS	Line of Sight
K	Rician Factor
SCF	Spectral Correlation Function
b_i	Basis Coefficient

Chapter I

Introduction

1.1 Motivations: Spectrum Sensing for Dynamic Spectrum Access

The available Electromagnetic Spectrum is becoming overcrowded day by day due to remarkable increment in wireless devices and transition from voice only communication to video applications. The current static frequency allocation schemes cannot accommodate the requirements of higher data rate devices. To cope up with this demand, Cognitive Radio (CR) is a solution of huge prospect which can ensure the efficient use of the radio that can adjust its radio resources. Spectrum sensing is a task of obtaining awareness about the spectrum uses and existence of primary users in a geographical area [1]. As per the definition adopted by Federal Communication Commission (FCC); Cognitive radio; A radio or system that senses its operational electromagnetic environment and can dynamically and automatically adjust radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interpretability, access secondary markets [2].

CR represents a possible solution to the problem of scarcity, due to the variety of bandwidth demanding newly developed wireless communication technology allows in principle flexible and agile access to the spectrum as well as improving spectrum efficiency substantially [3]. CR can be described as an intelligent and dynamically reconfigurable radio that can adjust its radio parameters in response to surrounding environment [3]. The ability of CR depends largely on its spectrum sensing, since it provides device excess to one spectrum band while avoiding interference to the other devices [4]-[7]. CR has been made feasible by advances such as software defined radio (SDR), machine learning techniques and smart antennas [8]. CR signifies a radio that employs model-based reasoning to achieve a specified level of competence in radio related domain [9].

One of the most important components of the cognitive radio concept is the ability to measure, sense, learn, and be aware of the parameters related to the radio channel characteristics, availability of spectrum and power, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. In cognitive radio terminology, primary users can be defined as the users who have higher priority or legacy rights on the usage of a specific part of the spectrum. On the other hand, secondary users, which have lower priority, exploit this spectrum in such a way that they do that they do not cause interference to primary users. Therefore, secondary users need to have cognitive radio capabilities, such as sensing the spectrum reliably to check whether it is being used by a primary user and to change the radio parameters to exploit the unused part of the spectrum[1].The designers of co-operative spectrum sensing scheme should

consider bandwidth usages for sharing the spectrum sensing data while improving spectrum sensing performance

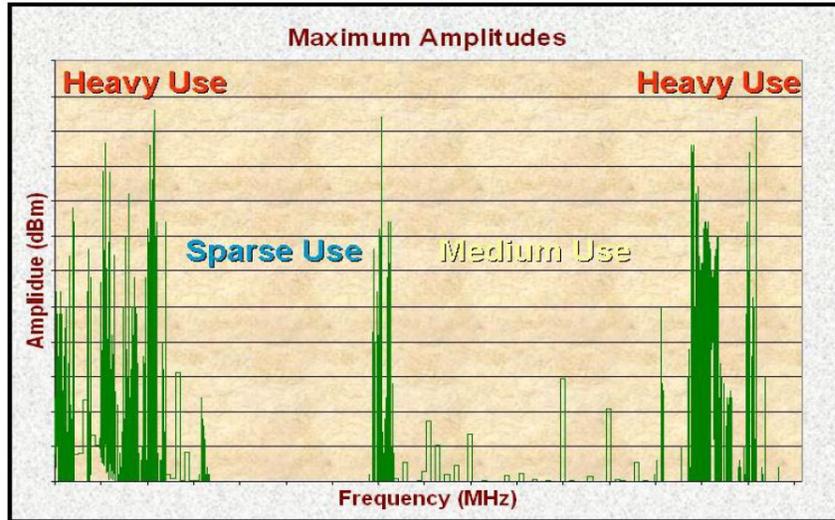


Figure 1.1: Spectrum allocation and spectrum usages measured from

The precious radio frequency (RF) spectrum is allocated by government spectrum regulators. In order to support various types of wireless devices and different kinds of services without interfering, spectrum regulators adopt a traditional fixed spectrum access (FSA) policy, which assigns each band of RF spectrum with particular bandwidth to wireless primary users. However, with the increase of new wireless products, especially the widely usage of machine-to-machine products [10] in the future, the spectrum demand is constantly increasing while, in several counties, most of the available spectrum has been fully utilized, which evidently shows that spectral resource will no longer be enough for new wireless products by using FSA police. On the other hand, a primary user is wasting its allocated spectrum when it is assigned a certain spectrum, but actually unused it. Recent researches on the measurements of actual spectrum utilization in Fig. 1.1 also have shown that only some portions of the whole spectrum have been highly used while large portions of them are severely under-utilized. For instance, the spectrum between 30 MHz and 3 GHz in New York, the maximal occupancy has been measured to be 13.1%, while the average occupancy from six locations is 5.2% [11].

To resolve the spectral scarcity problem mentioned above, cognitive radio (CR) is proposed to advance spectral usage [12]. The federal communications commission (FCC) allows secondary user (SU) to enter into one spectrum band when the primary user (PU) does not use its band after adopting CR techniques [2]. As Figure 1.2 shows, cognitive radio is designed to sense, detect surrounding PUs' state: 1) when PU is absent, SU reuses PUs' spectrum hole. 2) when PU is present, SU retreats from the PU spectrum hole. Thus, spectrum sensing is a critical part for a SU operation since all other SU's activities depend on the sensing result. Up to now, researchers have developed several local techniques to improve spectrum sensing performance [11]-[13]. However, these local techniques are not always

reliable and cannot provide a satisfactory detection performance when multipath and shadowing effects exist [14]. In many other wireless networks, relays have been introduced to solve the multipath and shadowing effects [15], [16].

1.2 Preliminaries of Cognitive Radio Networks

Most of today's radio systems are not aware of their radio system environment as they are designed to operate in a predefined frequency band using a specific spectrum access system. Overall spectrum illustration can be improved significantly by allowing secondary licensed users to dynamically access spectrum holes temporarily unoccupied by the primary user in the geographical region of interest as shown in the below figure. Here, I would like to highlight some basic features which are related to CR for better understanding.

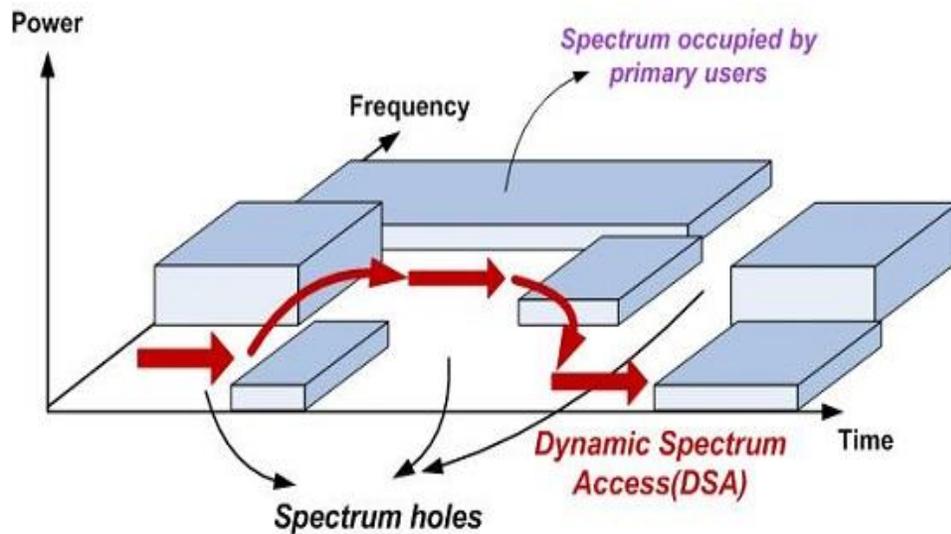


Figure 1.2: The concept of accessing spectrum hole dynamically

1.2.1 Spectrum Holes

Spectrum holes can be defined as band of frequencies which are currently vacant for the use of the PU in a specific time and geographic area [2]. It represents the potential opportunities for non-interfering (safe) use of spectrum and can be considered as multidimensional regions within frequency, time, and space. The spectrum holes can be identified in the following frequency and time.

1. **Spectrum Hole in Frequency Domain:** The activities of CR in this continuous band of frequencies do not cause any harmful interference to the PUs. By using modern spectrum sensing techniques, CR can explore the spectrum holes and avail the opportunity to access and use the holes without being degrading the performance of PUs or license users available in part of the frequency spectrum. The available spectrum is divided into narrower channels of bands.

Spectrum opportunity in this dimension means that all the bands are not used simultaneously at the same time, i.e some bands might be available for opportunistic usages.

2. ***Spectrum Hole in Time Domain:*** The spectrum hole in time domain can be defined as a frequency band which is not presently used by the PUs for a certain period of time. This involves the availability of a specific part of the spectrum in time. In other words, the band is not continuously used. There will be times where it will be available for opportunistic use.
3. ***Spectrum Hole in Spatial Domain:*** The spectrum can be available in some parts of the geographical area while it is occupied in some other parts at a given time. This takes the advantages of propagation loss in space. This measurement can be avoided by simply looking into the interference levels. No interference means no primary users transmission in a local area.

1.2.2 Radio Spaces

Radio space can be defined as “a theoretical hyperspace occupied by radio signals, which has dimensions of locations, angle, and arrival, frequency, time and possible others. Few of important radio spaces are:

1. ***White Spaces:*** In spectrum white spaces, license bands are no more exist at that time, only natural noise such as broadband thermal noise and impulsive noise are present.
2. ***Gray Spaces:*** In gray spaces which 0partially filled by low power interferes.
3. ***Black spaces:*** Those places are occupied by the high priority licensed users which is also called as PUs.

According to the space classification, a CR node can transmit in the gray and white space, but it is prohibited to operate in the black space once the PU is active.

1.2.3 Cognitive Radio Features

Cognitive Radio can be described as an intelligent and dynamically reconfigurable radio that can adjust its radio parameters in response to surrounding environment. CR is proposed by J. Mitola II in [12] and later officially defined as [2] A“Cognitive radio is a radio that can change its transmitter parameters based on interaction with environment in which it operates. From the above mentioned definition two major characteristics of cognitive radio can be summarized as cognitive capability and reconfigurability.

1.2.3.1 Cognitive Capability

The cognitive features enables the cognitive radio to interact with its environment in a real time manner and intelligently determine based on quality of service (QoS) requirements. It senses an unused spectrum in the surroundings, and then smartly selects optimal spectrum and appropriate parameters to access this spectrum via cognitive capability. This process can be described as a

cycle with three main operations: spectrum sensing, spectrum analysis and spectrum decision [20], thus the cognitive features are as follows:

1. ***Spectrum Sensing:*** In cognitive network, one cognitive radio captures some information from spectrum bands seeking for available holes. Also, the radio should keep monitoring spectrum bands and retreat from those holes when primary users want to reuse their spectrum. It is done by either cooperative or non-cooperative technique in which cognitive radio nodes continuously monitor the RF environment.
2. ***Spectrum Analysis:*** The surrounding spectrum bands are extracted and estimated from the information captured via spectrum sensing. It estimates the characteristics of spectrum bands that are sensed through spectrum sensing.
3. ***Spectrum Decision:*** An appropriate spectral band will be chosen for SU transmission according to the spectrum characteristics analyzed for particular cognitive radio node from the spectrum analysis operation. Meanwhile, the cognitive radio will also intelligently choose suitable parameters, e.g. transmission mode, data rate and bandwidth needed in transmission, for transmission in current communication.

1.2.3.2 Reconfigurable Features

Reconfigurable is another characteristic of CR enabling CR changes its parameters to adapt to a dynamic communication environment [20]. Some parameters introduced in the following are considered mostly in CR. In order to get adapted to RF environment cognitive radio should change its operational parameters are as follows:

1. ***Operating Frequency:*** It is available for cognitive radio to change the operating frequency for optimal transmission in a dynamic environment and protecting PU activity. CR is capable to varying its operating frequency in order to avoid the PU to share spectrum with other users.
2. ***Modulation Scheme:*** In order to adapt to SU's transmission requirements and channel conditions, a cognitive radio is available to adjust its modulation scheme According to the user requirements and channel condition CR is able to adaptively reconfigurable the modulation scheme.
3. ***Transmission Power:*** For the mitigation of interference and power efficiency enhancement, cognitive radio allows power reconfiguration based on power constraint or limit required in the networks. In order to improve the spectral efficiency or diminish interference transmission power can be reconfigurable.
4. ***Communication Technology:*** In heterogeneous networks, cognitive radio will adjust itself and be used in different types of communication systems with its interoperability by

changing modulation scheme interoperability among different communication systems can also be provided by CR.

1.3 Challenges of Dynamic Spectrum Access in Cognitive Radio Networks

There are many challenges that are yet to be resolved for obtaining the optimum performance from a cognitive radio network (CRN) which are:

1.3.1 Hardware Requirements

Spectrum sensing for CR applications requires high sampling rate, high resolution ADCs with high dynamic range, channel estimation, soft information generation, power control etc. The hardware development becomes very challenging to meet all the requirements. Moreover, the development of radio frequencies(RF) components like antennas, power amplifiers etc for operating large operating bandwidths and high speed processing units with relatively low delay became tremendous challenging task for CR. Spectrum sensing for cognitive radio applications requires high sampling rate, high resolution analog to digital converters (ADCs) with large dynamic range, and high speed signal processors. Noise variance estimation techniques have been popularly used for optimal receiver designs like channel estimation, soft information generation etc., as well as for improved hand-off, power control, and channel allocation techniques [21].

1.3.2 Detecting Hidden Primary Users

To manage and overcome hidden primary users caused by multipath fading or shadowing observed by secondary users transmission become very challenging task. The hidden primary user's causes unwanted interference to the PU (receiver) as the signals of the primary transmitter could not be detected because of the locations of devices. The hidden primary user problem is similar to the hidden node problem in Carrier Sense Multiple Accessing (CSMA). It can be caused by many factors including severe multipath fading or shadowing observed by secondary users while scanning for primary users' transmissions. Here, cognitive radio device causes unwanted interference to the primary user (receiver) as the primary transmitter's signal could not be detected because of the locations of devices. Cooperative sensing is proposed in the literature for handling hidden primary user problem [22-24].

1.3.3 Detecting Spread Spectrum Primary Users

Detecting the spread spectrum i.e. frequency hopping spread spectrum (FHSS) and direct sequence spread spectrum (DSSS) became very challenging task in CRN. FHSS devices change their operational frequency dynamically to multiple narrow band channels. This is known as hopping and performed according to a sequence that is known by both transmitter and receiver. Primary users that use spread spectrum signaling are difficult to detect as the power of the primary

user is distributed over a wide frequency range even though the actual information bandwidth is much narrower [25]. This problem can be partially avoided if the hopping pattern is known and perfect synchronization to the signal can be achieved as discussed in Section II. However, it is not straightforward to design algorithms that can do the estimation in code dimension.

1.3.4 Sensing Duration and Frequency

In order to prevent interference to and from primary license owners, cognitive radio should be able to identify the presence of primary users as quickly as possible and should vacate the band immediately. Sensing methods should be able to identify the presence of primary users within certain duration. This requirement poses a limit on the performance of sensing algorithm and creates a challenge for cognitive radio design. Hence, to prevent interference to and from primary license owners, the sensing frequency, channel detection time, channel move time, interference tolerance level of PUs and optimum sensing durations to search for an available channel and monitor a used channel creates a challenge for cognitive radio. The optimum value depends on the capabilities of cognitive radio itself and the temporal characteristics of primary users in the environment [26]. In addition to sensing frequency, the channel detection time, channel move time and some other timing related parameters are also defined in the standard [27]. Another factor that affects the sensing frequency is the interference tolerance of primary license owners. For example, when a cognitive radio is exploiting opportunities in public safety bands, sensing should be done as frequently as possible in order to prevent any interference. Moreover, CR should immediately vacate the band it is needed by public safety units. The effects of sensing time on the performance of secondary users are investigated in [40].

1.3.5 Decision Fusion in Co-Operative Sensing

CR uses co-operative sensing techniques to avoid the interference to the PUs in which sharing information among cognitive radios and combining results from various measurements is a challenging task. The optimum fusion rule for combining sensing information is the Chair-Varshney rule is used as solution. For hard decisions AND, OR or M out of N methods can be used for combining information from different CR. The shared information can be soft or hard decisions made by each cognitive device [28]. The soft information-combining output performs hard information combining method in terms of the probability of missed opportunity. On the other hand, hard-decisions are found to perform as good as soft decisions when the number of cooperating users is high in. The optimum fusion rule for combining sensing information is the Chair-Varshney rule which is based on log-likelihood ratio test and are used for decisions classification from secondary users in [28]-[30].

1.3.6 Security

In cognitive radio, a selfish or malicious user can modify its air interface to mimic a primary user. Hence, it can mislead the spectrum sensing performed by legitimate primary users. The challenging of CR is to develop an effective counter measures to identify the attack. Such a behavior or attack is investigated in [31] and it is termed as primary user emulation (PUE) attack. Its harmful effects on the cognitive radio network are investigated. The position of the transmitter is used for identifying an attacker in. A more challenging problem is to develop effective countermeasures once an attack is identified. Public key encryption based primary user identification is proposed in [32] to prevent secondary users masquerading as primary users. Legitimate primary users are required to transmit an encrypted value (signature) along with their transmissions which is generated using a private key. This signature is, then, used for validating the primary user. This method, however, can only be used with digital modulations. Furthermore, secondary users should have the capability to synchronize and demodulate primary users' signal.

1.4 Objectives and Research Contributions

The aim of this work is to analyze the performance of classical narrowband spectrum schemes namely Energy Detection, cyclo Stationary Feature Detection and Matched Filtering over different fading channels in CR. The performance has been analyzed over AWGN, Rayleigh Fading Channels and Rician Fading Channels. This work has compared the performance among them and proposes the effective one for further improvement of the detection performance. More specially, the thesis has the following objectives:

To develop system model and analyze the detection performance of narrow band detection i.e. Energy Detection, Feature Detection and Matched Filter Detection over AWGN, Rayleigh Fading Channels and Rician Fading Channels.

To propose the most effective method of narrow band spectrum sensing to mitigate the effects of AWGN, Rayleigh Fading Channels and Rician Fading Channels and to improve the detection performance. The work consists of total *five* chapters which are follows:

In Chapter 1, an introduction to the topics discussed in this work is presented. In particular, Chapter 1, the preliminaries of CR, their features, challenged and thesis contribution has been discussed has been discussed.

In Chapter 2, the state of art schemes of CR systems are described. In particular, state of art of dynamic spectrum access in CR networks and the spectrum sensing techniques are presented which are essential for understanding the rest of the chapters.

In Chapter 3, we have discussed about the Problem Formulation and System Modeling of different classical based narrowband sensing over different fading channel

In Chapter 4, the mathematical model and receiver operating characteristics have been developed using MATLAB simulation for the classical narrowband spectrum sensing techniques over

AWGN, Rayleigh Fading Channels and Rician Fading Channels. This work has compared the performance of the above mentioned classical narrowband spectrum sensing techniques over AWGN, Rayleigh Fading Channels and Rician Fading Channels. The work has also discussed the limitation of narrow band sensing and suggested the probable solutions and future challenges. At the end of this chapter the work summarizes the main contributions introduced in this thesis and introduces future research directions.

In Chapter 5, we have discussed about the concluding remarks and future works.

1.5 Thesis Outline

This work analyzed the Performance of Narrow Band Spectrum Sensing technology in classical approaches i.e. Energy Detection, Feature Detection and Matched Filter Detection over AWGN, Rayleigh Fading Channels and Rician Fading Channels. It will also propose the most effective method of narrow band spectrum sensing to mitigate the effects of AWGN, Rayleigh Fading Channels and Rician Fading Channels and to improve the detection performance.

- (1) The approach for formulation of mathematical model over different fading channels in different sensing techniques.
- (2) Simulation, analysis and compare the characteristics of different narrowband channel performance.
- (3) Suggestion of the techniques for optimum performance considering future trends and challenges of CR

Chapter II

State of the Art and Literature Reviews

2.1 Introduction

The demand of wireless communication is increasing day by day in the present context. Spectrum scarcity occurs due to the use of traditional static frequency allocation planning for communication protocol. To meet the increasing demand, CR concept came up with the possible solution to the problem of spectrum scarcity which brings the concept of Dynamic Spectrum Sensing (DSA). DSA makes it possible for a CR user to sense the vacant spectrum before using it temporarily and avoids interference to PU when PU reuses the spectrum [12]. In order to support spectrum accessing functionality, CR nodes have the duty to sense the radio environment dynamically for being aware of the highly polarized license while spectrum sensing is the most challenging task in the promising CR networks.

The idea of CR was first presented officially in an article by Joseph Mitola III and Gerald Q. Maguire, Jr in 1999. It was a new approach in wireless communication that Mitola describes as “The point in which wireless personal digital assistance (PDAs) and the related networks are efficiently computationally intelligent about radio resources and related computer to computer communication to detect user communications needs as a function of use context, and to provide radio resources and wireless services most appropriate to this need” [40]. This is an intelligent wireless communication system that is cognizant of its surrounding environment and uses a learning methodology to learn from the environment, adopt its internal states to statistical changes in the incoming radio frequency stimuli by making corresponding variation in certain operating parameters in real time and with two primary objectives: 1) highly reliable communication whenever and wherever needed 2) Efficient utilization of radio spectrum [41].

The concept of CR technology made feasible by recent advances such as software-defined radio (SDR) which allows in principle flexible and agile access to the spectrum as well as improving spectrum efficiency substantially. The concept of CR technology is the efficient utilization of the underutilized bandwidth which is called white spaces (WS). DSA senses the White spaces (WS) for opportunistic use and thus more likely to occur interference to the PUs. Therefore one of the main challenges in CR network is related to the management of the available radio resources among the PSs and cognitive users for satisfying the respective quality of service (QoS) requirements and limiting the interference to the PUs [3],[5].

The outside world provides stimuli. Cognitive radio parses these stimuli to recognize the context of its communications tasks [9]. Incoming and outgoing multimedia content is parsed for the contextual cues necessary to infer the communication context. The orient stage decides on the urgency of the communications in part from these cues in order to reduce the burden on the user. Cognitive radio is a goal driven framework in which the radio automatically observes the environment, infers context, assesses, and learns from its mistakes.

Interest is rapidly growing in lowering barriers to spectrum access and improving spectrum efficiency. The introduction of software-defined radios and the realization that new levels of computational performance applied to radios creates exciting new possibilities for wireless devices. This has resulted in explosive growth in interest in cognitive radios. The term *cognitive radio* was first used by Joe Mitola [9]. The concept and the term *cognitive radio* quickly caught the interest of many in the communications field. Cognitive radio technology enables a number of capabilities to improve the usefulness and effectiveness of wireless communications. Those functions include:

- Exploit locally vacant or unused radio channels, or ranges of radio spectrum, to provide new paths to spectrum access.
- Roam across borders and perform self-adjustment to stay in compliance with all local radio operations and emissions regulations.
- Negotiate as a broker on behalf of the radio user with multiple service providers to give network access best matched to the user needs at the lowest cost.
- Adapt itself without user intervention to save battery power or to reduce interference to other users.
- Make use of location awareness to ensure that radio emissions do not interfere with licensed broadcasters.
- Understand and follow the actions and choices taken by their users to become more responsive and anticipate user needs over time.
- Formulate and issue queries, one radio to another.
- Execute commands sent by another radio.

2.2 Architecture of SDR

It was thought of an ideal goal which a software defined radio (SDR) platform should develop reconfigurable wireless black- box that automatically varies its communication variables with network and user demands, [18]

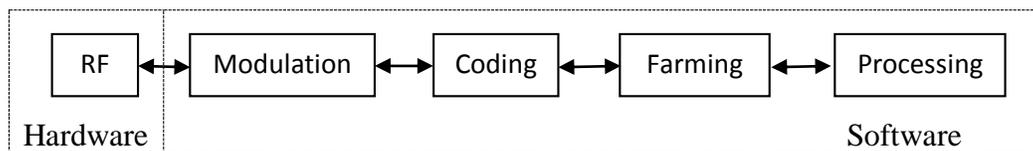


Figure 2.1: a. SDR

Software-defined radio (SDR) is a radiocommunication system where components that have been typically implemented in hardware (e.g. mixers, filters, amplifiers, modulators/demodulators, detectors, etc.) are instead implemented by means of software on a personal computer or embedded system. While the concept of SDR is not new, the rapidly evolving capabilities of digital electronics render practical many processes which used to be only theoretically possible. A software-defined radio can be flexible enough to avoid the limited spectrum assumptions of designers of previous kinds of radios, in one or more ways including:

- Spread spectrum and ultra wideband techniques allow several transmitters to transmit in the same place on the same frequency with very little interference, typically combined with one or more error detection and correction techniques to fix all the errors caused by that interference.
- Software defined antennas adaptively lock onto a directional signal, so that receivers can better reject interference from other directions, allowing it to detect fainter transmissions.
- Cognitive radio techniques: each radio measures the spectrum in use and communicates that information to other cooperating radios, so that transmitters can avoid mutual interference by selecting unused frequencies.
- Dynamic transmitter power adjustment, based on information communicated from the receivers, lowering transmit power to the minimum necessary, reducing the near-far problem and reducing interference to others, and extending battery life in portable equipment.
- Wireless mesh network where every added radio increases total capacity and reduces the power required at any one node. Each node only transmits loudly enough for the message to hop to the nearest node in that direction, reducing near-far problem and reducing interference to others.

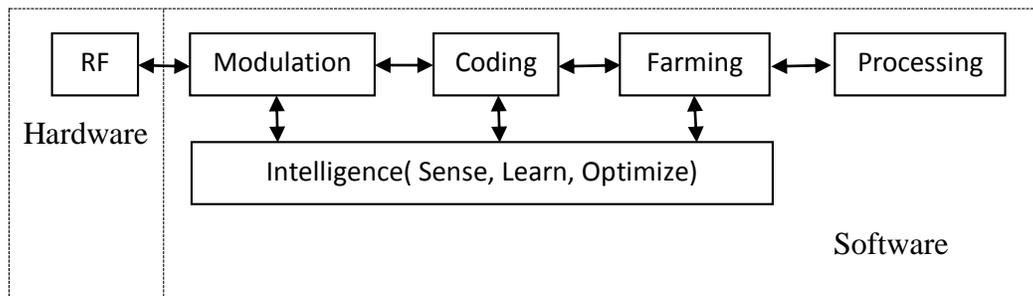


Figure 2.1: b. CR

CR is an autonomous agent that perceives the user 's situation to proactively assist the user with wireless information services, particularly if the user is too busy or otherwise occupied, such as when in personal distress.

2.3 Attributes of Cognitive Radio

The above definitions provide good boundaries for a working definition of a CR because it provides multiple valid perspectives of parties with vested interests in this technology. A number of attributes have been mentioned in the preceding section, which are now distilled. Therefore, depending on the perspective of who is defining a CR, it would possess any or all of the capabilities described in the following sections.

1. **Aware:** First of all, the CR possesses awareness. It can sense, store, recall, disseminate, and make inferences from information derived from its RF environment, geolocation, contextual, and is able to sense its current internal states.
2. **Adjustable:** The operating characteristics of the CR can change in response to its environment, of which it is aware. It can change its emissions (frequency, power,

&modulation) in real-time without user intervention in response to unexpected changes to its environment, or to save battery power or reduce interference to other users. Also, since the CR is spatially aware, it can cross political borders and adjust itself to stay in compliance with all local radio operation and emissions regulations.

3. **Automatic Operation:** The CR does not require user intervention in order to be adjustable. Fundamentally, it may have to perform spectrum sensing and exploitation to be adjustable. On its own the CR can exploit locally vacant or unused radio channels or ranges of radio spectrum to provide new paths to spectrum access, based on rules originating from local policy constraints.
4. **Adaptive:** The CR can understand and follow the actions and choices taken by its user and over time learn to become more responsive and to anticipate his needs.

2.4 Cognitive Radio Elements

In this section, we describe some of the elements or capabilities that may be found in a cognitive radio. These elements are used to provide inputs or constraints to the cognitive and policy engines.

2.4.1 Spectrum Sensing and Sensors

A cognitive radio requires current information regarding its awareness of its environment, its internal state, node capabilities, and current needs of its user. Environmental sensing may be local and self contained in a radio or remotely performed elsewhere in the network. In collaborative sensing for example, some other device or system collects information about a radios environment and that information may be relayed to the user's radio.

1. **Spectrum Sensing:** Spectrum sensing refers to the action of a wireless device measuring characteristics of received signals, which may include RF energy levels as part of the process of determining if a particular section of spectrum is occupied. Sensing in the spectrum domain is the detection of some signal features indicating the presence (or absence) of other users/services. These can include signal energy, periodic features (pilots, preambles, chip rates), likely identity of the other users/services, estimation of interference-tolerance capabilities and estimation of the duration of spectrum occupancy.
2. **Collaboration and Spectrum Sensing:** In cognitive radio systems, two or more wireless nodes combining their capabilities and spectrum-usage resources using negotiated or prior arrangements, is a common way for cognitive radios to have a more global sense of spectrum usage. Delegation of spectrum-usage tasks based on the expected global value of this action allows the network to select more globally optimal choices in minimizing interference over a larger region. The implementation of a collaborative communications solution may be more effective than individual 'greedy/selfish' approaches. The first stage of a collaborative approach is to identify and form the adhoc network using underlay and overlay communications. The capabilities and objectives of each node can then be assessed and a leader (if required) is elected. A consensus formation process is initiated, and during the implementation of the strategy, monitoring and strategy-update mechanisms accommodate change.
3. **Advanced Collaborative Sensing:** Individual cognitive radio devices could combine

cognition capabilities and information to achieve a set of goals that benefit all participants or reach a global consensus regarding a particular scenario. One example of this application is a distributed sensor mesh network used to build a map of the wireless activity in a wide area for frequency planning and allocation, device detection and movement pattern monitoring.

4. ***Inferred vs. Explicit Sensing:*** Inferred sensing refers to the act of monitoring performance indirectly through measures such as frame error rate. Explicit sensing refers to the act of explicitly taking steps and including circuits and devices to be able to directly measure an environmental quantity.

2.4.2 Awareness

Aware implies the ability to integrate sensations from the environment with one's immediate goals in order to guide behavior or draw conclusions. We recognize *Cognizant* as a formal equivalent of *aware* and the root of the name "Cognitive Radio". *Conscious* emphasizes the recognition of something sensed or felt. Cognitive radios are aware (conscious) radios with the following senses, and the ability to respond to those sensors.

1. ***RF/Environment Awareness:*** Physical quantities including received voltage and ambient temperature fall in this class. Received radio frequency energy is a measure of how much a section of spectrum is occupied at a point in space. Cognitive radio uses spectrum awareness to optimize performance and spectrum utilization by a number of factors based on orthogonality in the dimensions of time, frequency, code, or modulation. Identification of all the sources and infrastructures in current geographical area capable of servicing the user and compatible with the radio constitutes network awareness. This also involves being aware of subtle nuances within the network's structure such as the data links, transport, routing paths and management layers. Network awareness also includes network characteristics such as the QoS, frame error rate, frame delay etc.
2. ***Location Awareness:*** Geographical location identification by a radio constitutes location awareness. Location awareness is significant, particularly for international and coalition communications. This awareness provides the radio ability to discern local infrastructure or policy, primary incumbent transmitters and receivers, terrain, altitude, propagation channels, and the location of network members.

2. *User Awareness*

The ability to interpret a user's needs, preferences, service and operating Requirements constitutes user awareness. User awareness drastically simplifies the task of providing, choosing, and using a suitable wireless network service. The users are able to benefit from a targeted solution or a finite range of sufficient solutions, rather than simply being overloaded with choices. This also includes user speech, language and biometrics awareness.

3. ***Hardware Awareness:*** The available wireless device processing power, real time operating system and remaining energy fall in this category of hardware awareness. This also includes DSPs, RF and multimedia chipsets in the wireless device that, among other functions, manage modulation, cryptography, protocols, and source coding for voice, data, and imagery. High-

density FPGAs are also important resources of a radio enabling reconfiguration and provide capability to change waveforms and adjust performance characteristics, frequency, power, and other attributes. Cognitive radios need to be aware of the processing functionality and capability in order to keep size and power consumption to a minimum.

4. **Policy Awareness:** The ability to operate legally and agilely across multiple bands and in multiple different places using policies as a means to check whether you're legal and eligible constitutes policy awareness. The policies can include regulatory and system specific policies. Hard/soft-wired policies can determine when spectrum is considered as opportunity as well as providing constraints on using these spectrum opportunities.

2.5 Cognitive Cycle

The outside world provides stimuli. Cognitive radio parses these stimuli to recognize the context of its communications tasks. Incoming and outgoing multimedia content is parsed for the contextual cues necessary to infer the communication context.

The orient-stage decides on the urgency of the communications in part from those cues in order to reduce the burden on the user. Normally, the Plan-stage generates and evaluates alternatives, including expressing plans to peers and/or the network to obtain advice. The decide stage allocates computational and radio resources to subordinate software. The Act-stage initiates tasks with specified resources for specified amount of time.

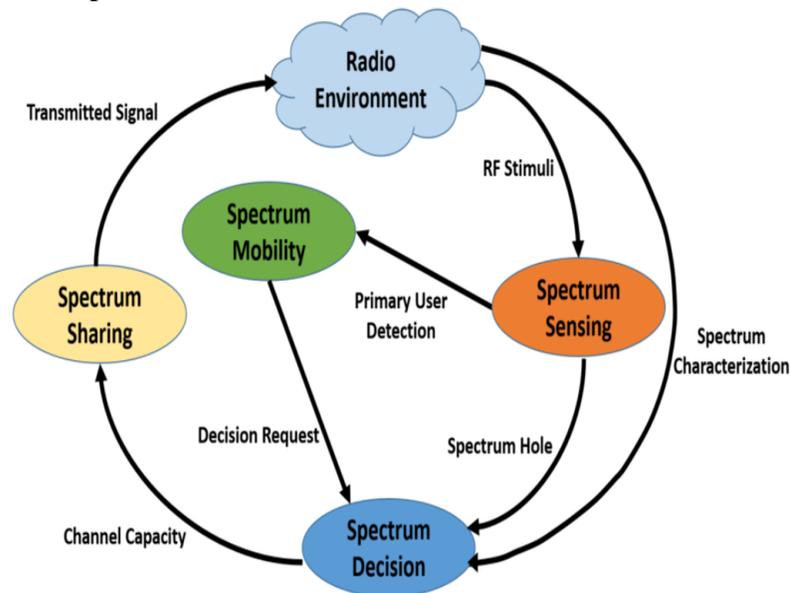


Figure 2.2: Cognitive Cycle

2.6 Spectrum Sensing Techniques

A major challenge in cognitive radio is that the secondary users need to detect the presence of primary users in a licensed spectrum and quit the frequency band as quickly as possible if the corresponding primary radio emerges in order to avoid interference to primary users. This technique is called spectrum sensing. Spectrum sensing and estimation is the first step to implement Cognitive Radio system [5]. We can categorize spectrum sensing techniques into direct method, which is considered as frequency domain approach, where the estimation is carried out directly from signal and indirect method, which is known as time domain approach, where the estimation is performed using autocorrelation of the signal. Another way of categorizing the spectrum sensing and estimation methods is by making group into model based parametric method and periodogram based non-parametric method. Another way of classification depends on the need of spectrum sensing as stated below [13]:

2.6.1 Spectrum Sensing for Spectrum Opportunities

1. **Primary Transmitter Detection:** In this case, the detection of primary users is performed based on the received signal at CR users. This approach includes matched filter (MF) based detection, energy based detection, covariance based detection, waveform based detection, cyclostationary based detection, radio identification based detection and random Hough Transform based detection.
2. **Cooperative and Collaborative Detection:** In this approach, the primary signals for spectrum opportunities are detected reliably by interacting or cooperating with other users, and the method can be implemented as either centralized access to spectrum coordinated by a spectrum server or distributed approach implied by the spectrum load smoothing algorithm or external detection.

2.6.2 Spectrum Sensing for Interference Detection

1. **Interference Temperature Detection:** In this approach, CR system works as in the ultrawide band (UWB) technology where the secondary users coexist with primary users and are allowed to transmit with low power and are restricted by the interference temperature level so as not to cause harmful interference to primary users.
2. **Primary Receiver Detection:** In this method, the interference and/or spectrum opportunities are detected based on primary receiver's local oscillator leakage power.

2.7 Dynamic Spectrum Access (DSA) in CR Networks

In order to meet the massive demand of frequency spectrum, the CR network has opened up a new way of sensing and utilizing properly wireless radio resources. In this section, the state of art DSA schemes will be discussed. Latest experiment on spectrum management[20] have shown that the licensed frequency bands are rigorously underutilized most of the time and a

particular geographic location mainly due to the traditional command and control type spectrum regulation. In order to use those remaining spectrum holes or white spaces, effort is put on achieving DSA. A taxonomy of the DSA scheme [50] is illustrated in the following figure (fig. 1).

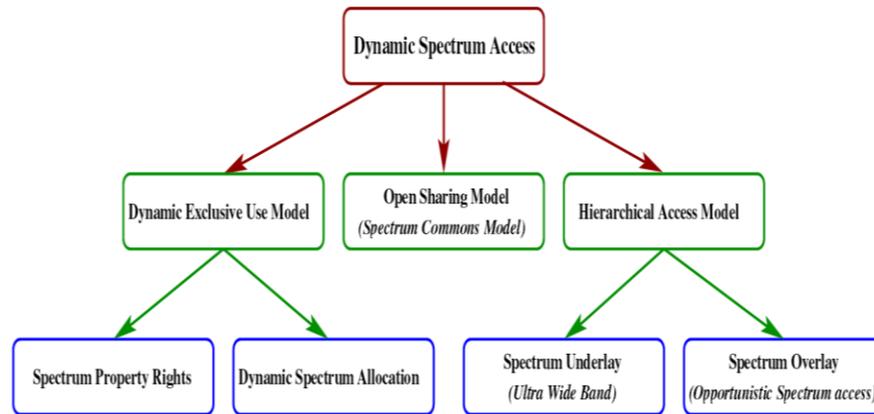


Figure 2.3: Fundamental Classification of Dynamic Spectrum Access

2.8 Hierarchical Access Model

In this model, a hierarchical access pattern for the primary and secondary users will be discussed. The fundamental concept is to open licensed spectrum to cognitive users while limiting the interference perceived by the primary users. This model can be categorized as two different approaches for allocation of the spectrum, i.e., spectrum underlay and spectrum overlay.

2.8.1 Spectrum Underlay

In an underlay system, regulated spectral masks impose stringent limits on radiated power as a function of frequency, and perhaps location. Radios coexist in the same band with primary licensees, but are regulated to cause interference below prescribed limits [50]. The underlying or the URs are sufficiently fast frequency hopping with relatively narrow bandwidth usage in each dwell, so that there is little interference from the URs. An underlay radio spectrum distribution is shown in the following figure (fig. 2).

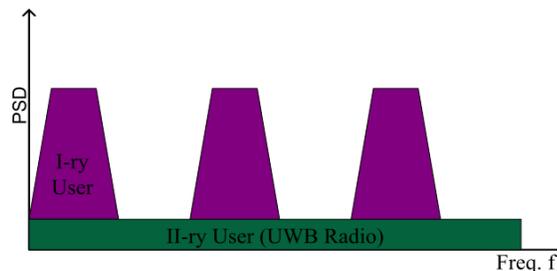


Figure 2.4: Spectrum Underlay

In order to spread out the signal over a large bandwidth, underlay radios can use spread

spectrum signaling systems, wideband orthogonal frequency division multiplexing (OFDM), or impulse radio.

2.8.2 Spectrum Overlay

Spectrum overlay or OSA, can be applied in either temporal or spatial domain. For the first case, secondary users aim to exploit temporal spectrum opportunities resulting from the bursty traffic of primary users and in the latter, cognitive users aim to exploit frequency bands that are not used by primary users in a particular geographic area[50]. A typical application is the reuse of certain TV white spaces that are not used for TV broadcasting) in a particular geographic location. In the TV broadcasting system, TV-bands assigned to adjacent regions are different to avoid co-site interference. Spectrum overlay mechanism is shown in the following (fig. 3).

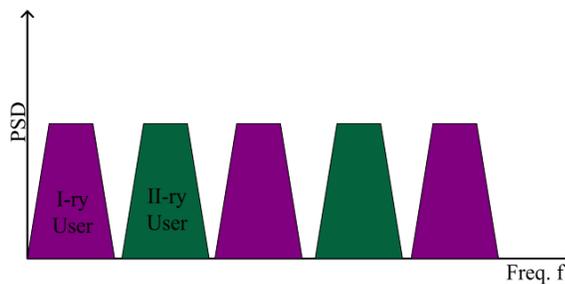


Figure 2.5: Spectrum overlay

Spectrum overlay is therefore defined as doing some pre-coding at the transmitter in order to diminish the interference at the receiver.

2.9 Classification of Spectrum Sensing Techniques

The Fig 2.6 shows the detail classification of spectrum sensing techniques. They are broadly classified into three main types, transmitter detection or non cooperative sensing, cooperative sensing and interference based sensing.

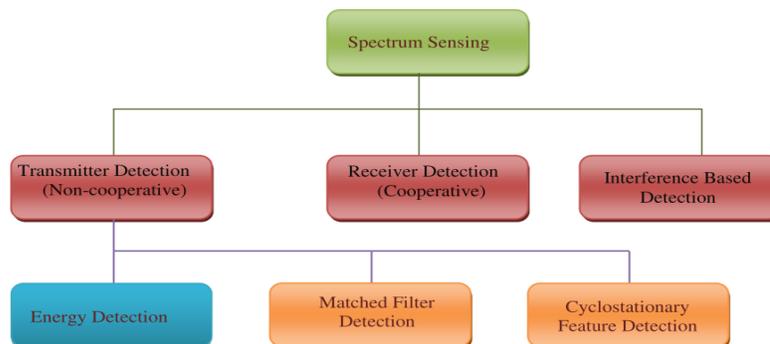


Figure 2.6: Classifications of spectrum sensing techniques

Transmitter detection technique is further classified into energy detection, matched filter detection

and cyclostationary feature detection [43]. In the remainder of this chapter we first briefly introduce the traditional spectrum sensing algorithms for narrowband sensing based on their implementation type. However, the work will also highlight on wideband spectrum sensing and co-operative spectrum sensing and review the state-of-the-art technique for each category. Most of the spectrum sensing schemes are aimed to detecting an active PU transmitter nearby the cognitive radio [19]. However, as primary receivers may be passive, such as TVs, some receivers are difficult to detect in practice. An alternative is to detect the primary transmitter by using traditional narrowband sensing algorithms including energy detection, matched filtering, cyclostationary feature detection etc. Here, the term “narrowband” implies that the frequency range is sufficiently narrow such that the channel frequency response can be considered flat. In other words, the bandwidth of our interest is less than the coherence bandwidth of the channel. The implementation of these narrowband algorithms requires different conditions, and their detection performances are correspondingly distinguished.

2.10 Narrowband Sensing

The most efficient way to sense spectral opportunities is to detect active primary transmitters in the vicinity of CRs. This work has focused on the effects of this noise over classical narrowband based sensing, namely energy detection, cyclostationary and matched filter. Generally, the performances of these three schemes depend largely on communication surroundings. These surrounding environments include additive white noise (AWGN), multipath fading, shadowing and the hidden terminal problem [S1], detection in spectrum sensing may be significantly affected.

2.10.1 Energy Detection

The energy based spectrum sensing and detection is the simplest method for detecting primary users in the environment in a blind manner [20]. The energy detector is computationally efficient and could also be used confidently with analog and digital signals that are at the RF/IF stages or at the base band. The Fig 2.4 represents the block diagram of energy detector.

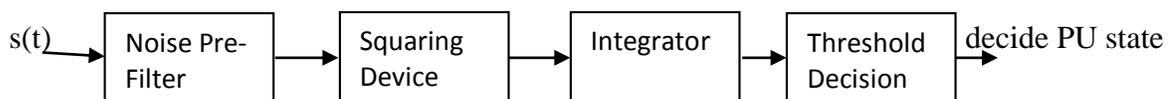


Figure 2.7: Block diagram of Energy Detector

It can be described as; the received signal is passed through the band pass filter and this filter selects the required frequency as f_c . The output of band pass filter is passed through the non-linear device called squaring devices, it will measure the energy associated with the signal. The non-linear device output is passed through an integrator; it will measure energy over the fixed duration of time window. After this block the energy $y(t)$ of the signal, is compared with the threshold value (λ) which depends on the noise floor.

This technique comprises low computational and implementation complexities, thus leads to its popularity. In addition, the notable advantages of this scheme are that it does not require any prior information about the PUs transmission [1]. When the signal-to-noise ratio is very low, it would

be hard to distinguish between the radio signal and noise signal, therefore the knowledge of the noise power can be used to improve the detection performance of the energy detector.

The performance of the detection algorithm can be determined by two probabilities as the probability of detection (P_d) and probability of false alarm (P_f). ED is considered a non-coherent detection method where knowledge of variance is adequate for choosing threshold to obtain a predetermined false alarm rate. Meanwhile, to design a standard CR system higher value detection probability as well as lower value of false alarm probability is anticipated. The decision threshold λ_g can be selected for finding the optimum balance between P_d and P_f however this requires knowledge of noise and detection signal powers. The noise power can be estimated, while the signal power is difficult to predict as it changes depending on the transmission characteristics and the distance between the CR and PU [1]. A major drawback is that it has poor detection performance under low SNR scenarios and cannot differentiate between the signals from PUs and the interference from other CRs.

The above figure (Fig-1) represents the block diagram of energy detector. It can be described as; the received signals passed through the band pass filter selects the required frequency f_c . Output of band pass filter passed through the non-linear device called square law devices it will measure the energy associated with the signal.

Non-linear device output is passed through an integrator; it will measure energy over fixed duration of time window. After this block the energy $y(t)$ of the signal, is compared with the threshold value (λ_g) to decide whether the primary signal is present or not. The sensing performance is degraded when the CR user effected by shadowing and fading even though it uses energy detector.

Energy detection will be optimal detection schemes when secondary user does not have the information of PU signal [19]. Since energy detection adopts non-coherent detection method, it does not require the complicated processing as matched filter detection requires. Fig.2.4 presents the structure of energy detection. Bandpass filter (BPF) first selects a centre frequency to receive signal from interested bandwidth [23] and then, the received signal is measured by a magnitude squaring device. Integrator controls the observation time, sums up all the received signals after squaring device measure during the observation time. Then the receiver compares the sum with predetermined threshold to estimate PU activity. Although energy detection can be performed without prior information obtained from PU's signal, and requires low implementation complexity, it performs poorly under low SNR conditions and cannot distinguish between signals of PU from signal of other secondary user. Also, noise level uncertainty results in energy detection poor performance since energy detection requires the knowledge of noise power.

2.10.2 Cyclostationary Feature Detection

Another promising spectrum sensing technique is based on feature detection. A feature is unique and inherent characteristics of the PUs signal and it is drawn as pilot signal, segment sync, field sync, and also the instantaneous amplitude, phase and frequency [36]. In practice, the instantaneous features are commonly perceived many signals employed in wireless communication and radar system [1]. Cyclostationary feature detection method detects and distinguishes between different types of PU signals by exploiting their cyclostationary features. Now a day, among to digital conversation has made the use of signal transformation practical in order to discover a specific feature. The fundamental and promising feature detection technique is based on the cyclic feature [1]. Cyclic feature detection approaches are based on the fact that modulated signal are usually coupled with sinusoidal carriers, hopping sequences, cyclic prefix, spreading codes or pulse trains, which result in a built in periodicity [36].

Cyclostationary features are originated by the periodicity in the signal in statistical manner like mean and autocorrelation or they can be intentionally used in order to sustain the spectrum sensing by analyzing a spectral correlation function (SCF) or cyclic spectrum [36]. This detection algorithms can differentiate noise from the signals as noise is wide-sense stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities. The block diagram of Cyclostationary feature detection is shown in fig 2.4.

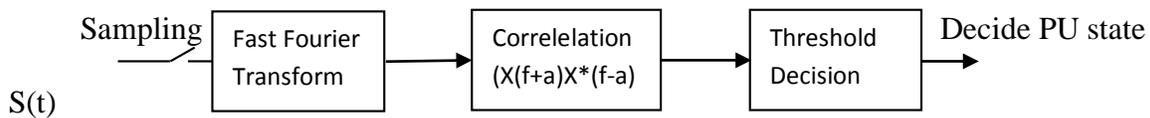


Figure 2.8: Cyclostationary feature detection

It exploits the periodicity in the received primary signal to identify the presence of primary users (PU). The periodicity is commonly embedded in sinusoidal carriers, pulse trains, spreading code, hopping sequences or cycloic prefixes of the primary signals. Due to the periodicity, these cyclostationary signals exhibit the features of periodic statistics and spectral correlation which is not found in stationary noise and interference. Cyclostationary feature detector can overcome the energy detector limits in detecting signals in low SNR environments [42]. In fact, signals with overlapping features in the power spectrum, can have non-overlapping features in the cyclic spectrum [1].

2.10.3 Waveform based or Coherent Sensing

Waveform based or coherent sensing is another promising feature detection scheme which patterns like preambles, repeatedly transmitted pilot patterns, spreading sequence, etc. in wireless system. In the presence of known pattern, sensing can be performed by correlating the received PU signal with a known copy of itself [1] which provides a barrier of this types of sensing. It is shown that waveform based sensing outperforms energy detector based sensing in terms of reliability and convergence time. Likewise, the performance of the algorithm increases if the length of the known signal pattern increases. The OFDM waveform is altered before transmission

to generate cycle frequencies at different frequencies which is effective to categories the signals [1].

Again if the number of features generated in the signal is increased, robustness against multipath fading is improved considerably at a cost of bigger overhead and bandwidth loss. The main advantages of the feature detection is easily distinguishable the signals from the noise. In contrast, feature detection requires long observation time and higher computationally complexities as it requires to calculate a two dimensional function dependent on both frequency and cyclic frequency and also this scheme needs a prior information of the PUs. However, there are two disadvantages in this detection technique. First, this detection technique requires partial information of the PU signal. Secondly, high costs of computation because of the introduction of cyclic correlation function.

Feature detection is proposed to overcome energy detection disadvantage where it cannot distinguish between different types of signals. Cyclostationary detection receiver detects the signal of PU via exploiting the cyclostationary features in the PU signal [20]. A block diagram of cyclostationary feature detection is present in Fig.2.5. Mostly, PU transmitted signals are modulated signals, which are modulated by pulse train, cyclic prefixes, or repeating spreading. Because of these modulated signals' autocorrelation, they are regarded as cyclostationary. Cyclostationary feature detection adopts cyclic correlation function for detecting PU signal with a certain modulation type with additive noise. After obtaining partial information of the PU signal, cyclic correlation function can distinguish certain modulated PU signals from other modulated signals and noise because different types of modulated signals exploit different cyclic characteristics and wide-sense stationary additive noise has no correlation.

2.10.4 Matched Filter Detection

The matched filter is the optimal linear filter [51] for maximizing the signal to noise ratio (SNR) [1],[39] in the presence of additive stochastic noise. It is commonly used in radar, in which a signal is sent out, and measures the reflected signals looking for something similar to what was sent out. In signal processing, a matched filter is obtained by correlating a known signal, or *template*, with an unknown signal to detect the presence of the template in the unknown signal.

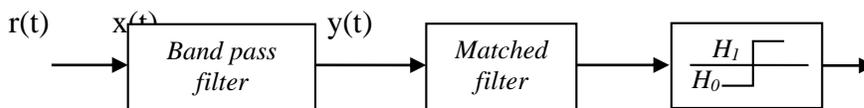


Figure 2.9: Matched filter block diagram

This is equivalent to convolving the unknown signal with a conjugated time-reversed version of the template. Matched filters are commonly used in radar, in which a known signal is sent out, and the reflected signal is examined for common elements of the out-going signal. Pulse compression is an example of matched filtering. It is so called because impulse response is matched to input pulse signals. Two-dimensional matched filters are commonly used in image processing, e.g., to improve SNR for X-ray. Matched filtering is a demodulation technique with

LTI (linear time invariant) filters to maximize SNR.

The advantages are achieved by correlating the received signal with a template for detecting the presence of a known signal in the received signal with a template for detecting the presence of a known signal in the received signal. However, it requires a prior knowledge of PUs and requires CRs to be equipped with carrier synchronization and timing devices that leads enhanced implementation complexity. At CR node, to maximize the output SNR for a certain input signal a matched filter is designed which belongs to the linear filter [3]. Matched filter detection is applied if a CR has a prior knowledge of PUs transmitted signal. Therefore, matched-filtering is known as the optimal strategy for detection of PUs in the presence of stationary Gaussian noise. The main advantages of matched filtering is the short time as it requires only $O(1/\text{SNR})$ samples to meet a given probability of detection constraint as compared to other detection schemes. As matched filtering requires a CR node to demodulate received PU signals and thus, it requires a prior information of the PUs transmission features such as bandwidth, operating frequency, modulation type and order, pulse shaping and frame format [36].

Further, if the CRs want to process a variety of signals, the implementation complexity of sensing unit is impractically large. In addition, this scheme consumes large power as various receiver algorithms require to be executed for detection and a prior knowledge requirement of PUs signals place it in the challenging to implement in CR networks [3]

The optimal detection about additive noise's status is matched filter detection if cognitive radio has PU signal's information because this detection maximizes signal-to-noise ratio (SNR)[38],[39]. Also, matched filter detection reduces observation time by coherent detection. The structure of a matched filter detection is present in Fig.2.3. But coherent detection requires a prior information about the PU signal, e.g. Pulse shape, packet format and modulation type, as a template for correlating with received signal and also needs carrier synchronisation and timing devices for signal processing. Thus, matched filter detection is more complexity compared with other classical detection schemes and it performs poorly when coherent detection knows few prior information obtained from PU's signal. synchronization and timing devices for signal processing. Thus, matched filter detection is more complexity compared with other classical detection schemes and it performs poorly when coherent detection knows few prior information obtained from PU's signal.

2.11 Wideband Sensing: Wideband spectrum sensing techniques aim to sense a frequency bandwidth that exceeds the coherence bandwidth of the channel. CR required exploiting spectral opportunities over wide frequency range from hundreds of megahertz to several GHz for achieving higher opportunistic throughput. The maximum theoretically achieved bit rate is directly proportional to the spectral bandwidth. Hence wideband spectrum sensing aims to find more spectral opportunities over wide range and achieve higher opportunistic aggregate throughput in CRN. Wideband spectrum sensing can be broadly categorize into two types (1) Nyquist wideband sensing and (2) Subnyquist wide band sensing.

2.11.1 Nyquist Wideband Sensing

1. **Multiband Joint Detection:** A multiband joint detection algorithm that can sense the primary signal over multiple frequency bands. The wide band signal first sampled by a high sampling rate ADC, after which a serial to parallel conversion circuit use to divide sampled data into parallel data streams. Then FFT use to apply to convert he wide band signals to the frequency domain. The wide band signal then divided into series of narrowband spectra. Finally spectral opportunities are detected using binary hypothesis.
2. **Wavelet- Based Spectral Detection:** In this algorithm the power spectral density (PSD) is modulated as a train of consecutive frequency sub bands, where PSD is smooth within each sub bands but exhibits discontinuities and irregularities on the border of two neighboring sub bands. The wavelets transform use to locate the singularities of the wideband PSD and spectral edge detection purpose.
3. **Filter Bank Detection:** In this techniques a bank of prototype filters are use to process the wide band signal. In each band, the corresponding portion of the spectral for the wideband signal is down converted to base band and then low-pass filtered.
4. **Sweep Time Detection:** Sweep time detector detects the spectrum by sweeping the span of the spectrum. The resolution is directly offer how long it takes to complete a measurement.

$$\text{Time Pass band} = \frac{RBW}{\text{Span}/ST}$$

where RBW indicates the resolution band and ST indicates sweep time.

2.11.2 SubNyquist Wideband Sensing

1. **Compressive Sensing:** Compressive sensing(CS) becomes a promising approach to recover the wideband signal extending only partial measurements. In the CS framework, a real-valued finite –length, one –dimensional time –variant signal $x(t)$, $0 \leq t \leq x$, can be denoted as a finite wideband sum of arthonormal basis functions

$$x(t) = \sum_{i=1}^N b_i \Psi(t) = \Psi b$$

Where b_i indicates basis co-efficient

2. **Multiband Joint Detection:** A multiband joint detection algorithm that can sense the primary signal over multiple frequency bands. The wide band signal first sampled by a high sampling rate ADC, after which a serial to parallel conversion circuit use to divide sampled data into parallel data streams. Then FFT use to apply to convert he wide band signals to the frequency domain. The wide band signal then divided into series of narrowband spectra. Finally spectral opportunities are detected using binary hypothesis.
3. **Multi Channel Sub-Nyquist Wideband Sensing:** It is mixed analog-digital spectrum sensing method also known as modulated wideband converter (MWC) that has multi sampling

channels. A unified digital architecture for spectrum-blind reconstruction was introduced in that scheme. The multi channel structure in MWC provides robustness against the noise.

4. **Multi Coset (MC):** It is another kind of multichannel sampling algorithm and applies when the frequency power distribution is sparse.
5. **Multi- rate Asynchronous Wideband Sub Nyquist Sampling:** The sampling of the wideband signals performed by the parallel low-rate sampling. It has better data compression capability, to have excellent performance in realistic wireless channels, and is more suitable to implement in CR networks.

2.11.3 Open Research Challenge

1. **Sparse Based Selection:** Nearly all subnyquist wideband sensing techniques require that the wideband signal should be sparse in a suitable basis.
2. **Adaptive Wideband Sensing:** The required number of measurement will proportionately change when the sparsity level of wideband signal varies.
3. **Cooperative wideband sensing**

2.11.4 Cooperative Spectrum Sensing

Since relays help networks increase spatial diversity [52] cooperative spectrum sensing mitigates shadowing and hidden terminal problem effects. Co-operative sensing can be divided broadly into 2 categories:

2.11.4.1 Centralized Sensing

In this sensing a central unit collects sensing information from cognitive devices, identifies the available spectrum and broadcast this information to other CRs or directly controls the CR traffic. The hard (binary) sensing results are gathered at a central place known as access point (AP). The user send the a quantized version of their local decisions to control unit (fusion centre) and the central unit is taken the final decision. The goal is to mitigate the fading effects of the channel and increase detection performance.

2.11.4.2 Distributed Sensing

Cognitive nodes (CN) share information with each other but they make their own decision as which port of the spectrum they can use. This makes low complexity with reduced protocol overhead.

2.11.4.3 External Sensing

External agent performs the sensing and broadcasts the channel occupancy information. The main advantages of external sensing are overcoming the hidden PUs problem and the uncertainty due

to shadowing and fading.

2.12 Cooperative Spectrum Sensing

Since relays help networks increase spatial diversity [52], [53], cooperative spectrum sensing mitigates shadowing and hidden terminal problem effects. For example, in a distributed network as shown Fig.2.6 from song p13, each SU observes PU activity independently, and forwards its received data or local decision to the SU, also regarded as destination. The destination is the SU who wants to utilize PU spectrum through report channel. Then the destination combines all the data or local decisions from other secondary users (relays) and its own received data or local decision to final decide on PU's activity. Up to now, researchers have designed several types of cooperative spectrum sensing schemes, i.e. *N-out-of-K* rule, maximal ratio combining (MRC) [54], square-law combining (SLC) [7], square-law selection (SLS) [7], and selection combining (SC) [5]. Based on the type of information transmitted in report channels, cooperative spectrum sensing schemes are classified into data fusion and decision fusion. Based on the methods to achieve cooperative sensing, cooperative spectrum sensing schemes have two models: parallel fusion model and game theoretical model.

2.12.1 Cooperation Fusion

Data Fusion: When secondary user relays received signal directly to destination without any further processing, the destination will receive these signal as reference when making final decision on PU status. If the destination knows well about the channel state information (CSI) between PU and the secondary users, MRC is the optimal scheme for spectrum sensing [55]. If the destination has partial CSI, which mostly considered as SNR in spectrum sensing case, between PU and the secondary users, selection combining is the best choice.

In practice, it is difficult to have perfect CSI at the destination, which makes MRC non-practical. When energy detection is employed in selection combining, each secondary user requires independently to send SNR and energy vectors to destination. This requires much bandwidth for report channels. Thus, SLC and SLS [5] [7] are proposed for bandwidth saving. In SLC and SLS schemes, secondary user only needs to send energy vector to destination, which saves nearly half of the bandwidth compared with the case of selection combining.

2.12.2 Decision Fusion: Diferent from data fusion model, in decision fusion model, each secondary user estimates received PU signal and takes local decision on the status of PU, independently. The destination combines local decisions from secondary users and its own local decision making a binary decision on PU's status. The decision fusion also known as *N-out-of-K* rule [33], including OR, AND and Majority rules. Suppose k represents the number of secondary users and destination, the destination with *N-out-of-K* rule makes final decision that PU is present when n or more local decisions show that PU is present.

2.12.3 Cooperation Models

Cooperation structure, also called cooperation model [50], should consider how to group secondary users, how to combine local observations for making final decisions on PU activity are made. Currently, there exist two common cooperation models: parallel fusion (PF) model and game theoretical model.

1. **Parallel Fusion Model:** Each SU has the same priority and should sense PU signal, report its received signal to the other SU. Thus, distributed cognitive network is a special case of parallel fusion model. For example, as Fig.2.6 shown, SU4 makes its final binary decision based on its local sensing and sensing data from other SUs via report channels. Thus, parallel fusion model requires SUs to be synchronized. Due to parallel fusion model's simple structure, data fusion and decision fusion are derived from this model.
2. **Game Theoretical Model:** In game theoretical model, secondary users are regarded as a set of players. Depending on the rules of the game, secondary users may have different performance. Based on game theoretical model, many game rules are developed [51] [5]. For example, in a coalitional game [5], secondary users are divided into groups freely, called *coalitions* based on their estimation about the communication surroundings. As Fig.2.7 shows, SU1, SU2 and SU3, belong to the same coalition 1, will sense the same specified PU1 spectrum. Then SU1 and SU2 will sense local data to SU3, which temporarily works as a local fusion center in coalition in this coalition, to make final decision. However, these coalitions are self-organized and not fixed; each secondary user joins or leaves freely depending on its utility value, which accounts for the tradeoff between receiving high probability of detection and energy cost incurred. Thus, cognitive networks achieve high probability of spectrum detection and spectrum management by introducing game coalitional.

Chapter III

System Model and Problem Formulation

3.0 Introduction

Spectrum sensing is the main feature of CR technology. Spectrum sense gives an idea of detecting the presence of PUs in a licensed user. In this work, we shall mainly discuss about the three classical method of narrowband spectrum sensing namely ED, Cyclostationary Feature Detection and Matched filter and compare their performance over different fading channel as the sensing performance can be degraded over AWGN, shadowing, multipath fading [5]. Energy detection is the most popular signal detection method due to its simple circuit in practical implementation. The principle of energy detector is to find the energy of the received signal and compares that with the threshold [45].

The basic scheme for spectrum sensing is based on energy detection where received PU is measured in a specific time period of a particular frequency band of interest.[3]. This non-coherent detection scheme will be optimal detection schemes when a secondary user does not have information of primary user signal. A cyclostationary process has statistical properties that vary periodically over time. It exploits this periodicity in the received primary signal to identify the presence of primary users. In this method the cyclic spectral correlation function (SCF) is the parameter that is used for detecting the primary user signals. Matched filter is the optimal detection method since it maximizes the SNR of the received signal.

3.1 Energy Detection Based System Modeling

Energy detection will be optimal detection schemes when secondary user does not have the information of PU signal [33]. Since energy detection adopts non-coherent detection method, it does not require the complicated processing as matched filter detection requires. Fig.31 presents the block diagram of energy detection. Bandpass filter (BPF) first selects a centre frequency to receive signal from interested bandwidth [34][35] and then, the received signal is measured by a magnitude squaring device. The Integrator controls the observation time, sums up all the received signals after squaring device measure during the observation time. Then the receiver compares the sum with predetermined threshold to estimate PU activity. Although energy detection can be performed without prior information obtained from PU's signal, and requires low implementation complexity, it performs poorly under low SNR conditions and cannot distinguish between signals of PU from signal of other secondary user. Also, noise level uncertainty results in energy detection poor performance since energy detection requires the knowledge of noise power.

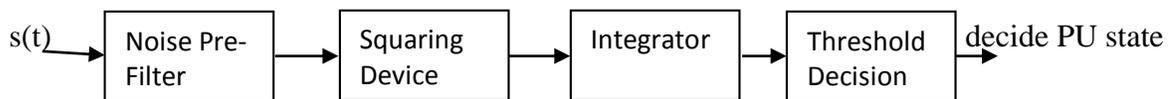


Figure 3.1: Spectrum Sensing of Energy Detection

Fig 3.1 represents the basic structure of energy detection. Band Pass Filter (BPF) first selects a

centre frequency to receive signal from interested bandwidth [23][35][38] and then the received signal is measured by a magnitude squaring device. Integrator controls the observations time and sums up all the received signals after squaring devices. Then the receiver sum with predetermined threshold to estimate PU activity. This spectrum sensing technique performs poorly under low SNR conditions and cannot distinguish between signals of PU from signals of other secondary user [25][46][47]. During the energy Detection based sensing there are two common assumption works i.e. the noise is stationary and variance is known. The performance of ED further degrades when the noise is not stationary and the variance is not known [59]. Other problems with the energy detector include baseband filter effects and spurious tones [60].

The received signal in narrowband energy detection follows a two hypothesis. Assume that the primary signal $s(t)$, is transmitted between PU and SU over a wireless fading channel and the received signal is $r(t)$. $r(t)$ is considered as binary hypothesis that follows: H_0 (representing the absence of PU) and H_1 (representing the presence of PU) and can be expressed as [2]

$$H_0: w(n) \tag{1}$$

$$H_1: r(t) = hs(n) + w(n) \tag{2}$$

Where $s(n)$ is the signal to be detected, $w(n)$ represent the additive white Gaussian noise (AWGN), n is sample index, h is complex fading envelope and $h=0$ or 1 under hypothesis H_0 or H_1 respectively. The received signal [5] is first pre-filtered by an ideal band pass filter with transfer function

$$H(f) = \begin{cases} \frac{2}{\sqrt{N_{01}}}, & |f - f_c| \leq W, \\ 0 & |f - f_c| > W, \end{cases} \tag{3}$$

The goal of Energy detector is to decide between the two hypotheses which can be achieved by forming a test signal. If the value of test signal is lower than predefined threshold value (λ_E), hypothesis H_0 is choose i.e. PU is absent, otherwise H_1 hypothesis is chosen. The output of this filter is then squared and integrated over an observation vector of N size to finally produce a measure of the energy of the received waveform.

The output of the integrator denoted by Y will act as test statistics to test the hypothesis H_0 and H_1 . Then the test of decision statistic Y can be written as

$$Y = \sum_{n=0}^N |y(n)|^2 \tag{4}$$

The performance of the detection algorithm can be summarized with two probabilities: probability of detection (P_D) and probability of false alarm (P_F) which can be generally computed by [5]

$$P_D = P_R (Y > \lambda_E | H_1) \quad (5)$$

$$P_F = P_R (Y > \lambda_E | H_0) \quad (6)$$

P_F should be kept as small as possible in order to prevent underutilization of transmission opportunities. The decision threshold λ_E can be selected for finding an optimum balance between P_D and P_F . However, this requires knowledge of noise and detection powers. The noise can be estimated, but the signal power is difficult to estimate as it changes depending on ongoing transmission characteristics and distance between the CR radio and primary user.

The white noise can be modeled as zero mean Gaussian random variable with variance σ_w^2 , i.e. $w(n) = N(0, \sigma_w^2)$. For a simplified analysis if the signal term as a zero-mean Gaussian variable then, $s(n) = N(0, \sigma_s^2)$. But the model for $s(n)$ is more complicated as fading should be also considered. Because of these assumptions, the decision metric (4) follows a central chi-square (χ^2) distribution with $2N$ degree of freedom χ_{2N}^2 and can be modeled as

$$Y = \begin{cases} \frac{\sigma_w^2}{2} \chi_{2N}^2 H_0 \\ \frac{\sigma_s^2 + \sigma_w^2}{2} \chi_{2N}^2 H_1 \end{cases} \quad (7)$$

For energy detector, the probabilities of P_D and P_F can be calculated as [5]

$$P_D = 1 - \Gamma \left(L_f L_t, \frac{\lambda_E}{\sigma_s^2 + \sigma_w^2} \right) \quad (8)$$

$$P_F = 1 - \Gamma \left(L_f L_t, \frac{\lambda_E}{\sigma_w^2} \right) \quad (9)$$

Where $\Gamma(a, x)$ is incomplete gamma function as given in [80] (ref. equation 6.5.1)

The corresponding probability density function (PDF) in the presence of AWGN is expressed according to [5, (3)], namely

$$f_Y(y) = \begin{cases} \frac{1}{2^N \Gamma(N)} y^{N-1} e^{-\frac{y}{2}} H_0 \\ \frac{1}{2} \left(\frac{y}{2\gamma} \right)^{\frac{N-1}{2}} e^{-\frac{2\gamma+y}{2}} I_{N-1}(\sqrt{2\gamma y}), & H_1 \end{cases} \quad (10)$$

Where $\Gamma(\cdot)$ is the incomplete gamma function, γ is the ratio of the Primary users signal power to noise power, i.e. $(\text{SNR}) = \frac{\sigma_s^2}{\sigma_w^2}$,

and $I_N(\cdot)$ is the N^{th} order modified Bessel function of the first kind.

The (6) can be derived by (10) [7]:

$$P_F = \frac{\Gamma(N \frac{\lambda_E}{2})}{\Gamma(N)} \quad (11)$$

The (5) can be obtained from (10) by using cumulative distribution function (CDF) of Y

$$\text{Hence, } P_D = 1 - F_Y(y) = Q_N(\sqrt{2\gamma}, \sqrt{\lambda_E}) \quad (12)$$

where $F_Y(y)$ represents the CDF of Y, $Q_N(\dots)$, represents the N^{th} order generalized Marcum-Q function.

If the signal power is unknown, we can first set the false alarm probability P_F to a specific constant. By equation (10), the detection threshold λ_E can be determined. Then for fixed number of samples the detection probability P_D can be evaluated by substituting the λ_E in (11). As expected P_F is independent of γ under H_0 there is no primary signal present. When h is varying due to fading, equation (12) gives the probability of detection as a function of the instantaneous SNR γ . In this case, the average probability of detection P_D may be derived by averaging (12) over fading statistics [25], [72]

$$P_D = \int Q_N(\sqrt{2\gamma}, \lambda_E) f_Y(y) dy \quad (13)$$

Where $f_Y(x)$ is the probability distribution function (PDF) of SNR under fading.

Where $F_Y(y)$ is the N^{th} order generalized Marcum-Q function given by [75]

$$Q_N(\sqrt{2\gamma}, \sqrt{\lambda_E}) = \frac{1}{\sqrt{2\gamma}^{N-1}} \int_{\lambda_E}^{\infty} t^N e^{-\frac{(\sqrt{2\gamma})^2 + t^2}{2}} I_{N-1}(\sqrt{2\gamma}t) dt \quad (14)$$

Here, I_{N-1} denotes the modified Bessel function of the first kind.

According to [76], equation (13) can be simplified and rewritten as

$$Q_N(\sqrt{2\gamma}, \sqrt{\lambda_E}) = e^{\frac{\lambda_E}{2}} \sum_{i=0}^{N-1} \frac{(\frac{\lambda_E}{2})^i}{i!} + e^{-\frac{\lambda_E}{2}} \sum_{n=N}^{\infty} \frac{(\frac{\lambda_E}{2})^n}{n!} (1 - e^{-\gamma} \sum_{k=0}^{n-N} \frac{\gamma^k}{k!}) \quad (15)$$

3.2 Energy Detection Performance

3.2.1 Raleigh Fading Channels

The Channel between PU and SU is modeled as Rayleigh fading channels, the SNR's (γ) PDF is following an exponential distribution given as [5]

$$f(\gamma) = \frac{1}{\gamma} \exp\left(-\frac{\gamma}{\gamma}\right) \quad (16)$$

where $\bar{\gamma}$ represents the average SNR in local channels. The average PD over Rayleigh fading channels is derived by averaging equation (12) and equation (16)

$$\bar{P}_D = \int_0^\infty Q_u(\sqrt{2\gamma}, \lambda_E) f_\gamma(\mathbf{x}) d\gamma \quad (17)$$

By using [75, Eq(30)], equation (17) can be expressed as

$$\bar{P}_D = e^{\frac{\lambda_E}{2}} \sum_{n=0}^{u-2} \frac{1}{n!} \left(\frac{\lambda_E}{2}\right)^n + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{u-1} \left[e^{-\frac{\lambda_E}{2(1+\bar{\gamma})}} - e^{-\frac{\lambda_E}{2}} \sum_{n=0}^{u-2} \frac{1}{n!} \frac{\lambda_E \bar{\gamma}}{2(1+\bar{\gamma})} \right] \quad (18)$$

3.2.2 Nakagami Fading Channel

Although Rayleigh and Rician distributions are the most popular distributions to model fading channels, some experimental data does not fit well into neither of these distributions. Thus, a more general fading distribution was developed whose parameters can be adjusted to fit a variety of empirical measurements [73]. This distribution is called Nakagami fading distribution. It is possible to describe both Rayleigh and Rician fading with the help of a single model using the Nakagami distribution. The Nakagami m -distribution is used in communication systems to characterize the statistics of signal transmitted through multipath fading channels.

The probability density function (PDF) γ in a Nakagami distribution follows an exponential PDF and given by [23]

$$f(\gamma) = \frac{1}{\Gamma(m)} \left(\frac{m}{\bar{\gamma}}\right)^m \gamma^{m-1} \exp\left(-\frac{m\gamma}{\bar{\gamma}}\right), \gamma \geq 0 \quad (19)$$

where m is the Nakagami parameter

The average P_D over Nakagami fading channel is derived by averaging equation (15) over equation (19) [77].

$$\bar{P}_D = e^{\frac{\lambda_E}{2}} \sum_{i=0}^{u-1} \frac{\left(\frac{\lambda_E}{2}\right)^i}{i!} + e^{-\frac{\lambda_E}{2}} \sum_{n=u}^{\infty} \frac{\left(\frac{\lambda_E}{2}\right)^n}{n!} \left(1 - \frac{1}{\Gamma(m)} \left(\frac{m}{\bar{\gamma}}\right)^m \sum_{k=0}^{n-u} \frac{\int_0^\infty e^{-\frac{m+\gamma}{\bar{\gamma}} \gamma} \gamma^{k+m-1} d\gamma}{k!}\right) \quad (20)$$

By using [78] equation (20) can be written as [77]

$$\bar{P}_D = e^{\frac{\lambda_E}{2}} \sum_{i=0}^{u-1} \frac{\left(\frac{\lambda_E}{2}\right)^i}{i!} + e^{-\frac{\lambda_E}{2}} \sum_{n=u}^{\infty} \frac{\left(\frac{\lambda_E}{2}\right)^n}{n!} \left(1 - \left(\frac{m}{m+\bar{\gamma}}\right)^m \sum_{c=0}^{n-u} \left(\frac{\bar{\gamma}}{m+\bar{\gamma}}\right)^c \frac{(m+c-1)!}{\Gamma(m)c!}\right) \quad (21)$$

3.2.3 Rician Fading Channel

Some types of scattering environments have a specular or LoS (Line of Sight) component. In this

case, the amplitude of received signals has a rician fading channel where the PDF of SNR(γ) will follow an exponential distribution given in [5]

$$f_{\gamma}(x) = \frac{k+1}{\gamma} \exp(-k \frac{k+1}{\gamma}) * I_0(2 \sqrt{\frac{k+1}{\gamma}}), \gamma \geq 0 \quad (22)$$

where k is the Rician factor. The average detection probability P_D over Rician fading channels is derived by averaging equation (15) over equation (22)

$$P_D = e^{\frac{\lambda E}{2}} \sum_{i=0}^{N-1} \frac{(\frac{\lambda E}{2})^i}{i!} + e^{-\frac{\lambda E}{2}} \sum_{n=N}^{\infty} \frac{(\frac{\lambda E}{2})^n}{n!} (1 - \frac{(k+1)e^{-k}}{\gamma}) \sum_{c=0}^{n-N} \frac{\int_0^{\infty} e^{-\frac{(k+1+\gamma)\gamma}{\gamma}} \gamma^c I_0(2\sqrt{\frac{k(k+1)\gamma}{\gamma}}) d\gamma}{c!} \quad (23)$$

3.3 Cyclostationary Feature Detection

A cyclostationary process has statistical properties that vary periodically over time. Cyclostationary feature detection method deals with the inherent cyclostationary properties or features of the signal. Such features have a periodic statistics and spectral correlation that cannot be found in any interference signal or stationary noise. It exploits this periodicity in the received primary signal to identify the presence of primary users, and that is why the cyclostationary feature detection method possesses high noise immunity than any other spectrum sensing method. In this method, the cyclic spectral correlation function (SCF) is the parameter that is used for detecting the primary user signals. The block diagram of cyclostationary feature detection is as follows:

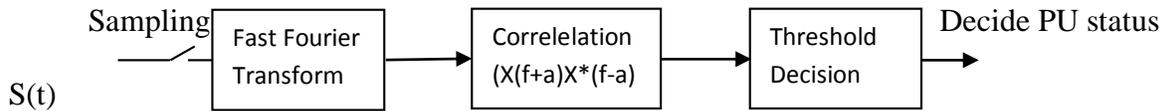


Figure 3.2: Spectrum Sensing of Cyclostationary Feature Detection

Cyclostationary spectrum sensing method performs better than energy detection method in low SNR regions, because of its noise rejection capability. This occurs because noise is totally random and does not exhibit any periodic form of behavior. When we have no prior knowledge about primary user's waveform, which is the scenario in real life, then best technique to be adopted is cyclostationary feature detection. As an advantage, the cyclostationary spectrum sensing method can be used to find out the type of modulation scheme used by the primary user signal. At the same time, the cyclostationary method has some disadvantages too. These include spectral leakage of high amplitude signals, their non-linearity etc. The method is computationally complex and hence requires significantly longer observation time and also costs high [1]. Also, when an insufficient number of samples are used, the detection performance will degrade due to the poor estimate of the cyclic spectral density.

3.3.1 Spectral Correlation Function (SCF)

Two dimensional spectral correlations is the way to extract the periodic features of the primary user signal. These signals are cyclostationary processes that are periodic in time t.They also possess a periodic autocorrelation function.

$$R_y(t+\tau)=R_y(t+T_0, \tau) \quad (24)$$

The Fourier transform of the cyclic autocorrelation function is given as follows:

$$R_y^\alpha(f) = \lim_{n \rightarrow \infty} \frac{1}{T} \int_T y\left(t + \frac{\tau}{2}\right) y^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi\alpha t} dt \quad (25)$$

In the above equation, α is the fundamental cyclic frequency and R_y^α is the cyclic autocorrelation function. If cyclostationary with period T then cycle autocorrelation has component at $\alpha=1/T$. The spectrum correlation density function is obtained by cyclic autocorrelation function and can separate the Wide-Sense Stationary noise from the primary signal. When the parameter $\alpha =0$, the SCF becomes power spectral density.

The cyclic spectral density (CSD) function of a received signal can be calculated as [29].

$$S_y^\alpha(f) = \int_{-\infty}^{\infty} R_y^\alpha(\tau) \exp(-j2\pi f\tau) d\tau \quad (26)$$

$$\text{Where } R_y^\alpha(\tau) = E[y(n + \tau)y^*(n - r)]e^{j2\pi\alpha n} \quad (27)$$

is the cyclic autocorrelation function(CAF) and α is is the clic frequency. The CSD in (26) is a function of the frequency f and the cyclic frequency α and any cyclostationary features can be detected in the cyclic frequency domain a property that is exploited to be used as a spectrum sensing technique. Cycle autocorrelation is time domain transforms, its frequency domain equivalent spectral correlation function (SCF) can be expressed as follows:

$$S_y^\alpha(f) = \lim_{\Delta t \rightarrow \alpha T} \lim_{T \rightarrow \alpha} \frac{1}{\Delta t} \frac{1}{T} \int_{-\frac{\Delta t}{2}}^{\frac{\Delta t}{2}} Y_T\left(t, f + \frac{\alpha}{2}\right) Y_T^*\left(t, f - \frac{\alpha}{2}\right) dt \quad (28)$$

$S_y^\alpha(f)$ is a two dimensional complex transform on a support set (f, α) . Spectral correlation function can be used for feature detection. Autocorrelation function is also quadratic transform thus feature of modulated signals that are function of symbol rate, carrier, etc. can be detected. The probability of detection and probability of false alarm in a cyclostationary feature detection can be expressed as [79]:

$$P_D = P_R \left(\sqrt{\frac{2\gamma}{\delta}}, \frac{\lambda_E}{\delta} \right) \quad (29)$$

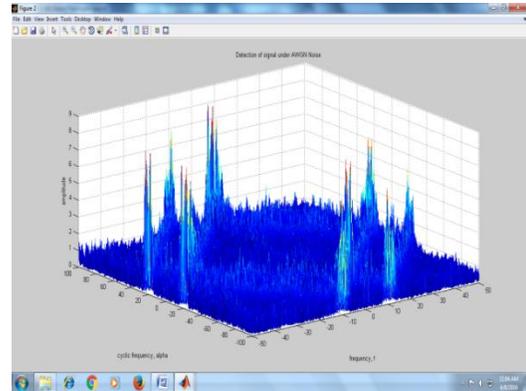
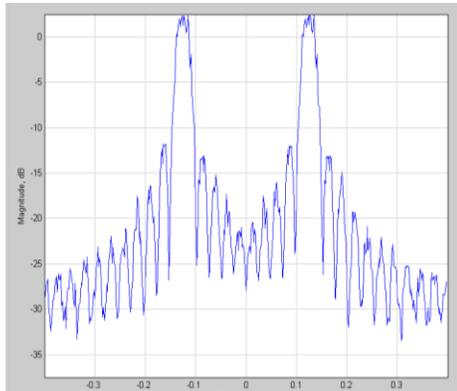
$$P_F = \exp \left[\frac{-(2N+1)\lambda_E^2}{2\delta^4} \right] \quad (30)$$

Where γ represents SNR, δ represents average energy of received signal and N is number of samples. CSD is computed and averaging over a sufficient number of samples. The received signal is compared with the decision threshold and we can get the probability of detection and probability of false alarm of cyclostationary feature detection over different fading channel. The correlation and averaging also done to get cyclic spectrum (Equation (18), (21), (23), (29) & (30) refers).

When SCF is plotted, the occupancy status of the spectrum can be found out. If a primary user signal is present in the operating frequency range, the SCF gives a peak at its centre. The peak will not be present in the case when there is no primary user signal present in the concerned frequency range. In addition to this, the SCF can be used to find out the type of modulation scheme used by the primary user signal. This can be achieved by counting the number of secondary peaks at the double frequencies. If the modulation scheme involved is BPSK, there will be single secondary peaks at the double of operating frequency. Instead if the modulation scheme involved is QPSK, there will be two such secondary peaks at the double of operating frequency.

3.3.2 Simulation Model of Proposed System

Some random signal is taken as the primary user signal. The signal from primary user is modulated and then relayed by multiple cognitive relays and the data is send to the fusion center. The relaying method involved here is amplifying and forward relaying. At the fusion center, either hard or soft combination schemes or any of the majority combining rules, AND, OR rules etc can be used.



Then after passing through the wireless channel (here AWGN is used as the channel) it reaches the cyclostationary feature detector (CFD) section. This section involves a band pass filter, an analog to digital convertor, finding the fast Fourier transform, correlating averaging and feature detection. Final output of the CFD section is the estimated cyclic SCF. This spectral correlation function is analyzed to detect the signals in the cyclostationary -based spectrum sensing method. CFD output is demodulated using an appropriate scheme before it reaches the primary user's receiver.

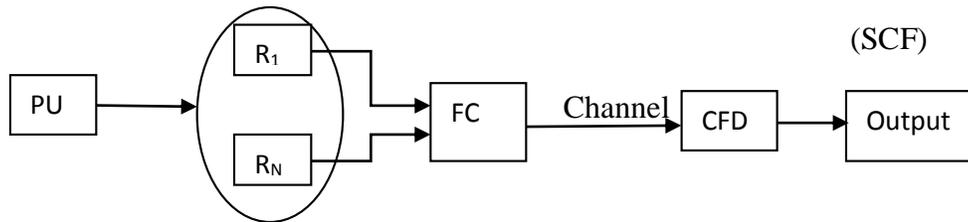


Figure 3.4: Block Diagram of SCF

The CSD function outputs peak values when the click frequency is equal to the fundamental frequencies of transmitted signal $x(t)$. Cyclic frequencies can be assumed to be known [20], [22] or they can be extracted and used as features for identifying transmitted signals [2]. As a result cyclostationary feature detector can overcome the energy detector limits in detecting signals in low SNR environments. In fact, signals with overlapping features in the power spectrum, can have non overlapping features in the cyclic spectrum. The cyclic spectrum is a much comfortable domain for signal detection than typical power spectral density.

Thus cyclostationary feature detection is robust to noise uncertainties and performs better than energy detection in low SNR region. The detection method is improving the overall CR through its cooperative sensing method.

3.4 Matched Filter Based Detection

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known [39]. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of missdetection[49] as compared to other methods. In fact, the required number of samples grows as $O(1/\text{SNR})$ for a target probability of false alarm at low SNRs for matched-filtering [49]. However, matched-filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation type and order, pulse shaping, and frame format which maximizes signal to noise ratio. The primary users signaling can be obtained by using CR devices with carrier synchronization and timing devices that leads enhanced implementation complexity [1],[4].

3.4.1 System Modeling

The matched filter detection based sensing is exactly the same as the traditional matched filter detection technique deployed in digital receivers of the primary user signal is required (such as the modulation format data rate, carrier frequency, pulse shape, etc). It is a system of linear filter used in the framework of the digital signal processing. It is used to optimize the SNR in presence of the additive noise stochastic.

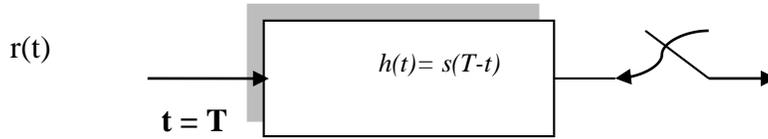


Figure 3.5: Matched filter based spectrum sensing and detection of primary users.

The matched filter detection technique is a very well-treated topic in literature, and therefore, we just present the fundamental results on matched filter detection in this section. Given a real transmit signal waveform $s(t)$ defined over $0 \leq t \leq T$ the corresponding matched filter maximizing the signal to noise ratio at the output of the filter sampler is given by

$$h(t) = \begin{cases} s(T - t); & 0 \leq t \leq T \\ 0; & \text{elsewhere} \end{cases} \quad (31)$$

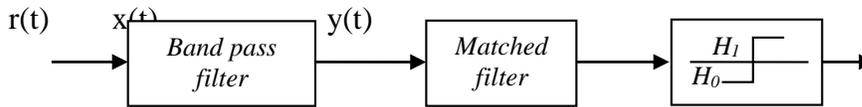


Figure 3.6: Block diagram of matched filtering based sensing

The fig 3.5 depicts matched filter based spectrum sensing method for primary user detection. Considering that complete signal information of the primary user signal is required in this case the matched filter method is not really recommended by the system designers to suit our purpose here unless when the complete signal information is known to the secondary user. Then based on the test statistic $\xi(nT)$ at the output of the filter sampled every $t=nT$ seconds, the detector is given by

$$D(nT) = \begin{cases} 0; & \xi(nT) < \lambda_E \\ 1; & \xi(nT) \geq \lambda_E \end{cases} \quad (32)$$

The matched filter-based detector gives better detection probability compared to the previously discussed methods using the energy detector and the cyclostationary feature based detector; however as mentioned, it requires complete signal information and needs to perform the entire receiver operations (such as synchronization, demodulation, etc.) in order to detect the signal. Obviously for match filter based spectrum sensing a complete knowledge.

3.4.2 The Key Parameters of Performance for Matched Filter

The decision test statistics $T(X)$ of the MF detector decides H_1 if;

$$T(X) = \sum_{n=0}^{N-1} x[n] s[n] > \lambda_E \quad (33)$$

where $H_0: x[n] = w[n]$, $n= 0, 1 \dots N-1$

$H_1: x[n] = s[n] + w[n]$, $n= 0, 1 \dots N-1$ and

λ_E is decision threshold .

The distribution of the test statistics under either hypotheses, H and H_1 respectively

$$T \sim \begin{cases} N(0, \sigma^2 \varepsilon) & \text{under } H_0 \\ N(\varepsilon, \sigma^2 \varepsilon) & \text{under } H_1 \end{cases}$$

The performance of the MF detector is based on the following two parameters: the probability of detection (P_D) and the probability of false alarm (P_F). The probability of false alarm is when there is no signal, i.e. just the noise, and we detect signal, from the distribution H_1 of the test static T under hypothesis H_0 we have:

$$\begin{aligned} P_F &= P_r(T > \lambda_E | H_0) \\ &= P_r(T' > \frac{\lambda_E}{\sqrt{\sigma^2 \varepsilon}} | H_0), \quad T'(X) = \frac{T(X)}{\sqrt{\sigma^2 \varepsilon}} \\ P_F &= Q \left(\frac{\lambda_E}{\sqrt{\sigma^2 \varepsilon}} \right) \text{ or } \lambda_E = Q^{-1}(P_F) \sqrt{\sigma^2 \varepsilon} \end{aligned} \quad (34)$$

Where $T(X)$ is the Gaussian random variables, $Q(\cdot)$ is the standard Gaussian complementary Cumulative Distribution Function (CDF) and $Q^{-1}(\cdot)$ is considered as the inverse standard Gaussian complementary CDF and ε is the energy of the signal source $s[n]$. During the presence of signal, the probability of detection (P_D) under hypothesis H_1 is:

$$\begin{aligned} P_D &= P_r(T > \lambda_E | H_1) \\ &= Q \left(\frac{\lambda_E - \varepsilon}{\sqrt{\sigma^2 \varepsilon}} \right) = Q \left(Q^{-1}(P_F) - \frac{\varepsilon}{\sqrt{\sigma^2 \varepsilon}} \right) \end{aligned} \quad (35)$$

From the equation (34) and (35) (over (18), (19) and (22))we can get the probability of detection and probability of false alarm of matched filter detection over different fading channel.

Chapter IV

Performance Analysis and Simulation

4.0 Introduction

In the previous chapter we have discussed about the mathematical model of classical spectrum sensing. In this chapter, this work the performance of the different classical narrowband sensing methods will be compared in order and analyzed for better application.

An extensive set of simulations have been conducted using the system model as described in the previous section. The emphasis is to analyze the comparative performance of classical spectrum sensing techniques. The results are conducted on the basis of probability of false alarm and

probability of false alarm detection under different SNR in different channels namely AWGN, Rayleigh fading and Rician fading. All simulation was done on MATLAB version R2011a under AWGN, Raleigh and Rician fading channel. We have used receiver characteristics (ROC) analysis for the signal detection theory to study the performance of the energy detector. ROC has been widely used in the signal detection theory due to the fact that it is an ideal technique to quantify the tradeoff between the probability of detection (P_d) and the probability of false alarm (P_f).

4.1 Performance Analysis and Simulation of Fading Channels

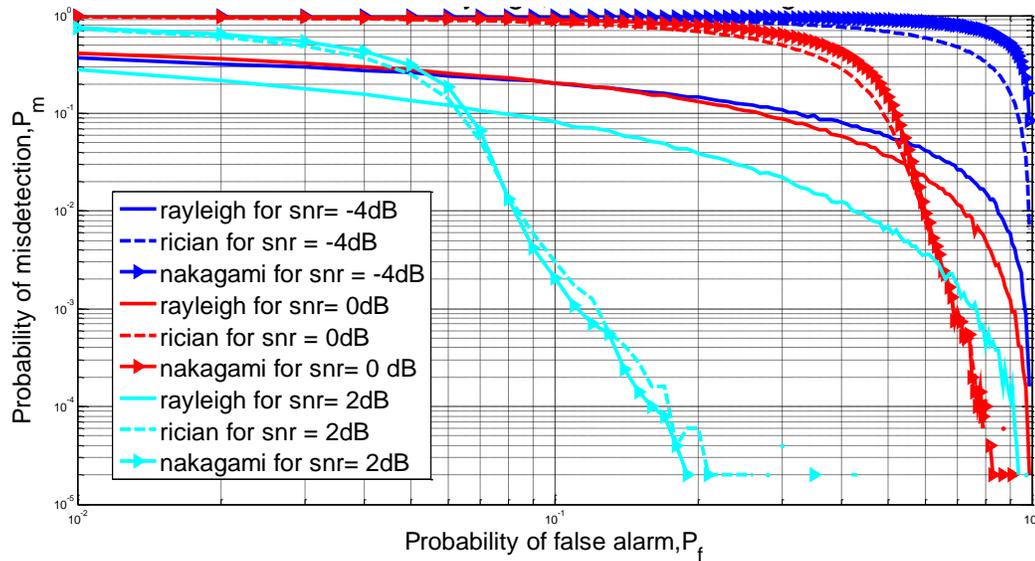


Figure 4.1: CROC Curve Under Rayleigh, Rician and Nakagami Channel

From the Figure 4.1, it is observed that with varying fading channel the performance of misdetection and false alarm varies. At Nakagami factor $m=0$, the channel become AWGN, at $m=1$, channel become Rayleigh channel and $m>.5$ it become Rician channel. The performance also varies with the varying SNR value.

4.2 Performance Analysis and Simulation of ED based Detection

Theoretically with the increase of SNR values γ and decision threshold λ_E , the detection probability of Energy Detection under AWGN will increase. Simulation of Energy Detection has been performed on MATLAB over different fading channels and what interests us in this simulation is the receiver performance. The receiver operating characteristics (ROC) curves (P_F Vs P_D) of the said detection system for one CR are plotted for different SNR values according to the above mentioned equations. A ROC curve allows exploring the relationship between the sensitivity and specificity of a sensing method for a verity of different thresholds, thus allowing the determination of an optimal threshold.

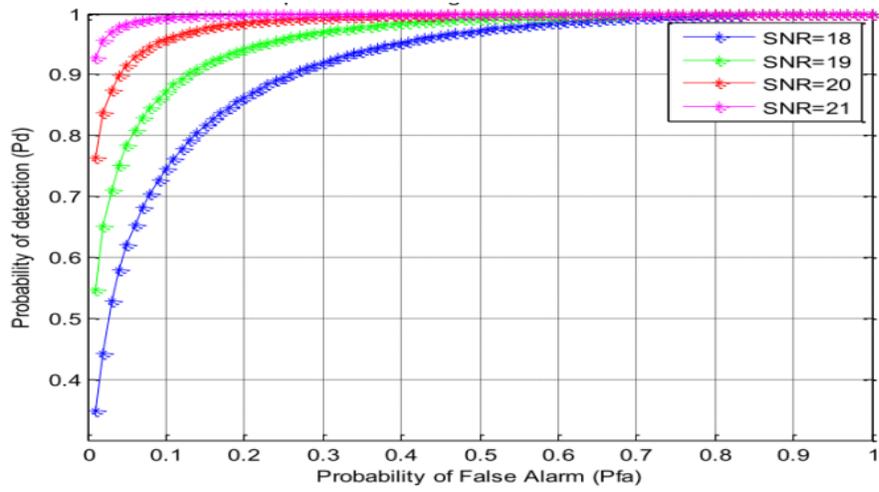


Figure 4.2: ROC of Spectrum Sensing for Different Pfa under AWGN

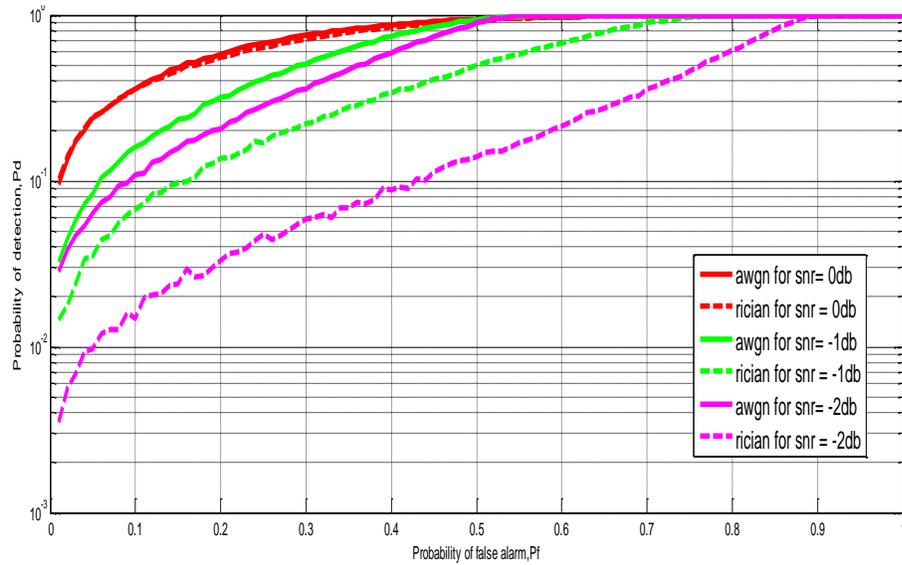


Figure 4.3: ROC curve under AWGN and Rician Channel

The ROC Curve represents the comparative performance analysis of energy detection under AWGN channels in different SNR values. The curve of figure 4.3, shows that with the increase of SNR value, the probability of detection increases and the probability of false alarm decrease and the AWGN have the minimum false detection as compared to the Rician fading channel.

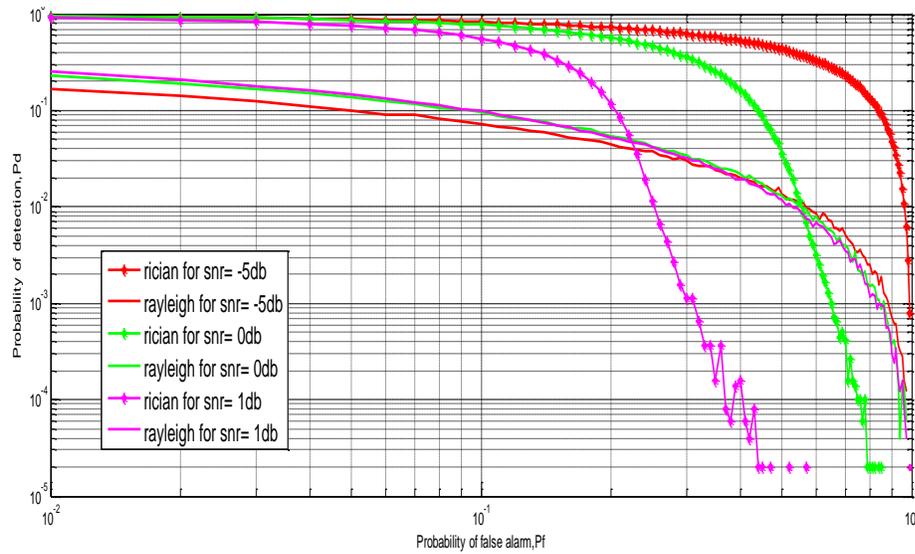


Figure 4.4: Energy Detection ROC Curve under Rician and Rayleigh Channel

Through Rayleigh fading channel large number of signal scattered and the signal amplitudes follows a Rayleigh distribution and the SNR γ follows an exponential PDF. Fig 4.4 shows the ROC curves for ED in Rayleigh and Rician fading scenarios. From the figure it is observed that the Rayleigh fading performance degrades significantly when it uses energy detector under fading conditions for different SNRs. By observing the graphs it is clear that detection probability is less in Rayleigh fading when compared to AWGN and Rician fading. This performance indicates that, spectrum utilization is less when fading is considered. Theoretical results which are obtained are perfectly matched with our simulation results.

4.3 Performance Analysis and Simulation of Cyclostationary Features Based Detection

Cyclostationary Features Detection is a medium accuracy medium complex sensing method. In the absence of Rayleigh fading channel and Rician fading channel it performance better. But with the increase of noise level the performance of this method degrades.

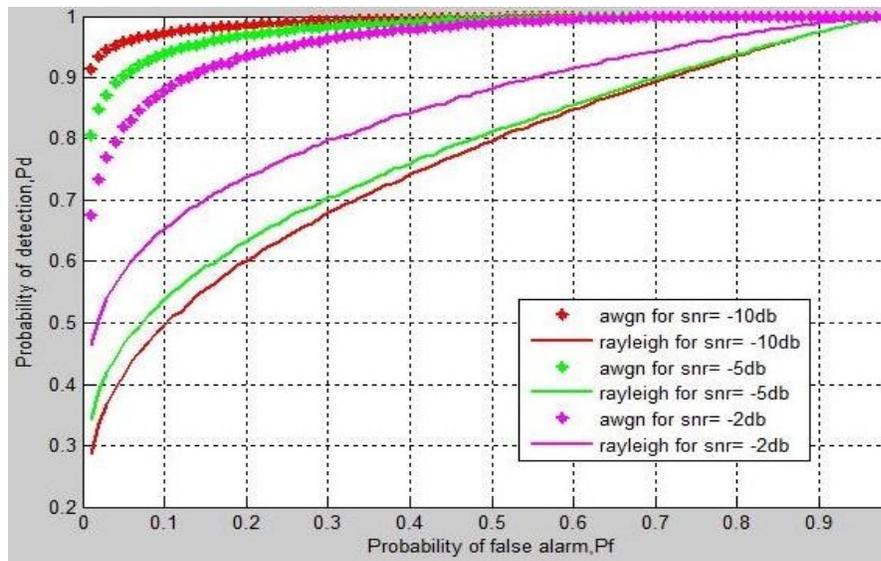


Figure 4.5: Cyclostationary feature detection ROC CURVE for QPSK UNDER AWGN & RAYLEIGH CHAN

4.4 Performance Analysis and Simulation of Matched Filtered based Detection

This sensing method is the robust methods among all classical sensing methods. But with the decrease of SNR the performance of the sensing methods decreases as shown in the graphs.

The figure 4.6 shows that with the increase of SNR values the detection probability increases in Matched filtered based sensing

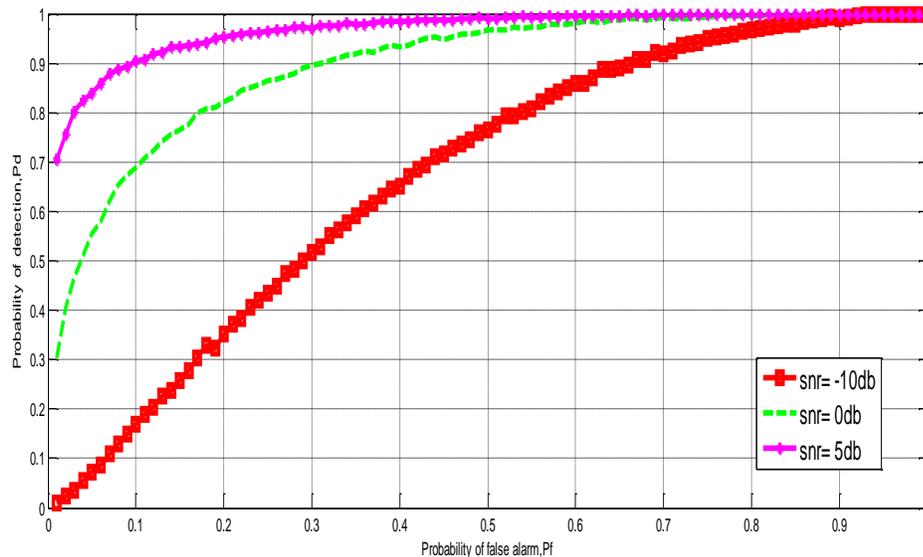


Figure 4.6: MATCHED FILTER ROC CURVE UNDER AWGN

The Fig 5.7 Shows that the performance of matched filter under AWGN channel is better than Rayleigh channel in all SNR conditions

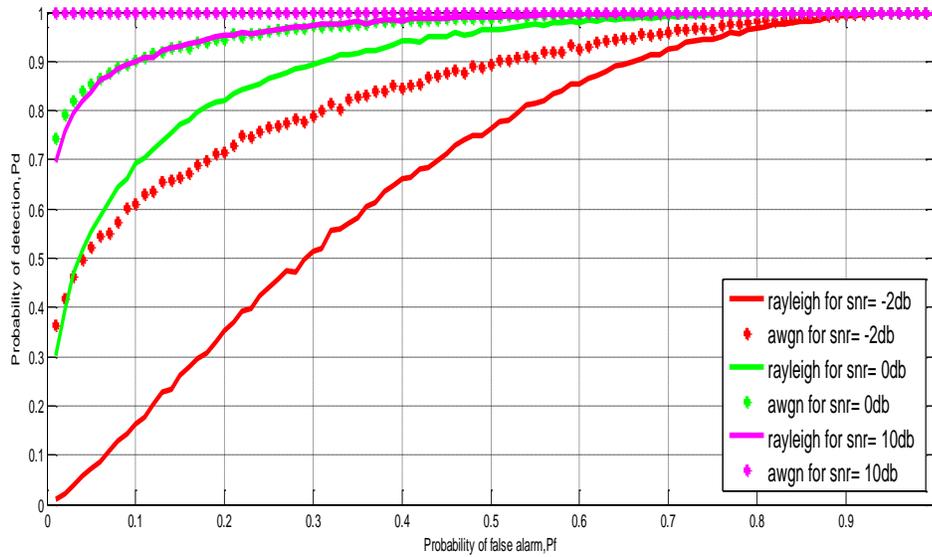


Figure 4.7 MATCHED FILTER ROC CURVE UNDER AWGN & RAYLEIGH CHANNEL

4.5 Performance Comparison among Different Classical Narrowband based Sensing

A basic comparison of the sensing methods given in this section is presented in Fig. 4.8 and Fig 4.9

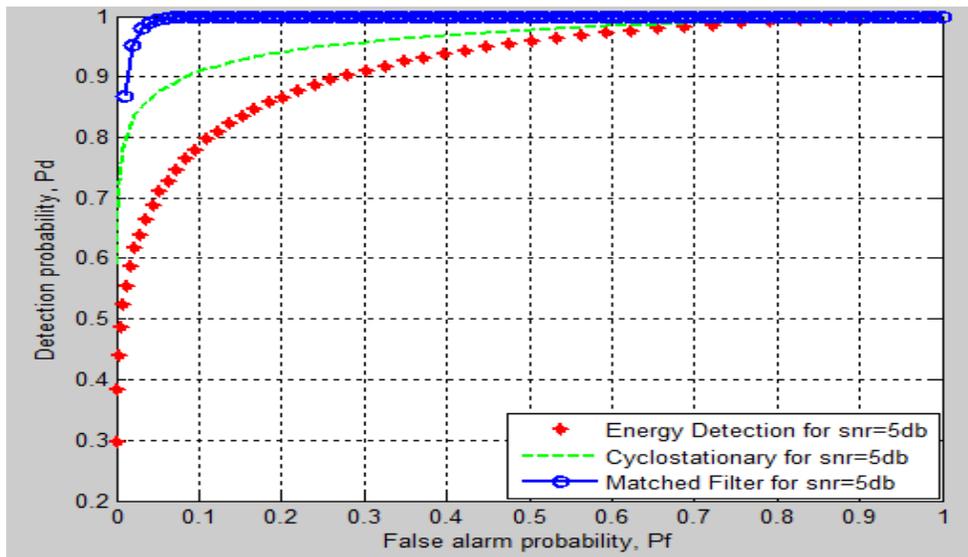


Figure 4.8 Comparison between Energy Detection, Cyclostationary Detection, Matched Filter

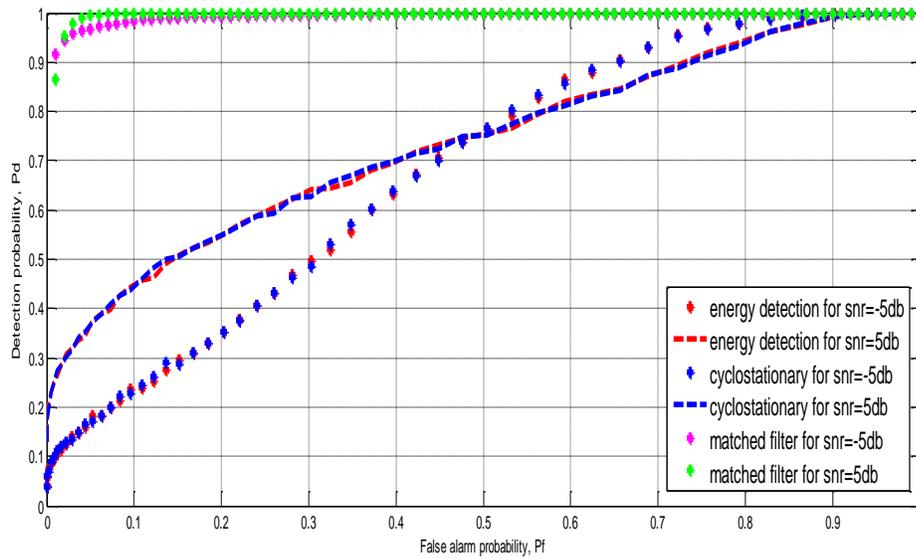


Figure 4.9 ROC under Energy Detection, Cyclostationary and Matched Filter in different SNR

The ROC curve shows that in general the performance of Energy Detection based sensing are limited comparing with the three classical based spectrum sensing techniques. Its performance is the simplest one when the noise is not stationary and its variance may not be known. But the signals completely lost during the presence of White Stationary Gaussian Noise and when its variance is not known. Other problems with the with the energy detector include base band filter effects and spurious tones [59].

In general Cyclostationarity-based sensing performs better than ED based sensing because in the presence of co-channel and adjacent channel the noise became stationary for cyclostationary based sensing. However, the cyclostationary-based methods perform worse than energy detector based sensing methods when the noise is stationary. Cyclostationary features may be completely lost due to channel fading [61], [62]. The model uncertainties cause an SNR wall for cyclostationary based feature detectors similar to energy detectors [63]. Furthermore, cyclostationarity based sensing is known to be vulnerable to sampling clock offsets [64].

The matched filtered based sensing is more robust than energy detector and cyclostationarity based methods because of the coherent processing that comes from using deterministic signal component [Arslan48]. However, there should be a priori information about the primary user's characteristics and primary users should transmit known patterns or pilots.

Based on the ROC analysis it is observed that the matched filtering sensing is more robust than other transmitter based methods because of the coherent processing [65]. However, there should be prior information about the primary user's characteristics.

4.6 Limitations of Classical Based Spectrum Sensing Method

The ED based approach is the common way of spectrum sensing because of its low computational and implementation complexities. In this technique signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. The challenges with energy detector based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from PUS and noise, and poor performance under low signal to noise ratio (SNR) values. Moreover, ED does not work efficiently for detecting spread spectrum signals. The performance of ED degrades considerably under Rayleigh Fading. The performance of ED based sensing is limited when two common assumptions do not hold [24]. The noise may not be stationary and its variance may not be known. Other problems with the ED include baseband filter effects and spurious tones [68]. With all these disadvantages, the most advantages of ED are it does not require any prior knowledge about the transmission signal to be received.

It is medium accuracy and medium complex sensing method where the periodicity in the signal or in its statistics like mean and autocorrelation feature is used to identify the signal from noise. Noise is a wide sense stationary (WSS) with no correlation while modulated signals are cyclostationary periodicities. However, this comes at the expense of increased overhead and bandwidth loss. Cyclostationary based methods perform worse than energy detector based sensing methods when the noise is stationary. However, in the presence of co-channel or adjacent channel interference, noise becomes non-stationary. Hence, ED based schemes fail while cyclostationary based algorithms are not affected [69]. On the other hand, cyclostationary features may be completely lost due to channel fading [100]. It is shown in [100] that model uncertainties cause an SNR wall for cyclostationary based feature detectors similar to energy detectors [A 92]. Furthermore, cyclostationary based sensing is known to be vulnerable to sampling clock offsets [85].

Matched filtering is known as the optimum method for detection of primary users when the transmitted signal is known i.e. The primary users signalling features such as bandwidth, operating frequency, modulation type and order, pulse shaping and frame format etc. It correlates the received signal with a template for detecting the presence of a known received signal. It is of two types i.e. narrow band matched filtering and wideband matched filtering. In narrowband matched filtering normally the sampling rate is at the Nyquist rate. In wideband matched filtering the sampling rate is sub-Nyquist rate. The matched filtering based sensing method is more robust than other sensing methods because of its coherent processing that comes from using deterministic signal component [A 48]. However, there should be prior information about the primary user's characteristics and primary users should transmit known patterns or pilots.

4.7 *The Problem of Stand Alone Transmitter*

Till now, we have discussed about The problems of a stand-alone transmitter to sense the neighboring radio environment are it suffers in multipath fading and shadowing environments where deep and fast fades of the received signal strength and make the spectrum less reliable. Through the standalone sensing method the improvement in SNR cannot be made by higher transmit power or additional bandwidth. Hidden terminal problem can lead to incorrect spectrum utilization which must be overcome to ensure that primary users of a band are protected from interference. It also leads to less accurate signal detection, increased false alarm probability and decreased in agility. In the single radio architecture, only a specific time slot is allocated for spectrum sensing. Due to limited sensing duration, only certain accuracy can be guaranteed for spectrum sensing results. Moreover, the spectrum efficiency is decreased as some portion of the available time slot is used for sensing instead of data transmission.

However, the probability of detection can be improved by using multiple antennas (diversity) methods for energy detection based systems like equal gain combining (EGC), selection combining (SC), maximal ratio combining (MRC) etc. Cyclostationarity based algorithms works better than ED in presence of cochannel or adjacent channel interference [64]. During the presence of multiple obstacles like high rise building, Rician fading channel may be used instead of Rayleigh fading. Cyclostationarity features may be completely lost due to the Rayleigh channel fading [62], [64]. In situations also, AGWN and Rician channel is better than Rayleigh channel fading.

4.8 *Cooperative/ Compressive Sensing to Solve the Stand Alone Terminal Problem*

The solution of the hidden terminal problem is cooperative spectrum sensing techniques. Cognitive radio co-operative spectrum sensing occurs when network of cognitive radios share the sensing information with each other and combining results from various measurements is a challenging task. The shared information can be soft or hard decisions made by each cognitive device [66]. The operation of this technique can be performed as follows:

Step1: Every cognitive radio performs local spectrum measurements independently and then makes a binary decision.

Step 2: All the cognitive radios forward their binary decisions to a common receiver which is an access point (AP) in a wireless LAN or a base station (BS) in a cellular network.

Step 3: The common receiver combines those binary decisions and makes a final decision to infer absence or presence of the primary users in the observed band.

In the above mentioned process number of sensing nodes use to do the data fusion and decision fusion process as mentioned below:

4.8.1. Data Fusion

Data fusion is a process of combining data or information to estimate or predict entity states. The estimates and assessments are incremental and the evolution of the need for additional sources modification is performed to improve the quality of the output.

4.8.2 Decision Fusion

Decision fusion is a special case of data fusion which is known to be a means for improving quality of pattern recognition and analysis. The class of decision function systems, as defined in is a subclass of data fusion system.

The optimum fusion rule for combining sensing information is the Chair-Vershney rule which is based on log-likelihood ratio test [67]. The following statistics, termed as the Chair-Vershney fusion statistics been shown to be a high SNR approximation to \mathcal{A}

$$\mathcal{A}_1 = \sum_{\text{sign}(y_k)=1} \text{Log} \frac{P_{dk}}{P_{fk}} + \sum_{\text{sign}(y_k)=-1} \text{Log} \frac{1-P_{dk}}{1-P_{fk}}$$

Here, P_{fk} and P_{dk} are the fading channel and local channel performance indicates respectively. \mathcal{A}_1 does not requires any knowledge regarding the channel gain, but does requires values of P_{fk} and P_{dk} for all k. This approach suffers significant performance loss at low to moderate channel SNR. It turns out that the sufficient statistics for the various sensors with weights that are functions of the individual probabilities of false alarm P_f and the probabilities of detection P_d . The information fusion at the AP is made by considering credibility which is transmitted by CR along with their decisions. The credibility of channel condition depends upon channel conditions and their distance from a license user. When hard decision are used AND, OR or M out of N methods can be used for combining information from different cognitive radios.

4.9 Compressive Sensing

Compressive Sensing (CS) becomes promising approach to recover the wideband signal expending only partial measurements. In the CS framework a real valued, finite-length, one dimensional time-variant signal $x(t)$, $0 \leq t \leq x$, can be denoted as a finite weighted sum if orthonormal basis functions

$$x(t) = \sum_{i=1}^N b_i \Psi_i(t) = \Psi_b \quad \text{Where } b_i \text{ is basis coefficient}$$

4.9.1 Basis Pursuit(BP)

The Time-Frequency and Time-scale communities have recently developed a large number of over complete waveform dictionaries i.e stationary wavelets, wavelet packets, consine packets, chirplets and warplets etc. Decomposition into over-complete systems is not unique and several methods for decomposition have been proposed, including the Methods of frames

(NOF), Matching Pursuit (MP) and for special dictionaries, the Best Orthogonal Basis (BOB). The Basis Pursuit (BP) is a principle for decomposing a signal into an optimal superposition of dictionary elements, where optimal means having the smallest l_1 norm of coefficients among all such decompositions [Phd20]. BP finds signal representation in over-complete dictionaries by convex optimization: it obtains the decomposition that minimizes the l_1 norm of the coefficients occurring in the representation.

4.9.2 Matching pursuit (MP)

Matching pursuit is a sparse approximation algorithm which involves finding the "best matching" projections of multidimensional data onto the span of an over-complete (i.e., redundant) dictionary. The basic idea is to approximately represent a signal from Hilbert space as a weighted sum of finitely many functions (called atoms) taken from. An approximation with atoms has the form where c_k is the scalar weighting factor (amplitude) for the atom ϕ_k . Normally, not every atom in Φ will be used in this sum. Instead, matching pursuit chooses the atoms one at a time in order to maximally (greedily) reduce the approximation error. This is achieved by finding the atom that has the biggest inner product with the signal (assuming the atoms are normalized), subtracting from the signal an approximation that uses only that one atom, and repeating the process until the signal is satisfactorily decomposed, i.e., the norm of the residual is small,

4.9.3 Modulated Wideband Converter

Conventional sub-Nyquist sampling methods for analog signals exploit prior information about the spectral support. In future the available spectrum for secondary user will be reduced and option will be more challenging task to sense spectrum blindly using sub-Nyquist sampling of multiband signals. The modulated wideband converter (MWC) is the first system for sub-Nyquist sampling, which can be realized with existing devices and handle wideband analog signals.

4.9.3.1 System Model: The Fourier transform of wideband signals often occupies only a small portion of a wide spectrum, with unknown frequency support. For example: in wideband communication, the receiver sees the sum of several radio-frequency transmissions. Each signal is modulated around an unknown and different carrier frequency.



Figure: 4.10: The Multiband Spectrum

With an efficient hardware implementation and low computational load on the supporting digital processing, the modulated wideband converter (MWC) can blindly sample multiband analog

signals at a low sub-Nyquist rate. The MWC first multiplies the analog signal by a bank of periodic waveforms. Then the product is lowpass filtered and sampled uniformly at a low rate. The waveform period and the uniform rate can be made as low as the expected width of each band, which is orders of magnitude smaller than the Nyquist rate. Reconstruction relies on recent ideas developed in the context of analog compressed sensing, and is comprised of a digital step which recovers the spectral support. The MWC enables baseband processing, namely generating a low rate sequence corresponding to any information band of interest from the given samples, without going through the high Nyquist rate. In the broader context of Nyquist sampling, the MWC scheme has the potential to break through the bandwidth barrier of state-of-the-art analog conversion technologies such as interleaved converters.

4.10 Potential Solution

Cognitive Radios utilize and handle the spectrum through spectrum sensing, spectrum management, spectrum mobility and spectrum sharing which leads to many challenges in CRN development and boost up. Security concern and local of computing power are among a list of critical issues to boost the CR user performance. Most of the challenges are related to frequency agility and computational power and those two abilities are physically constrained. Due to the nature of optimistic spectrum access, multichannel option is required to be consideration for the secondary user to maintain reliable connectors. RF of a CR has to have relatively wide bandwidth and be able to switch between frequency bands. The increased frequency band has to be coupled with increased linearity range in order to present the desired signal from being distorted. The radio communications signals are emitted in electromagnetic format and achieving wireless security is every difficult by stopping the signal leakages. Reducing signal leakage enhances overall security. Encryption and authentication based security techniques have seen proceed effective, but all of them need to consume additional radio resources, Additional security means, there are some physical-Layer techniques to strengthen security by reducing radio signal leakage.

Orthogonal frequency Division Multiplexing can be applied so each sub channel can be viewed as a flat fading channel. The intelligence of a true CRN relies heavily on the implementation of computational intelligence and machine learning. We need to seek solutions to provide increased computing power. For instant, some physical-Layer techniques may be used to enhance CRN security, collaborative sensing can be considered to increase spectrum sensing performance, and off-board computing resources may join with on-board computing resources to handle computational burden.

- 1. Enhancement of Security:** The characteristic of a wideband frequency electric channel is location dependent, which can be utilized to offer certain security enhancement.
- 2. Wideband Transmit, Wave Form Design to Minimize Information Leakage:** Wideband communication systems can be benefited by spectrum shaping via transmit wave form design, With the ability of programmable transmit wave forms, and advanced spectrum sensing, the interferences generated by secondary users in the CRN can be well controlled.
- 3. Enhancement of Computing Power:** A practically solution Impelling added features requires additional signal processing and computing power, but the fact is that onboard

computing power is very limited. Nowa day's many electronic devices are highly networked and it is likely a cognitive radio transreceiver can take advantage of surrounding computing resources. For other words, time critical tasks like modulation/demodulation are handled by the onboard real-time processors, and delay tolerable tasks like knowledge database updating are taken care of by the off by the off-board networked computing engines in a collaborative fashion.

Chapter 5

Concluding Remarks & Future Work

5.1 Concluding Remarks

Spectrum sensing is a very valuable resource in wireless communication systems, and it has been a focal point for research and development efforts over the last several decades. The recent interest in cognitive radio related research has attracted a great deal of interest in spectrum sensing and detection of radio users in the environment. The key objective behind spectrum sensing and detection is to see how reliably one could detect the radio users given a particular scenario with an acceptable payoff or trade-off. In other words, the main objective is to maximize the probability of detection without losing much on the probability of false alarm while minimizing the complexity and time to sense/detect the radio.

Cognitive Radio which can change its parameters based on interaction with environment in which it operates, became one of the efficient dimension for sensing the available spectrum opportunities. In this work, initially we have discussed the requirement of opportunistic spectrum sensing, preliminaries of cognitive radio, their features, capability and challenge to develop a viable futuristic CRN system. Thereafter in the state of the art and literature reviews chapter we have discussed about the basic architecture of CR & SDR, its attributes, cognitive cycle and different sensing techniques.

In chapter 3 we have developed the problem formulation and system modeling of three classical transmitter based sensing methodologies namely ED, Cyclostationary feature detection and Matched Filter (MF). ED is the easiest one but it suffers multipath fading and completely loses the signal during low SNR values. Cyclostationary feature detection medium complex and works based on co-relation function. MF is the optimal detection method when the transmission signal is known. Thereafter, have simulated the receiver operating characteristics (ROC) of all the classical transmitter based sensing over AWGN, Rayleigh Fading Channel and Rician Fading Channel with an aim to compare the performance of the sensing techniques among them and suggest the best sensing technique at different environment.

The simplest form of detection technique is energy detection. It has been observe that with the increase of probability of false alarm in ED, the probability of detection has also increased. The probability of detection also increases with the increase of signal to noise ratio. The decision threshold can be selected for finding an optimum balance between probability of detection and probability of false alarm. In practice, the threshold is chosen to obtain a certain false alarm rate. Hence, knowledge of noise variance is sufficient for selection of a threshold.

The cyclostationarity based detection lies between ED and matched filter detection. The Cyclostationary based detection algorithms can differentiate noise from primary user's signals. Because noise is wide sense stationary with no correlation while modulated signals are Cyclostationary with spectral correlation due to the redundancy of signal periodicity. The cyclic frequencies can be extracted and used as features for identifying transmitted signals.

The performance of matched filter is more robust when the prior information of the sensing signals is available. However, MF requires CR to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features like bandwidth, operating frequency, modulation type and order, pulse shape, frame format etc. The implementation complexity of sensing unit is impractically large.

5.2 *Future Work*

Cognitive radios utilizes and handle the spectrum through spectrum sensing, spectrum management, spectrum mobility and spectrum sharing which leads to many challenges in CRN development and boosting up. In real cognitive network scenario, spectrum access management is a major challenge for SUs competing for the channel. The received PU signal at a single CR terminal may be severely degraded, basically due to hidden terminal problems, multipath fading or shadowing problems, lead to sensing performances in a challenge. In future the available spectrum for secondary user will be reduced and it will be difficult to use the spectrum for secondary users by sensing only narrow band spectrum.

To get rid of from the hidden terminal problem and multipath fading problems and obtain highly reliable detection performance, cooperative sensing strategies may be employed. Broadband compressive sensing may be obtained for highly reliable detection performance. This leads to more challenging task to sense spectrum blindly using sub-Nyquist sampling of multiband signals by modulated wideband converter (MWC) which can blindly sample multiband analog signals at a low sub-Nyquist rate which can be good option for future spectrum sensing. This leads to further future challenges in respect of computational complexity and hardware constraint, information leakage etc. Usually, control channels can be employed using suitable methodologies to share common spectrum sensing outcomes. Thus, challenges for future work are to integrate the proposed combining schemes with spectrum access management and investigate the optimal performance of these schemes. Spectrum sensing is a challenging problem in signal processing and estimation in view of the complexity of observed spectrum signatures from multiple devices, along with noise and channel impairments.

Review of spectrum sensing methods remains an important area of investigation by the wireless research community. Methods under consideration include:

- Simple energy detectors which are independent of known signal properties
- Matched filter detection of known signals such as 802.11x, Bluetooth or cellular
- Cyclostationary detectors which employ second-order signal structure for improved detection
- Collaborative (networked) sensing by multiple radios in which multiple spatial observations are combined to form an improved signal estimate.

Each of these methods needs to be studied in terms of performance (both static and dynamic), complexity, implement ability, and real-world prototyping experience on available cognitive radio platforms. For example, a recent study of cooperative sensing algorithms applied to a shared unlicensed band environment with overlapping 802.11b and Bluetooth signals showed that significant performance gains can be achieved with collaborative networked methods. As the next step, it is important to evaluate these sensing methods in real-world environments. Researchers on this topic need large scale open CR network deployments with flexible radios, multiple types of services and real-end users in order to further evaluate and compare the performance of different sensing technologies.

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