Combined Spectrum Sensing Technique for Cognitive Radios

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CERTIFICATE

I, Ramandeep Gill, hereby certify that the work which is being presented in this dissertation entitled "**Combined Spectrum sensing Technique for Cognitive Radios**" by me in partial fulfillment of the requirements for the award of degree of Master of Engineering in wireless communication Engineering from Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Ankush Kansal Assistant Professor, ECED** and refers other researcher's works which are duly listed in the reference section.

The matter presented in this dissertation has not been submitted in any other University/Institute for the award of any other degree.

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(Ramandeep Gill)

Table of Contents

List of Figures

ABSTRACT

As more and more wireless systems are being developed in order to operate in crowded spectrum bands, radio spectrum is being used inefficiently or is underutilized. Most of the spectrum has been allocated to specific users, while other spectrum bands that haven't been assigned are overcrowded because of overuse. However, most of the allocated spectrum is idle sometimes; it has been observed that a large part of the allocated spectrum is underutilized. The solution to this problem is Cognitive Radio. Cognitive radio senses the radio spectrum and collect information from the past behavior of the primary user. It detects the spectrum hole of the same bandwidth as required by the SU and allocates the spectrum dynamically without interfering with primary user. There are many techniques which can be used for spectrum sensing such as Energy detection (ED), Matched Filter Detection (MFD), and Cyclostationary Feature Detection (CFD). Out of these techniques, Energy detection is the best choice for spectrum sensing if no prior knowledge about the signal is required. This technique is easy to implement but is not suitable for low SNR (signal to noise ratio) environment and conditions where noise is uncertain in channel. Matched Filter Detection on other hand can detect signals with low SNR, but it requires prior knowledge about primary user which limits its application. Cyclostationary feature detection is the most suitable choice as compared to ED and MFD. Cyclostationary processes are random process for which the second order statistics such as mean and autocorrelation change periodically with time. Most of the manmade signals are random in nature i.e. they exhibit underlying periodicities in their signal structures and hence can be called as cyclostationary processes. But many of the technologies that are employed for spectrum sensing are based on stationary statistics which uses probabilistic models to analyze noise contaminated communication signals and hence are not appropriate for received manmade signals. In this work, two main techniques namely Energy Detection and Cyclostationary Feature Detection are investigated. Results show that in case of Energy Detection for 10% probability of false alarm, the probability of miss is 21%. Then comparison of Energy detection and CFD is carried out which shows that CFD reduces probability of miss by 88.57% as compared to ED. Then strategy is proposed based on combination of both the

techniques for spectrum sensing which outperforms both the existing techniques and achieves reduction in probability of miss by 98.33% as compared to ED.

CHAPTER-1
INTRODUCTION

1.0 PREAMBLE

Wireless communication has been the fastest growing segment of the communications industry in the last decade. As a result, wireless systems have become ubiquitous with several applications (e.g., cellular telephony and wireless internet) and various devices (e.g., mobiles, laptops, and tablets). In addition, new applications like wireless sensor networks, automated factories, smart home appliances, remote telemedicine, and many more are emerging from research ideas to concrete systems [1]. With the incredible growth in the number of wireless systems and services, the availability of high quality wireless spectrum has become severely limited. This can be observed in the following graph:

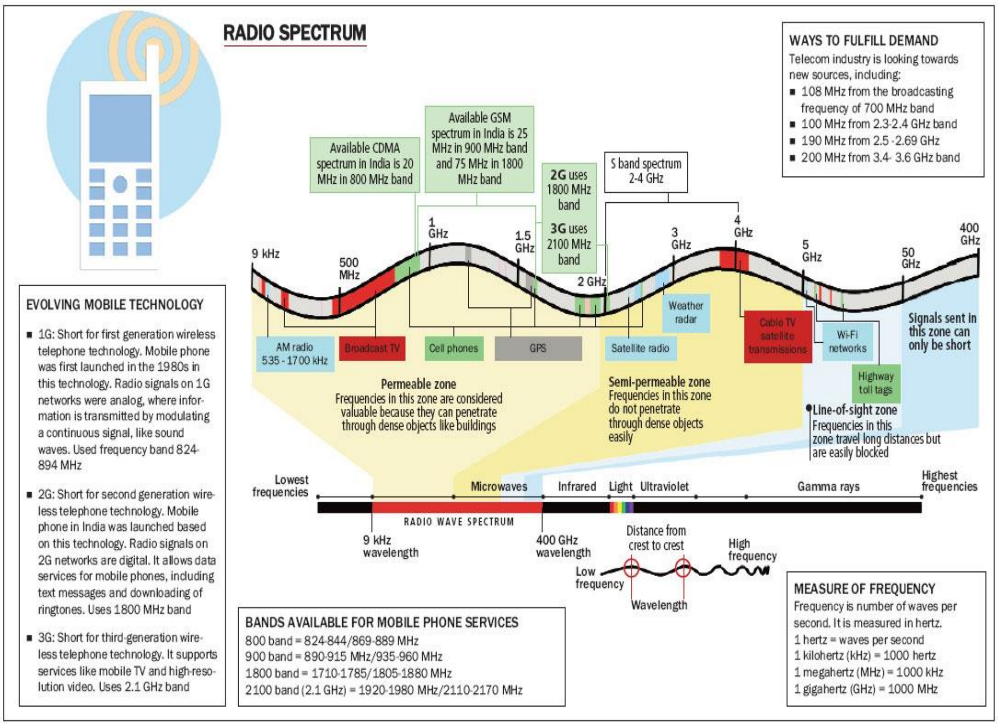


Fig.1.1: Radio spectrum Usage in India [1]

This has lead to a common belief that the spectrum is a scarce resource and it is difficult to find spectrum for new applications. However, actual measurements carried out in various countries show that most of the radio frequency spectrum is inefficiently utilized with spectrum utilization mostly in the range of 5%-50% [2]. Therefore the real problem is not the spectrum scarcity but the inefficient spectrum usage. This inefficiency results from static spectrum allocations, rigid regulations, fixed radio functions, and limited network coordination.

1.1 COGNITIVE RADIO

Cognitive radios are self-aware and intelligent software which offers an alternative to the current system of static spectrum allocation policy by allowing an unlicensed user to share the radio spectrum resources with the primary user.

1.1.1 Definition

Definition of cognitive radio adopted by the Federal Communications Commission (FCC): *Cognitive Radio: a radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjusts its radio operating parameters to modify interference, facilitate interoperability, and access secondary markets* [3].

In cognitive radio terminology, a primary user (PU) is defined as a legacy user or a licensed user who has higher rights on particular part of spectrum. Examples of licensed technology are Global System for Mobile Communications (GSM) [4-5], worldwide interoperability for microwave access (WiMax) [6-7], and Long Term Evolution (LTE) [7-8] while examples of legacy technology are microphone and wireless local area network (WLAN) [7-9]. On the other hand, unlicensed cognitive users with lower priority are defined as secondary users (SUs). A SU can access spectral resources of a PU when the PU is not using them. However the SU has to vacate the frequency band as soon as the PU becomes active so that negligible (or no) interference is caused to the PU. Such opportunistic access of the PU resources by the SUs is called as dynamic spectrum access. A SU can opportunistically utilize different spectrum holes corresponding to different PUs in order to satisfy its bandwidth requirement without causing interference to the PUs as shown in Fig. 1.2.

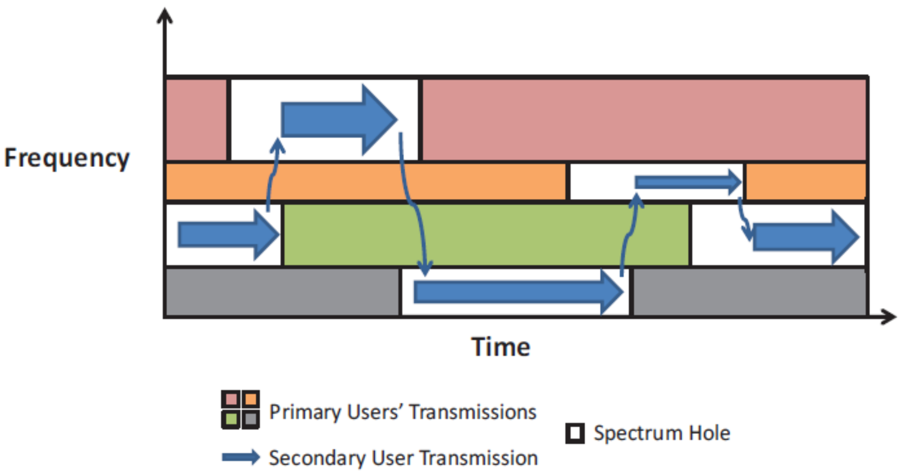


Fig.1.2: Spectrum Usage in cognitive radios [3]

In cognitive radios Spectrum sensing is a key method for dynamic spectrum access. Spectrum sensing obtains the information about the radio spectrum and identifies idle spectrum. When required bandwidth of hole is available, SUs is enabled to explore and exploit the unused PU spectrum. Moreover, it manages the level of interference between SUs and PUs. Spectrum sensing can be done in two ways: one is called as local detection, where sensing is done by an individual S and other is cooperative sensing, where different SUs collaborate to detect the presence of a PU. Single-user sensing faces difficulty in propagation environments like multipath fading, Doppler spread, and shadowing. In such a scenario a SU has to distinguish between a white space and a deep fade. Cooperative sensing (CS), on the other hand provides diversity gains to tackle the fading and shadowing. CS also increases the SNR gain and network coverage, decrease the detection time, and simplifies the detector design.

1.1.2 Applications

Cognitive radio has numerous revolutionary applications apart from dynamic spectrum access. They provide the facility of mobility, optimum performance, location services and coexistence of heterogeneous wireless systems.

1. CR provides location services to help users find train, flights, restaurants, rental cars in a new country [10].
2. CR detects and inter-operates with different networks like WMAN, WLAN, and Bluetooth etc. to provide seamless mobility.

3. Cognitive radios optimize the service cost, usage of spectrum, data rates and minimization of battery power.
4. Coexistence of heterogeneous wireless systems in the same frequency bands (e.g., IEEE 802.15.4 Zigbee and IEEE 802.11 WLAN) results in severe interference caused by different power levels, asynchronous time slots, and incompatible MAC and physical layer protocols [11]. This interference in turn severely degrades the performance of the coexisting wireless systems. Cognitive radio can provide solutions to reduce the interference among the coexisting heterogeneous wireless systems and improve their performance [11].

1.1.3 Components of Cognitive Radio

Cognitive Radio consists of many highly multidisciplinary and practical components [12] like sensors, software technologies and SDR. These are discussed below:

Sensors create awareness about the environment. Such as sensors like biometric scanners, microphone, and camera create user awareness by avoiding unauthorized user access. It also provides user centric experience in a multiuser scenario. Another popular sensor is GPS which provides location awareness and enables several useful applications for a cognitive radio.

Software technologies of cognitive radio include advanced signal processing, policy engine, networking protocols and machine learning [13]. Use of spectrum is controlled by regulatory body and regulation policies which may vary depending on country, time, software, and hardware developers. Advanced signal processing finds applications in communications such as channel estimation, filtering, equalization, modulation/demodulation, forward error correction and sensor signal processing which includes feature extraction, pattern recognition, wavelet synthesis and spectrum analysis. Policy engine helps in adhering to different regulations by having a library of policies in the form of downloadable software. Networking protocols enable cooperation between different SUs which has the potential of increasing the cognitive radio capability. Moreover they may help SUs to coexist with the PUs and the other SUs. Examples of networking protocols are routing and medium access protocols. Machine learning focuses on automatically learning and making intelligent decisions based on the available information. Examples of machine learning approaches are artificial neural networks, reinforcement learning, and genetic algorithms.

A software defined radio or SDR is a radio communication system which consists of components (e.g. mixers, filters, amplifiers, modulators/demodulators, detectors, etc.) in software using digital signal processing (DSP). Therefore to change functions of radio simply modifying or replacing software programs need to be done. This flexibility of radio functions allows the use of different wireless communication techniques in a single portable device making SDR a key enabling technology for cognitive radios. Some examples of commercially available SDR are Universal Software Radio Peripheral (USRP), USRP2, and FLEX-5000A [14].

1.2 DYNAMIC SPECTRUM ACCESS (DSA)

Currently DSA is the most important application of cognitive radios. It has attracted lots of interest among policy makers, regulators, network operators, and researchers [15]. Fig.1.3 shows the considered scenario for dynamic spectrum access where multiple Pus and SUs are coexisting.

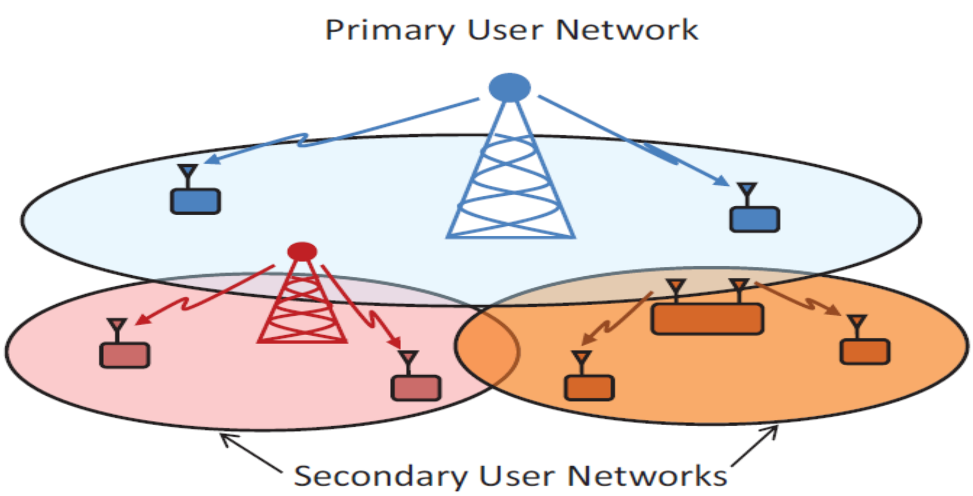


Fig 1.3: Coexistence of multiple primary and secondary user networks (homogeneous or heterogeneous) [15].

The SU networks opportunistically access the PU bands such that the interference caused to the PUs is negligible. The SU networks operating may be homogeneous or heterogeneous. Examples of heterogeneous networks operating in the same frequency bands are WLAN (IEEE 802.11), Bluetooth, and Zigbee (IEEE 802.15.4). Based on the sharing models or how the PUs share the spectrum with SUs.

1.2.1 Types of DSA

Dynamic spectrum access can be broadly classified into three types [16]: dynamic exclusive use, spectrum commons, and hierarchical access [17].

In the **Dynamic Exclusive use Model**, the basic structure of the current spectrum policy is kept while introducing flexibility to improve spectrum utilization. There are two approaches under this model. First approach is spectrum property rights [18], where the license holder can trade spectrum and choose technology based on the market trend. Second approach is dynamic allocation [18], where spectrum allocation is varied at a faster scale as compared to current regulations by using the spectrum usage statistics of the PU in a particular location.

In **Spectrum Commons Model**, every user has equal rights for using the spectrum. This is also called as open spectrum model and has been successfully applied for wireless services operating in the ISM (industrial scientific and medical) radio band

In **Hierarchical Access Model**, SUs can use the primary resources such that the interference to the PU is limited. There are three approaches under this model [19]: underlay, overlay, and interweave. While the SU utilizes gray spaces for the underlay and overlay approaches, the SU utilizes white spaces for the interweave approach. For the underlay approach, the SU transmits in the manner of ultra wideband (UWB) systems with sufficiently low power to limit the interference to the PU. In the overlay approach, SUs use the Partial or full knowledge of the PU information like codebooks or transmitted data to boost the PU performance and mitigate the interference from the PUs.

1.2.2 Functions of DSA

DSA consists of three main functions: spectrum awareness, cognitive processing, and spectrum access. Spectrum awareness creates awareness about the RF environment while spectrum access provides ways to exploit the available spectrum opportunities for efficient reuse. Cognitive processing is the intelligence and decision making function that includes several subtasks like learning about the radio environment, designing efficient sensing, and access policies along with managing interference for coexistence of the SU networks with the PU networks. Cognitive processing uses spectrum information, bandwidth requirement, and regulatory policies as inputs while it provides sensing task and spectrum allocations as outputs. Next we present a brief overview of these three functions. Fig.1.4 shows these three functions and their interactions.

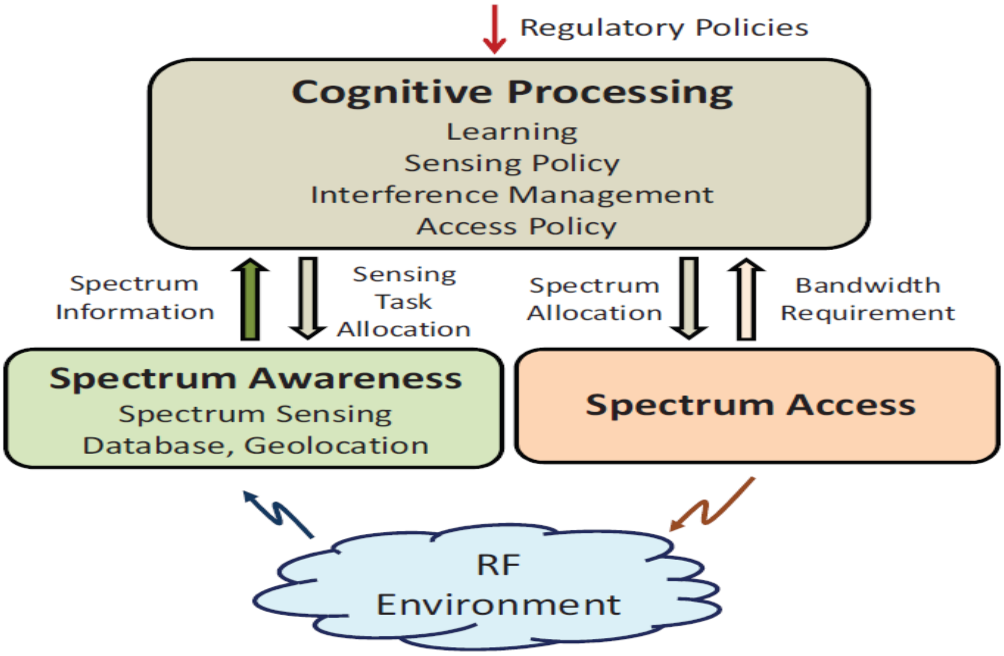


Fig 1.4: Functions of Dynamic spectrum access [19]

1.2.2.1 Spectrum Awareness

Spectrum awareness obtains the information about spectrum usage and locations of primary users and secondary users in geographical area. Spectrum usage can be classified into three categories [19]: black spaces, gray spaces, and white spaces. Black spaces are occupied by high power local interferers; gray spaces are occupied by low power interferers, while white spaces are free of any interferer excluding ambient noise. The white and gray spaces are the spectrum opportunities or spectrum holes, which can be used by the SUs. There may be additional dimensions that can be utilized [20]: code, polarization, and angle of arrival. In addition to the detection of spectral opportunities, spectrum awareness can also provide various other useful information [20] such as radio environment map, channel gain map as well as locations and statistics of the PUs and SUs.

There are two methods of obtaining spectrum awareness: Active method and Passive method. In the active method or spectrum sensing, the radios become spectrum aware by detecting and estimating the spectrum. Active methods have broader application areas and lower infrastructure requirement. In passive methods, the information regarding the unoccupied spectrum is provided to the SU. For example, use of geolocation, database, and beacons fall into this category [21]. Passive methods need support from the PUs who is under no obligation to change their operation to aid the SU network. Therefore passive methods may be difficult to implement. An alternative

solution might be to use a dedicated sensor network maintained for creating databases and PU information in a geographical location to aid an incoming SU [21]. Although the users might have sensing capabilities, such supporting sensor network may be necessary in the start-up phase of the cognitive service and in rural areas with low population. However the infrastructure requirement in this case may be complex and expensive.

Spectrum Sensing schemes can be classified based on different criteria: detection target, architecture, number of primary users, number of secondary users, and number of bands to be sensed which are discussed below:

a) Target of Detection

Based on the target for detection, there are two approaches to spectrum sensing: detecting the transmitter and detecting the receiver. The receiver is the actual victim of the secondary transmissions and detecting the transmitter only gives an approximate idea of the location of the receiver. Therefore detecting the receiver is an important task. Algorithms for detection of receiver have been considered in [22] which exploit the local oscillator power emitted by the RF front end of the receivers. However, detecting the receiver may be a demanding task as the power of the oscillator leakage is low thereby restricting the reliable detection range below 20 m [22].

b) Architectures

Sensing can be performed via two different architectures [23]: single and dual radio. In single radio, sensing is time multiplexed with the data transmission/reception while in dual radio, there is a dedicated RF front-end for both sensing and data transmission/reception. Single radio architecture has the advantages of low power consumption and hardware costs over dual radio architecture at the cost of sensing accuracy and efficiency.

c) No. of Bands

Based on the number of bands to be sensed, sensing can be classified as single-band and multi-band sensing [24]. There may be a case when there are multiple primary users in a given frequency band. For example, there are multiple users in a code division multiple access (CDMA) systems while WLAN and Bluetooth systems share the same bands. Detection of multiple users has been studied in [24] while performance analysis of spectrum sensing in the presence of multiple PUs has been done in [24].

d) No. of SU's

Based on the number of secondary users for cooperation, sensing can be classified as single-user and multiuser sensing. Multiuser cooperative detection has several advantages over single-user detection (or local detection) like improved detector performance, increased coverage, and simplified local detector design. However these advantages come at the costs of increased complexity and overhead.

e) Priority of Target

Sensing can also be classified based on the priority of the target: detecting PU and detecting SU. Most of the techniques applicable for detecting the PUs are also applicable for detecting SUs. Due to the possibility of coordination between different SU networks, detecting SUs may be easier especially for the case of homogeneous SU networks [25]. Detecting PUs is much more important than detecting SUs as the secondary access is permitted only if the interference to the PUs is within a tolerable limit. These techniques are applicable to both single and dual radio architectures. Without loss of generality, we have assumed detection of only PUs in this thesis.

1.2.2.2 Cognitive Processing

Cognitive processing is the task of optimizing the sensing and access of the spectrum opportunities based on the sensing information, databases of spectrum occupancy, and regulatory policies. There are four subtasks of the cognitive processing: learning, sensing policy, interference management, and access policy. These four subtasks are inter-related to each other and will be discussed in the coming subsections. The cognitive processing function can be implemented in a centralized or distributed manner. In the centralized implementation, SUs process the observations and send sensing information to a centralized entity which performs the cognitive processing. In the distributed implementation of cognitive processing, SUs may or may not exchange information among each other but implement cognitive processing functionality on their own.

a) Learning

Learning is the subtask of estimating the current state and quality of the PU channels using experience rather than sensing alone which may be expensive. The occupancy and channel quality statistics are estimated in the frequency bands which may be favorable for the SUs requesting bandwidth. This helps in making efficient sensing policy, interference management, and access policy. Assuming there are multiple frequency bands to be scanned, the SUs have to decide if they should exploit the identified spectrum opportunities or explore new frequency bands in hope of better opportunities at a later instant. Thus optimizing the sensing and access policies is similar to a bandit problem often encountered in stochastic optimization. Therefore, reinforcement learning methods which are often employed for the bandit problem can also be employed for designing sensing and access policies in cognitive radio networks [26]. In reinforcement learning, the SUs learn from experience and experiments. Thus its operation is in between the other two machine learning methods: supervised (teacher assisted) and unsupervised learning methods. Sensing and access policies based on reinforcement learning methods have been proposed for cognitive radios in [27].

b) Sensing Policy

Sensing policy defines which SUs sense which frequency bands and when. A sensing policy is needed as sensing the entire spectrum of interest simultaneously is demanding for the hardware and may be energy inefficient. Assuming the frequency bands to be sensed are decided or known, the sensing policy has two tasks: user selection and sensing scheduling. Although sensing scheduling can be implemented individually or collaboratively, user selection is specific to cooperative sensing.

Sensing scheduling decides which sub-bands will be sensed and when. Scheduling helps in improving the efficiency of spectrum exploration. It is worth sensing bands which are unused persistently so that the secondary throughput is increased while the sensing effort is reduced. As the sensing and access policies are closely connected to each other, cooperating SUs can jointly optimize the sensing and access efforts. The joint optimization of sensing and access policies is much easier in a centralized approach as compared to a decentralized approach. Individual sensing policies have been proposed in [27] using a decision-theoretic approach by formulating the design of optimal sensing policy as a partially observable Markov decision process (POMDP). Similarly cooperative sensing policies have been proposed in literature using different approaches: negotiation based policy, pseudo random policy, and reinforcement learning [28].

User selection tells which SUs will participate in the cooperation. It is important to choose SUs experiencing independent fading and shadowing effects so that maximum diversity gain is achieved. In addition, inclusion of malicious users in the group should be avoided to ensure the reliability of the network. User selection can be implemented in two ways: centralized and cluster based [29]. Grouping different users for cooperation can also be modeled using game theory. Depending on the behaviors of different games, behaviors of the SUs can be modeled differently: coalitional game [30] and evolutionary games [30].

c) Interference Management

Interference management is important in cognitive radio networks since secondary usage is allowed only if the SU interference does not degrade the PU quality of service below a tolerable limit [30]. In addition, there may be interference between different SU networks due to the lack of coordination resulting in substantial reduction of SUs' throughputs [31]. Interference temperature model was introduced by the FCC for quantifying and managing the interference [31]. Fig. 1.5 shows the received power of the licensed signal transmission as the distance from the transmitter.

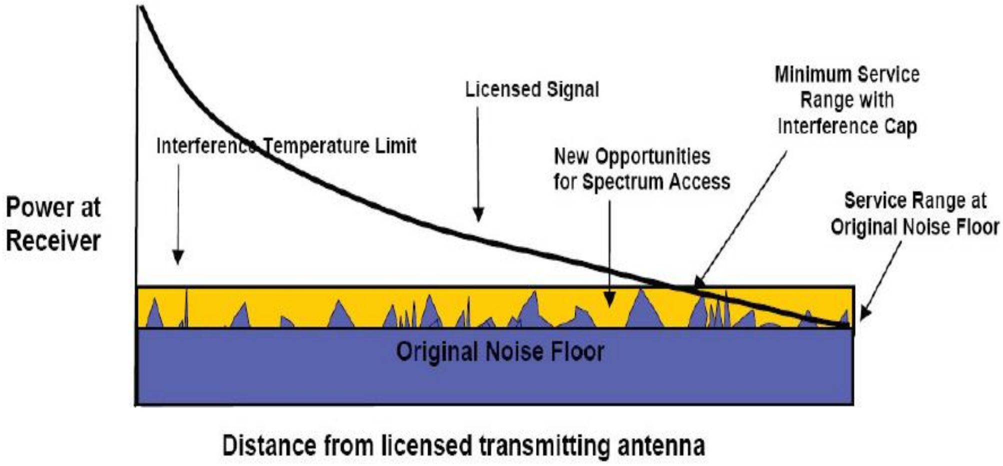


Fig1.5: Received power of the licensed signal transmission as a function of the distance from the transmitter to illustrate the interference temperature concept [31]

In this interference model, each primary receiver has an interference temperature limit that defines how much noise and interference it can tolerate to guarantee certain quality of service. This creates spectrum opportunities for the SUs. Using this model, cognitive radios can measure and model the interference environment and adjust their transmission characteristics such that the interference to PU is not above the regulatory limits. However, major drawback of the model is to measure the interference temperature at the primary receivers which is unfeasible in practice. The FCC has abandoned the concept of interference temperature as unworkable [32]. At the same time, the FCC has also encouraged the researchers to solve the problems related to the interference temperature and make it feasible.

Techniques managing the interference to the PUs can be broadly categorized into three groups [32]: interference avoidance, interference control, and interference mitigation.

The interference avoidance approach is same as the interweave approach. The effects of errors in the detection of white spaces on the performances of both PU and SU network has been studied in [32]. To minimize the interference from the SU transmission to a PU becoming active, algorithms using hidden Markov model (HMM) to estimate the state of the channel in the next instant have been proposed in [33]. The interference control approach is same as the underlay approach. Different methods are suggested for limiting the power directed towards the PU: estimating the PU location, spectrum shaping, beam-forming, and water-filling [33]. In interference mitigation, SUs use the partial or full knowledge of the PU information like codebooks or transmitted data while operating in gray spaces. The interference mitigation approach is same as the overlay approach.

Interference among the SU networks is also an important concern. Although most systems use interference avoidance mechanisms like listen before-talk, they are designed to resolve the collisions between homogeneous networks. These mechanisms are less effective for heterogeneous networks where the employed standards, frame structure, communication protocols, and transmission powers are different in addition to the lack of coordination and synchronization [34].

d) Access Policy

In the case of cooperating SUs, the problem is how to allocate the available channels among the SUs to optimize a given network objective function. Few examples of such network objective functions: maximize the sum capacity of the secondary network, maximize the minimum capacity for an individual SU or minimize the interference to the primary network with constraints on transmit power or/and fairness of resource allocations [34]. Note that the design of the access policy is also related with different medium access techniques such as time division multiple access (TDMA), frequency division multiple access (FDMA), and CDMA. Similarly the access policy is closely connected to the sensing policy and both these policies can be jointly optimized as done in [35].

There are several approaches for designing policies to allocate or access the spectrum opportunities. These access policies can be divided into two categories [36]: direct access based and dynamic spectrum allocation. The dynamic spectrum allocation policies exploit complex optimization algorithms to achieve a global purpose in an adaptive fashion. However they have issues of low scalability, negotiation delay and complexity. Examples of dynamic spectrum allocation policies are graph coloring scheme, game theory, stochastic algorithms, genetic algorithms, and swarm intelligence. The direct access based policies do not allow any global network optimization. However they are simple and have low computational cost and latency. The Direct access based methods can be further classified as contention based and coordination based. In contention based policies, sender and receiver SUs exchange their sensing information. Then the pair compares available resources and negotiates the channel for communication. Examples involving contention based policy are cognitive MAC (COMAC) [36], heterogeneous distributed MAC (HDMAC) [36]. In coordination based policies, each SU shares its channel usage information with its neighbors to increase sensing reliability and improve overall system performance. Example involving coordination based access policy is multichannel MAC for cognitive radio (MMAC-CR) [36].

1.2.2.3 Spectrum Access

Once the spectrum opportunities are found, several SUs may want to access the spectrum opportunities to transmit their data. This may lead to collisions in the absence of coordination even when sufficient spectrum opportunities are available. In the case of limited spectrum opportunities, collisions between different SU transmissions and the resulting interference become unavoidable. Spectrum access or spectrum sharing is the task of accessing the unused PU spectrum by SUs such that the collisions and interference among different SUs are strictly controlled. Thus spectrum access helps in improving secondary network throughput [37].Note that spectrum access is different from access (or allocation) policy which is part of cognitive processing. Spectrum access defines how different SUs access the given spectrum opportunities. On the other hand, the spectrum access policy defines which SUs access which spectrum opportunities and when. Spectrum access policies have been explained earlier and this subsection focuses on spectrum access mechanisms.

Spectrum access can be classified based on the cooperation model used by the SUs: cooperative and non-cooperative. Cooperative access schemes require coordination among the cooperating SUs. Examples of cooperative spectrum access schemes are coordination based multiple access schemes such as TDMA, FDMA, CDMA, and orthogonal frequency division multiple access (OFDMA). Since SUs may need to transmit over noncontiguous frequency bands, OFDMA is an attractive candidate for medium access in cognitive networks. The reconfigurable subcarrier structure of OFDMA allows SUs to efficiently fill the spectral gaps left by the PUs without causing significant interference. However the subcarrier spacing and symbol interval need to match with the spectral and temporal duration of spectrum opportunities. Moreover, there may be adjacent channel interference due to nonlinearity of the transmitter's power amplifier. In the absence of information from other users, SU can use non-cooperative access schemes. Although the non-cooperative access schemes are easy to implement, the absence of coordination among the SUs results in a performance loss compared to the cooperative access schemes. Examples of non-cooperative spectrum access schemes are contention based protocols like carrier sense multiple access with collision avoidance (CSMA/CA).

In case of homogeneous secondary networks, both cooperative and non-cooperative spectrum access techniques are easier to implement as the networks have same PHY/MAC protocols. However in case of heterogeneous secondary networks, different PHY/MAC strategies may limit the effectiveness of the non-cooperative listen-before-talk mechanisms in achieving fairness. For example, consider a coexistence scenario between CSMA/CA based devices and TDMA based devices. In this case, CSMA/CA devices will back off when there are TDMA transmissions while TDMA devices will not listen before transmitting. In case of cooperative access schemes, communication between the heterogeneous networks is required which limits the implementation of cooperative spectrum access schemes among heterogeneous networks, Even in case there are mechanisms such as a common control channel for sharing relevant coexistence information, a tight synchronization is required across all devices belonging to different networks. Moreover a negotiation process is involved between different competing networks.

Nowadays, radio systems often require larger bandwidths. In addition, the available spectrum opportunities at a given time instant may result from multiple PUs and may be scattered in the frequency domain. Therefore to be able to provide larger bandwidths in multiuser environment, especially in an opportunistic manner, multi-band operation could allow to perform spectrum aggregation or spectrum pooling of multiple spectrum segments from different spectrum owners (cellular, satellite, military, etc.) into a common pool [38]. Multi-band operation in a multiprimary environment significantly improves the spectrum usage in the considered bands [39].

1.3 Standardization Efforts

With the rising interest in cognitive radio technology, wireless standards developed recently or currently under development have started incorporating cognitive features [40]. IEEE 802.22 is the first worldwide effort to define a standardized air interface based on cognitive radio techniques for the opportunistic use of TV white spaces (TVWS) [41]. The standard is designed for the secondary usage of TVWS on a non-interfering basis so as to prevent any harmful interference to the incumbent operation (such as digital TV and analog TV broadcasting) and low power licensed devices (such as wireless microphones and medical telemetry devices). The primary application of this standard is fixed broadband access especially for hard-to-reach, low population density areas (typical of rural environments) and thus has a great potential for worldwide applicability. Cognitive functionalities included in the standard are PU detection, geolocation, coexistence with other WRANs, and frequency agility. The implementation of a database is mandatory for PU detection while sensing is optional.

Other standardization initiatives related to cognitive radios are IEEE 802.11, dynamic spectrum access networks standards committee (DySPAN - SC), IEEE 802.16, and IEEE 802.19. IEEE 802.11af standard, which is currently under development, aims to define modifications to IEEE 802.11 PHY/MAC for TVWS operation [34]. IEEE 802.16h [35] defines modifications to IEEE 802.16 PHY/MAC for coordinated and uncoordinated coexistence among homogeneous or heterogeneous users in an unlicensed band. The DySPAN-SC develops standards for radio and spectrum management. It was also formerly known as IEEE Standards Coordinating Committee 41 (SCC41) and IEEE P1900 standards committee. IEEE 802.19 focuses on coexistence between different unlicensed wireless networks in 802.11 group of standards like IEEE

802.11 (WLAN), IEEE 802.15 (WPAN), 802.16 (WMAN), 802.22 etc. IEEE 802.19 task group 1 focuses on wireless coexistence in the TVWS.

CHAPTER-2

LITERATURE REVIEW

W.Y Lee et al. [3] introduced an optimal sensing framework with three different functionalities. Firstly, sensing parameter optimization is proposed to maximize the sensing efficiency. Secondly, a spectrum selection and scheduling algorithm based on opportunistic capacity concept is introduced to extend multi-spectrum environment and lastly cooperation sensing is used.

L. Giupponi et al. [6] proposed a technique called fuzzy based approach for spectrum handoff where aggregate interference caused by secondary user to primary user is calculated. If this value exceeds threshold then secondary user has to initiate spectrum handoff to vacate the channel it is occupying.

T. Yucek et al. [8] re-examined various aspects and methodologies of spectrum sensing. Various challenges related to spectrum sensing are discussed along with their possible solutions like cooperative sensing, external sensing algorithm and other alternatives. Furthermore, in order to predict PU behavior a statistical modeling of network traffic is studied and utilization of these models is discussed.

X. kang et al. [11] designed a model to allocate spectrum to SU when PU is not using it and two cases re studied named as perfect sensing case and imperfect sensing case. For former case Lagrange dual decomposition is used to achieve ergodic capacity and for latter case, an iterative algorithm is applied to achieve optimal sensing time and power allocation strategy. It is shown that the SU can achieve a significant capacity gain under the proposed model, compared to the standard spectrum sensing model.

D.J. Lee et al. [15] studied the effect of unnecessary spectrum handoff due to false alarm and formulated an optimization problem to minimize spectrum sensing time of secondary user. Cooperative sensing also reduces the spectrum sensing but it increases the energy consumption. This disadvantage is overcome by the proposed method in this paper.

Z. Han et al. [16] designed a model that places spectrum sensing device in the network of primary user which detects its activities and handoff the control to secondary user when primary user is idle. This technique replaces the expensive sensing device of secondary user and lowers the cost for consumers. The performance of the model is analyzed with the theory of Lamé curve. Analysis is carried out for collision probability for both the cases of single and multi user and a handshake technique is also proposed for the case without a separate control channel, for handshakes between the sensing device and the SU.

W. Zhang et al. [17] implemented cooperative sensing with energy detection where multiple cognitive radios are used to detect spectrum holes to optimize the performance of detection. In this technique value of detection threshold is optimized by using optimal voting-rule. This technique requires fewer no of cognitive radios than cooperative sensing and is fast for spectrum sensing for a given error bound.

K.L. Du et al. [18] established an effective spectrum sensing method called as adaptive cyclostationary beamforming with for multiple-antenna cognitive radio. In this paper, a new spectrum-sensing method is introduced that exploits a beamforming algorithm, called as ACS algorithm (i.e. adaptive cross-self-coherent-restoral). The difficulty of the resultant algorithm is higher than that of the energy detector but is smaller than that of the cyclostationary feature detection.

J.F. Segura et al. [19] designed a framework for optimal joint detection and parameter estimation using GLRT (generalized likelihood ratio test) and derived the related spectrum sensing algorithms by using the statistics of the received signal and the prior information on the channel. For slow fading channels an iterative GLRT sensing algorithm is used and for fast fading channels non iterative GLRT sensing algorithm is developed .The proposed techniques are also extended for OFDMA system MIMO system.

X.Y. Wang et al. [22] introduced a scheme called extended knowledge based reasoning (EKBR) for spectrum sensing of MAC layer for cognitive radios. This scheme uses prior knowledge about signal to achieve large trade-off between transmission rate of data and sensing overhead. Multi-dimensional absorbing Markov chain is used to carry out performance analysis of EKBR. Also simulations are carried out to compare the proposed scheme with previous techniques which shows that proposed scheme has large throughput as compared to previous techniques.

T. Do et al. [25] proposed a joint spatial-temporal scheme for spectrum sensing. This scheme uses the information of spatial sensing to achieve better results in temporal sensing. In earlier techniques either spatial or temporal technique is applied for spectrum sensing. To verify the performance of the proposed technique, its results are compared to pure spatial and pure temporal sensing technique with the help of counting rule and LQ (linear quadratic) detectors.

R. Wang et al. [26] implemented a technique called as ITC (information theoretic criteria) blind method that can effectively sense spectrum with the help of prior knowledge. In this method a model is constructed with multiple antennas or by oversampling at SU to build an over- determined channel. Then a simplified algorithm is introduced to compute decision threshold which has reduced the computational complexity compared to the original ITC method. Performance of the proposed technique is evaluated with a simulation which shows better results as compared to existing blind spectrum sensing methods.

W.B. Chien et al. [28] performed cooperative sensing with the use of partial FFT and frequency diversity in order to conserve energy. To enhance the overall detection performance two techniques are proposed namely DRP (detection result prediction) and DRM (decision result modification). This technique improved the detection performance and saves energy.

J. Meng et al. [30] proposed a technique of applying compressive sensing on collaborative spectrum detection in CR network where each node of cognitive radio is equipped with a frequency selective filter to combine information from multiple channels, which linearly combines multiple channel information and sent to fusion center where decoding of channel occupancy is performed. Decoding is performed with two different approaches, one is based on matrix completion which collects small number of valid reports to form complete CR report in order to recover channel occupancy information and the other is based on joint sparsity recovery which reconstructs information based on the fact that every channel is observed by multiple CR nodes.

W. Lee et al. [31] proposed a scheme that has not been proposed in literature before. In this method number of spectrum sensing operations performed by cognitive terminals is differentiated and no-talk zone of primary user is considered to optimize the cooperative spectrum. In this scheme zero forcing is used for simultaneous sensing of spectrum and transmission of data. The simulation results shows increase in spectral efficiency of cognitive radio especially when sensing is large.

K.J.R. Liu et al. [33] studied the effect of errors in the spectrum sensing process on the performance of the multiple access layers of both primary and secondary networks and concluded that using different designs for spectrum sensing and the channel access mechanisms can Detroit the performance of both primary and secondary networks. So in this paper a joint design of spectrum sensing and channel access mechanisms is proposed which uses binary hypothesis testing to check the reliability of outcome. Proposed technique achieves significant improvement in throughput of both PU and SU networks.

R. Mahesh et al. [35] proposed a technique for mobile cognitive radio handsets based on RDDC (reconfigurable digital down converter) and reconfigurable filter. The proposed technique is less complex and highly flexible as compared to conventional filter bank approach. In this technique spectrum is rotated using RDDC and desired portion is filtered using reconfigurable filter to achieve low complexity. Performance of the system is verified using virtex-4 FPGA, it shows that propos technique consumes less power, has reduced gate count and delay as compared to conventional method.

S. Stotas et al. [36] studied outage capacity and TIFR (truncated channel inversion with fixed rate) capacity of cognitive radio system under two cases i.e. With missed-detection and without missed-detection interference power constraints, for both Rayleigh and Nakagami-m fading channels to protect PU. In this paper, various constraints including average transmit power constraints peak interference power constraints, average interference power constraints and target detection probability constraints are analyzed. Finally, it is shown that proposed method achieves higher outage and TIFR capacity compared to conventional method.

S.J. Kim et al. [38] investigated a spectrum sensing algorithms for cognitive radio that support QoS (quality of service).In this algorithm, in order to reduce sensing delay Multiple bands are sensed in parallel, with a fixed minimum rate for transmissions and given outage probability. Interference constraints are also imposed to protect PU transmissions. To minimize sensing delay, two algorithms are discussed namely FSS (fixed sample size) and sequential sensing algorithms. Simulation results show that sequential sensing has smaller average sensing delays than those of FSS sensing.

J. Kim et al. [41] investigated the performance of opportunistic scheduling in uplink CR systems. In this paper, novel optimal and suboptimal scheduling schemes are proposed by considering the spectrum sensing reliability and the data channel quality simultaneously. It is analyzed that to maximize the capacity of SU, the spectrum sensing reliability should be considered. Moreover, MUD (multiuser diversity) gain of one of the proposed suboptimal scheduling schemes is analyzed, which shows that for uplink CR systems MUD gain grows significantly slower than that of conventional multiuser systems. Analytical and simulation results confirm that the proposed technique yield significant performance gains compared with conventional opportunistic scheduling.

N. Pillay et al. [42] presented maximum–minimum-Eigen value and energy-minimum-Eigen value sensing technique for the Nakagami-m fading channel. In this technique many parameters like probability of detection, probability of false alarm and threshold are calculated along with simulation results for the maximum-Eigen value-to-trace method and the arithmetic-to-geometric-mean method. Improved performance is achieved by decreasing the number of samples and increasing the numbers of cooperating users. Simulation results shows that proposed technique performs better even in noisy environments and is better than other schemes. Analytical expressions are also presented. The Eigen value detection methods exhibit good performance in noisy environments and are matched by their bounds.

Z. Gao et al. [44] studied potential security threats using collaborative spectrum sensing in cognitive radio network. Some of the earlier technique in the same field is reviewed. Furthermore, to prevent location privacy leaking, a novel privacy preserving framework is proposed and a real-world test-bed is designed and implemented to evaluate the system performance. It is shown that proposed method can significantly improve the location privacy of SU with a minimal effect on the performance of collaborative sensing.

Y.E. Lin et al. [45] proposed interference-aware spectrum sensing and performance is measured in terms of the probability of interference and probability of missed detection for better. Threshold is calculated for both single detector and cooperative detectors. To prove the benefits of interference-aware metric. Simulation results shows that by allowing SU to maximize its opportunity of transmission without interfering PU, the proposed interference-aware spectrum sensing technique can result in better utilization of the spectrum as compared to conventional method.

S. Maleki et al. [47] designed a censored truncated sequential technique for spectrum sensing as an energy-saving approach. To design this technique, average energy consumption of each sensor is minimized to a lower bound of probability of detection and an upper bound of false alarm rate to control the interference to the PU due to miss detection and the network throughput as a result of a low false alarm rate. Lastly, the performance of the proposed scheme is compared with a fixed sample size censoring scheme under different cases and it is shown that that for low-power cognitive radios, proposed technique outperforms existing technique.

J. Lunden et al. [50] proposed a policy which is distributed, multiuser and multiband for spectrum sensing based on multi agent reinforcement learning. The problem of spectrum sensing is considered as a partially observable stochastic game and proposes policy is employed to find a solution. In this policy, the SUs are combined to improve the sensing reliability and to distribute the sensing tasks among the network nodes. The SUs share their information on the frequency bands sensed with their neighbors and a map of spectrum occupancy in a local neighborhood is created that maximizes the amount of free spectrum. Simulation results show that the proposed sensing policies provide an efficient way to find available spectrum in multiuser multiband CR case.

CHAPTER-3

GAPS, OBJECTIVES AND METHODOLOGY

3.0 GAPS

1. Work had been done on spectrum identification and detection but spectrum tracking and exploitation areas were still unexploited.
2. Hybrid sensing techniques are not discussed which could be effective instead of single technique.
3. The existing implementation of cognitive radios is very Complex
4. The spectrum sensing is Time consuming
5. Existing techniques are power consuming.

3.1 OBJECTIVES

1. Study of various spectrum sensing techniques in cognitive radios.
2. Implementation of Energy Detection and cyclostationary feature detection on cognitive radios
3. Combining Energy Detection and Cyclostationary Feature Detection to reduce Probability of False alarm.

3.2 METHODOLOGY

Cognitive radio is a very broad and a highly multidisciplinary technology involving several fields of research such as smart antennas, hardware architectures, signal processing, communication theory, and Medium Access Control (MAC), learning mechanisms, dynamic spectrum allocation methods, cognitive network architecture, and protocol design. However the main focus of this thesis is on the analysis of two detection techniques namely Energy Detection and Cuclosatationary Feature Detection and designing of a new technique by combining above two techniques.

The **First Goal** of this thesis is to develop simple and computationally efficient spectrum sensing technique called as Energy Detection. The basic approach behind this technique is the power estimation of the licensed user (primary user) signal. The performance of the technique is measured with the help complementary ROC curve (i.e. P_m versus P_f curve). However, this technique does not perform well in low SNR.

The **Second Goal** is to develop a better technique which could overcome shortcoming of Energy Detection called as Cyclostationary Feature Detection. The basic approach of this technique is to use the feature of cyclostationarity to calculate cyclic spectrum to determine the presence or absence of Primary User. Simulation results are shown to compare the performance of CFD and ED.

The **Third Goal** of this thesis is to achieve better results as compared to CFD. This is achieved by combining above discussed techniques i.e. Energy Detection and CFD. This is proved with the help of a 3D plot of cyclic spectrum which shows better results as compared to CFD. Moreover, complementary ROC curve is also shown to compare the performance of proposed technique with that of ED.

CHAPTER-4

COMBINED SPECTRUM SENSING TECHNIQUE

4.0 COGNITIVE RADIO TECHNIQUES

There is an important role of spectrum sensing in cognitive radios because there is need to continuously sense the spectrum by secondary users in order to check the presence of primary users. In this work, two main techniques namely Energy Detection and Cyclostationary Feature Detection are investigated. A strategy is proposed based on combination of both the techniques for spectrum sensing.

4.1 THE GENERAL SPECTRUM SENSING PROBLEM

The basis of spectrum sensing is signal detection. Signal detection is a process for identifying the presence of a signal in a noisy environment. It has been thoroughly studied since fifties for radar purposes [36].

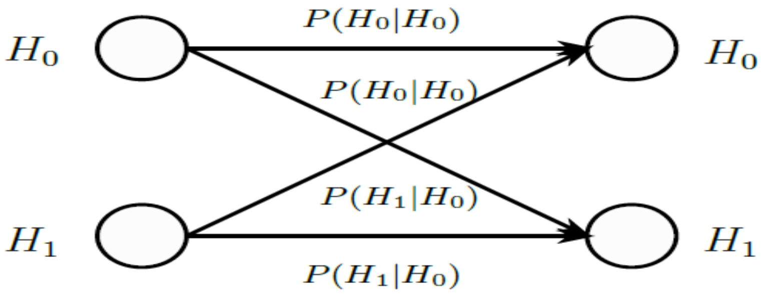


Figure 4.1: Hypothesis test and possible outcomes with their corresponding probabilities [36]

Signal detection can be carried out with the help of Hypothesis test [36] as shown in above figure which can be formulated as follows:

$$y(k)=\begin{cases} n(k): & H_0 \\ s(k)+n(k): & H_1 \end{cases} \tag{1}$$

Where $y(k)$ is the sample to be analyzed at each instant k, $n(k)$ is noise (not necessarily white Gaussian noise) of variance σ^2,$s(k)$ is the signal the network wants to detect, and H_0 and H_1 are the noise-only and signal plus noise hypotheses, respectively. H_0 and H_1 are the sensed states for absence and presence of signal, respectively.

Then, as seen in Fig. 1.6 we can define four possible cases for the detected signal:

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

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

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

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

Case 2 is known as a correct detection, whereas cases 3 and 4 are known as a missed detection and a false alarm, respectively. An ideal signal detector is expected to achieve correct detection all of the time, however due to the statistical nature of the problem, this can never be achieved. Therefore, signal detectors are designed to operate within prescribed minimum error levels. The biggest issue for spectrum sensing is missed detections because in that case SUs interferes with PUs. Also, the system is expected to have low false alarm rate for spectrum sensing so that all possible transmission opportunities can be exploited.

The most important metric to test the performance of the spectrum sensing technique is probability of false alarm$P_f = P(H_1|H_0)$. The performance of the technique is measured in terms of receiver operation characteristics (ROC) curves, which plot the probability of detection $P_d = P(H_1|H_1)$as a function of the probability of false alarm P_f or complementary ROC which plot probability of miss detection as a function of probability of false alarm.

It can be observed in Equation (1) that in order to distinguish H_0 and H_1, a reliable way to differentiate signal from noise is required. There are two cases where it becomes difficult to distinguish the signal from noise: one is where SNR is low and the other is where the statistics of the noise are not well known.

Clearly, in spectrum sensing noise characteristics plays an important role. The noise in most of the cases is assumed to be Additive White Gaussian Noise (AWGN), as according to Central Limit Theorm many independent sources of noise are added. But in reality, the scenario is different as receivers modify the noise through processes such as filters, amplifier non-linearities and automatic gain controls [37].

Poor performance in a low SNR regime means that all of the techniques available are negatively affected by poor channels. In the case of variable channel gains, Eq. (1) is rewritten as:

$$y(k) = \begin{cases} n(k): & H_0 \\ h(k)s(k)+n(k): & H_1 \end{cases} \tag{2}$$

Where $h(k)$ is the channel gain at each instant k. In a wireless radio network, since it is reasonable to assume that the spectrum sensing device does not know the location of the transmitter, two options arise:

- A low $h(k)$ is solely due to the path loss (distance) between the transmitter and the sensing device meaning that the later is out of range and can safely transmit;
- A low $h(k)$ is due to shadowing or multipath, meaning that the sensing device might be within the range of the transmitter and can cause harmful interference.

In the second case, fading causes a critical problem. The effect of the fading is discussed in the well known "hidden node" problem [38]. In this problem, the spectrum sensing terminal is deeply faded with respect to the transmitting node while having a good channel to the receiving node. The spectrum sensing node then senses a free spectrum to transmit data such that there is no interference with primary user. Thus, fading here introduces uncertainty regarding the estimation problem.

4.2 SPECTRUM SENSING FROM THE COGNITIVE RADIO NETWORK PERSPECTIVE

As discussed above in the general case, for spectrum sensing the only aspect which is taken into account is signal detection. In contrast, if seen from a cognitive radio perspective spectrum sensing has very strict restrictions imposed mainly by the policies these cognitive radio networks face in order to be able to operate alongside legacy networks. Some of these restrictions are summarized below:

4.2.1 No Prior Knowledge on the Signal Structure

Certain part of the spectrum is shared by multiple technologies with the help of different protocols, so management of existing multiple technologies as well as new technologies that appears appear across the span of the wireless radio spectrum must be managed by Cognitive Radio networks. If the technology used is known to the network then this information can be used to improve the performance of spectrum sensing for example through the detection of known pilot sequences within the signal [39]. However, if the technology is not known, even then these networks should be able to discover the state of the medium.

4.2.2 Sensing Time

In general, there is compromise between the number of samples and accuracy for individual spectrum sensing technique. Since importance is given to Primary Users, so for efficient use of spectrum it is required that Secondary Users must be designed such that it takes least possible number of received samples to sense the available spectrum and to free the medium as soon as it senses that a Primary User has initiated a transmission.

4.2.3 Fading Channels

As discussed earlier, spectrum sensing is particularly sensitive to fading environments. Communication systems operate in diverse environments, including those prone to fading. Thus, in many situations spectrum sensing devices must be able to detect reliably even over heavily faded channels. This work has focused in sensing for the fading environment in the non-cooperative setting.

4.3 NON-COOPERATIVE SENSING TECHNIQUES

In a realistic spectrum sensing scenario there are situations in which only one sensing terminal is available or in which no cooperation is allowed due to the lack of communication between sensing terminals. In this section we will explore the main single user sensing schemes.

Single user spectrum sensing approaches have been heavily studied in the literature, in part because of the relationship to signal detection. There are several classical techniques for this purpose, including the energy detector (ED) [40], the matched filter (MF) [41] and the cyclostationary feature detection (CFD) [42].

4.3.1 Detection Techniques

Three schemes are generally used for detection according to the hypothesis model:

1. When the information of the PU signal is known to the cognitive user, the optimal detector in stationary Gaussian noise is the matched Filter (coherent detection) since it maximizes the received signal-to-noise ratio (SNR). While the main advantage of the matched Filter is that it requires less time to achieve high processing gain due to coherency, implementing this type of coherent detector is difficult since a SU would need extra dedicated circuitry to achieve carrier synchronization with each type of license user. Moreover there may be cases in practice where matched Filltering is ruled out due to the lack of knowledge about PUs.

2. If the receiver cannot gather any information about the PU signal, the optimum detector is an energy detector (non-coherent detection). Since it is easy to implement, and also it is the most general technique since it applies to any signal type, recent work on detection of the PU has generally adopted the energy detector [43]. It requires minimum information about the signal, including only signal bandwidth and carrier frequency. However, the performance of the energy detector is susceptible to an uncertainty in the noise power. Another shortcoming is that the energy detector cannot differentiate signal types but can only determine the presence of the signal. Thus, the energy detector is prone to false detection triggered by the unintended signals.

3. An alternative detection method is the cyclostationary feature detection [44]. Modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading, hopping sequences, or cyclic prefixes, which result in built-in periodicity. These modulated signals are characterized as cyclostationary signals since their mean and autocorrelation exhibit periodicity. These features are detected by analyzing a spectral correlation function. The main advantage of the spectral correlation function is that it differentiates the noise energy from modulated signal energy, which is a result of the fact that the noise is a wide-sense stationary signal with no correlation, while modulated signals are cyclostationary with spectral correlation due to the embedded redundancy of signal periodicity. Therefore, a cyclostationary feature detector can perform

better than the energy detector in discriminating against noise due to its robustness to the uncertainty in noise power. However, it is computationally complex and requires prior knowledge about the PU signal structure and significantly long observation time.

These techniques are discussed in detail below:

4.3.1.1 Energy Detection

Energy detection (ED) is the most optimal choice for the spectrum sensing where it is difficult for the CR to get the adequate information about the licensed user waveform. The ED is the most suitable choice when the CR has information about the power of the random Gaussian noise. The basic approach behind this technique is the power estimation of the licensed user (primary user) signal. In this technique, energy of the desired transmitted signal is detected then this detected energy is compared with a threshold value. The threshold is a pre-defined value. If the detected energy is below than threshold value then it is pretended that the licensed user is not present and the spectrum is free. Oppositely, if the detected energy is above the threshold value then it is assumed that the spectrum is not free as shown in Figure 1.

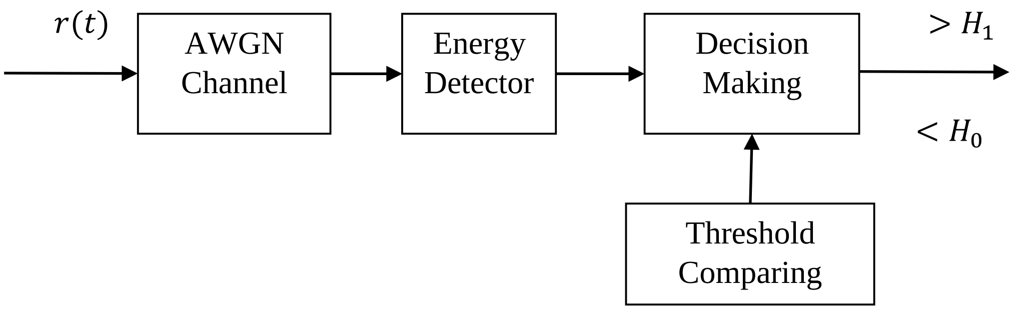


Fig.4.2: Block Diagram of Energy Detection Technique [45]

The block named Energy Detector consist of three main components, these are BPF, squaring device, and integrator as shown in fig.4.3

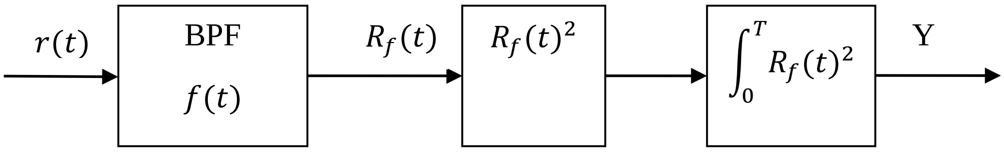


Fig.4.3: Block diagram of Energy Detector [45]

Input and output of BPF are $r(t)$ and $R_f(t)$ respectively.

$$r(t)=hs(t)+n(t) \tag{3}$$

Where

$s(t)$ →Detected signal waveform

$n(t)$ →AWGN noise signal

$h=0$ Under hypothesis H0 (no PU present)

$h=1$Under hypothesis H1 (PU is present)

The input band-pass filter selects the centre frequencyf_s, bandwidth of interest W and impulse response $f(t)$

$$R_f(t)=f(t)*r(t) \tag{4}$$

Then BPF is followed by a squaring device to measure the received energy and an integrator which determines the energy Y of the received signal $r(t)$ over a period T. output Y is compared with threshold value which is given by two different distributions for both hypothesis as given below:

$$Y=\begin{cases} \chi^2_{2TW} & :H_0 \\ \chi^2_{2TW(2\gamma)} & :H_1 \end{cases} \tag{5}$$

Where χ^2_{2TW} is central chi-square distribution with probability distribution function given as:

$$f(x;k)=\begin{cases} \dfrac{x^{(k/2)-1}e^{-x/2}}{2^{k/2}\Gamma(k/2)} & ,x\geq 0 \\ 0 & ,otherwise \end{cases} \tag{6}$$

Where $\Gamma(k/2)$ denotes a gamma function and k is degree of freedom.

And $\chi^2_{2TW(2\gamma)}$ is conditionally non-central chi-square distribution with probability density function given as:

$$f_X(x;k;\lambda)=\sum_{i=0}^{\infty}\frac{e^{-\lambda/2}\left(\lambda/2\right)^i}{i!}f_{y_{k+2i}}(x) \tag{7}$$

Where λ is a non-centrality parameter.

In order to measure the performance of the applied technique three main parameters are calculated. These are:

a) **False Alarm Probability**

False alarm probability for energy detection is calculated as:

$$P_f = (Base)^2 \tag{8}$$

Where

Base = 0.01:0.02:1

b) **Probability of Detection**

Probability of detection is given by:

$$P_d = Q\left(\sqrt{SNR_{avg} * 2 * m}, \left(\sqrt{Th(i)}, m\right)\right) \tag{9}$$

Where

m -> Time Bandwidth product

$$Th(i) = gaminv\left(1 - P_f(i), m, 1\right) * 2 \tag{10}$$

c) Probability of Miss

Probability of miss is given by:

$$P_m = 1 - P_d \tag{11}$$

Limitations of Energy detector

1. The require time to achieve the desire probability of detection may be higher.
2. The detection performance depends on the uncertainty of the noise.
3. It is impossible to make distinguish between different primary users because energy Detector is not able to differentiate between the sources of the received energy.
4. It cannot be used for the detection of spread signals
5. The computation of the threshold value used for detection is highly susceptible for the Variation of the noise levels which leads to a low SNR environment.

4.3.1.2. Cyclostationary Feature Detection

Most of the signal processing techniques used currently uses probabilistic methods to intercept signal i.e. they describe the signal on average as discussed in energy detection above, which reduces the amount of data required for featuring a signal and deriving information from it. But most of the signals used in communication system varies with time like AM, PM, FM, ASK, FSK etc. this requires that the random signal be modeled as cyclotationary, in which the statistical parameters vary in time with single or multiple periodicity.

4.3.1.2.1 Cyclostationarity

Consider a signal

$$x(t) = a\cos(2\pi\alpha t + \theta) \text{ With } \alpha \neq 0 \tag{12}$$

If Fourier coefficient of the above signal given by equation below calculated is no n zero then the signal is said to exhibit first order periodicity.

$$F_x^\alpha = \langle x(t) e^{-j2\pi\alpha t} \rangle \tag{13}$$

Fourier coefficient of above signal is:

$$F_x^\alpha = \frac{1}{2} a e^{j\theta} \tag{14}$$

In above equation operation is the time averaging operation given by:

$$\langle \, . \rangle \triangleq \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} (.)\, dt \tag{15}$$

PSD of above signal is given as:

$$\left| F_x^\alpha \right|^2 \delta(f-\alpha) + \delta(f+\alpha) \tag{16}$$

This shows that PSD of $x(t)$ includes two spectral lines at $f = \alpha$ and $f = -\alpha$. So a signal is said to be cyclostaionary signal if its Fourier coefficient is non zero and its non linear transformation produces spectral lines. Implementation of CFD is discussed below:

Block diagram of CFD is shown in Fig.4.5;

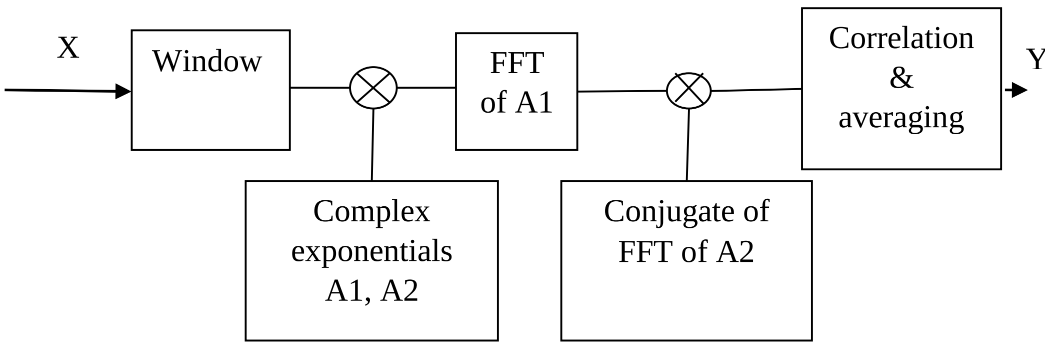


Fig.4.4: Block diagram of Cyclostationary Feature Detection [47]

Input signal is passed through a window to limit the length of the signal. It is then multiplied with complex exponentials say A1 and A2. Then N-point FFT of both A1 and A2 is calculated and conjugate of A2 is carried out. In next step these two signals are again multiplied and finally correlation and averaging is done to get cyclic spectrum as output.

Limitations of the Cyclostationary detection

The CFD is more robust to uncertain levels of noise and gives much better performance in low SNR regions. However, this technique has its own limitations:

1. High computational complexity.
2. Long Sensing Time
3. senses spectrum over a small range of frequency

4.4 COMBINATION OF ED AND CFD

In the combined technique first an ASK signal is generated and energy detection method is applied on the signal. In energy detection power of the signal is calculated for AWGN channel and this signal is then fed to cyclostationary feature detection to obtain cyclic spectrum.

Cyclostationary processes are random process for which the second order statistics such as mean and autocorrelation change periodically with time [49]. A zero-mean continuous signal $x(t)$ is called second order (wide sense) cyclostationary if its time varying autocorrelation function $R_{xx}(t,\tau)$ defined as:

$$A_{xx}(t,\tau) = E\left\{x(t)x^*(t+\tau)\right\} \tag{17}$$

$A_{xx}(t,\tau)$ is periodic in time t for each lag parameter τ and it can be represented as a Fourier series

$$A_{xx}(t,\tau) = \sum_{\alpha} A_{xx}^{\alpha}(\tau)e^{j2\pi\alpha t} \tag{18}$$

Where the sum is taken over integer multiples of fundamental cyclic frequency α, for which cyclic autocorrelation function is defined as:

$$A_{xx}^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{\frac{-T}{2}}^{\frac{T}{2}} A_{xx}(t,\tau)e^{-j2\pi\alpha t}dt \tag{19}$$

The Fourier transform of $A_{xx}^{\alpha}(t,\tau)$ is called the cyclic spectrum (CS) which is defined as:

$$C_{xx}(\tau)=\int_{-\infty}^{\infty}A_{xx}^{\alpha}(\tau)e^{-j2\pi f\tau}d\tau \tag{20}$$

A discrete cyclic autocorrelation function of discrete time signals x[n] with a fixed lag l is defined in the similar manner as:

$$A_{xx}^{\alpha}(l)=\lim_{n\to\infty}\frac{1}{N}\sum_{m=0}^{N-1}x[m]x^{*}[m+l]e^{-j2\pi\alpha m\Delta m} \tag{21}$$

Where N is the number of samples of signal x[m] and Δm is the sampling interval. By applying the discrete Fourier transform to $A_{xx}^{\alpha}(l)$, the cyclic spectrum is given as

$$C_{xx}^{\alpha}(f)=\sum_{l=-\infty}^{\infty}A_{xx}^{\alpha}(l)e^{-j2\pi fl\Delta l} \tag{22}$$

4.4.1 Cyclic Spectrum Estimation

In order to detect and classify signals one of the methods is to estimate its cyclic spectrum. In practice there are two algorithms to estimate the cyclic spectrum, called the FFT Accumulation Method (FAM) and the Strip Spectral Correlation Algorithm (SSCA).Both methods are based on modifications of time smoothed cyclic cross periodogram which is defined as

$$C_{xyT}^{\alpha}(n,f)=\lim_{n\to\infty}\frac{1}{2n+1}\sum_{n=-N}^{N}\frac{1}{T}X_{T}\left(n,f+\frac{\alpha}{2}\right)Y_{T}^{*}\left(n,f-\frac{\alpha}{2}\right) \tag{23}$$

Where $X_T(n,f+\frac{\alpha}{2})$ and $Y_T^{*}(n,f-\frac{\alpha}{2})$ are the complex envelopes of narrow band, bandpass components of the signal x[n] and y[n] respectively. These complex envelopes are computed in the following way,

$$X_{T}(n,f)=\sum_{k=\frac{-N'}{2}}^{\frac{+N'}{2}}a(k)x(n-k)e^{-j2\pi f(n-k)T_s} \tag{24}$$

$$Y_{T}(n,f)=\sum_{k=\frac{-N'}{2}}^{\frac{N'}{2}}a(k)y(n-k)e^{-j2\pi f(n-k)T_s} \tag{25}$$

Where $a(k)$is data tapering window of length $T = N' * T_s$ seconds and sampling periodT_s. In this paper, the cyclic spectrum estimation is implemented by FAM method [49] which is shown below with the help of Fig. 4.7

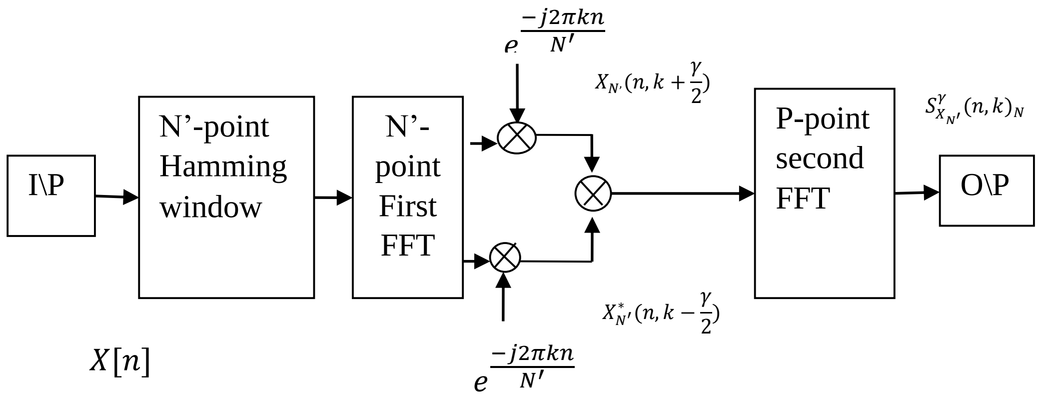


Fig.4.5 FFT Accumulation Method [50]

In FAM as shown above input is read and necessary parameters such as $f_s, \Delta f$ and $\Delta\alpha$ are initialized and$N' = \frac{f_s}{\Delta\alpha}$. In order to make advantage of FFT without using zero-padding we take value of N to the power of 2 equal to or larger than the value given by above relation. Take $L = \frac{N'}{4}$ and then the complex envelopes are computed efficiently by means of a sliding N'-point FFT followed by downshifting of frequency to baseband signal. Then complex conjugate of the

downshifted signal is calculated and the product of complex envelope and its conjugate is carried out. Again P-point FFT is calculated where P is given by$P = \frac{f_s}{L\Delta\alpha}$.

CHAPTER-5

RESULTS AND DISCUSSION

5.0 RESULTS FOR ENERGY DETECTION

As discussed in section 4.3.1.1, in order to determine the presence of PU using Energy Detection, power of the signal is calculated and compared to predefined threshold value. In this section, numerical results are presented to evaluate the performance for Energy Detection using complementary ROC curve.

Fig. 5.1 shows plots of complementary receiver operating characteristic (ROC) (probability of a miss P_m versus probability of False Alarm P_f) under AWGN channel. We assume that average SNR γ =1 dB and Time Bandwidth product m = 5. For given 10 % probability of false alarm, the probability of detection is 89 % under AWGN channels that means probability of miss is 21% as shown in Fig. 5.1.

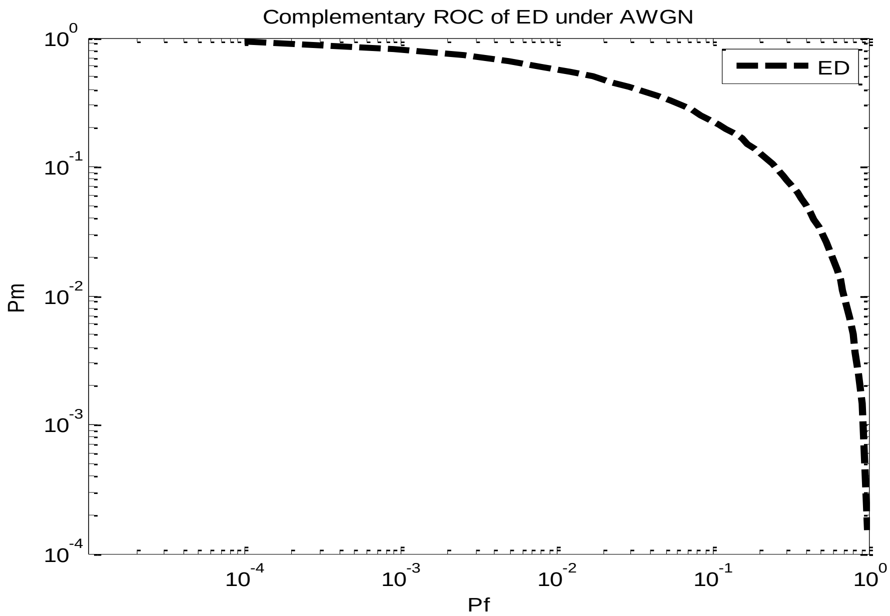


Fig.5.1: Complementary ROC under AWGN

As discussed above in chapter 4 that limitation of Energy Detection technique is that its performance decreases at low SNR. This is shown in Fig. 5.2 below where complementary ROC curve of ED is plotted for different values of SNR =1, 3, 5.

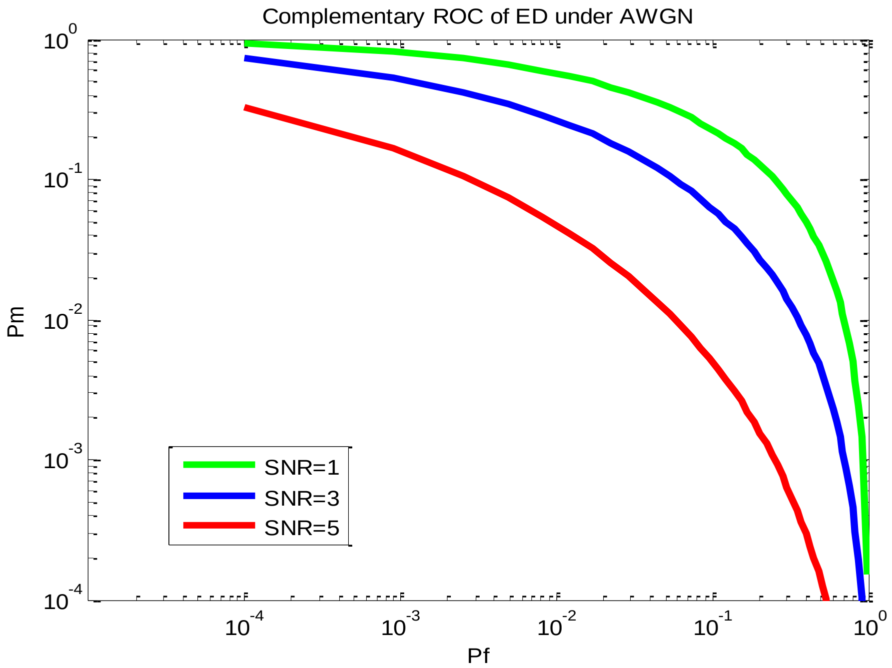


Fig. 5.2: Plot of ED for different values of SNR

Fig. 5.2 shows complementary Region of Convergence plot for Energy Detection. It can be observed that as we decrease the SNR, the performance of ED degrades. For $P_f = 10^{-2}$, SNR=5, P_m obtained is 0.95, as we increase the SNR=3 probability of miss is increased by 76.25% and further to 86.42% for SNR=1.

5.1 RESULTS FOR CYCLOSTATIONARY FEATURE DETECTION

Before employing the cyclostationary feature extraction method to identify the cyclostationary signatures of the signal, it is important to show the characteristics of the ASK signal which is used as an input signal. It is assumed that carrier frequency is 30 Hz, pulse frequency is 5 Hz and amplitude of the wave is 3.This is shown in Fig. 5.3 below:

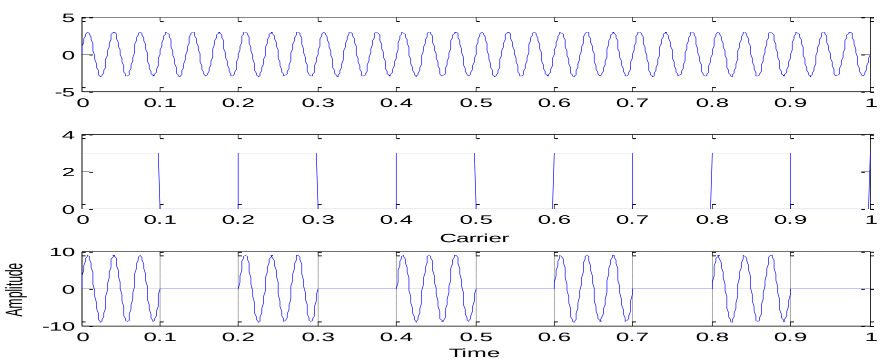


Fig. 5.3: Generation of ASK signal

This signal is passed through window to limit the length of the signal. Then N-point FFT is carried out followed by correlation and averaging of the signal to obtain cyclic spectrum as shown in Fig.5.4 below:

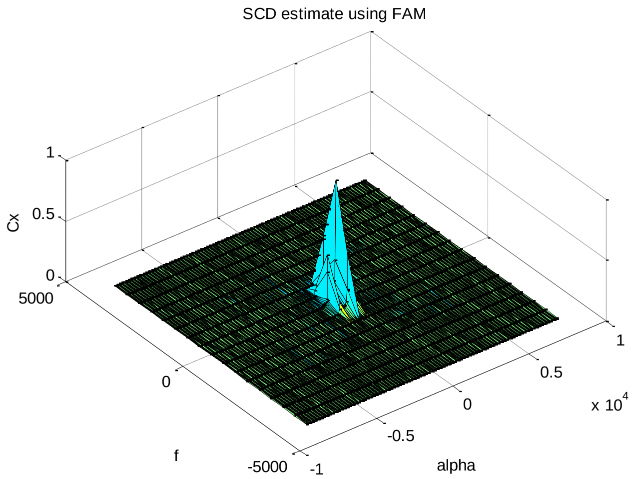


Fig. 5.4: Cyclic Spectrum of CFD

Fig. 5.4 shows a 3D plot plotted for three parameters namely Cyclic Spectrum, Frequency and Cyclic Frequency. The plot shows the presence of primary user at alpha=0, for a small range of frequency with Cyclic spectrum value= 0.5 (approx). However, this technique outperforms Energy Detection at low SNR which is shown in Fig.5.5 below:

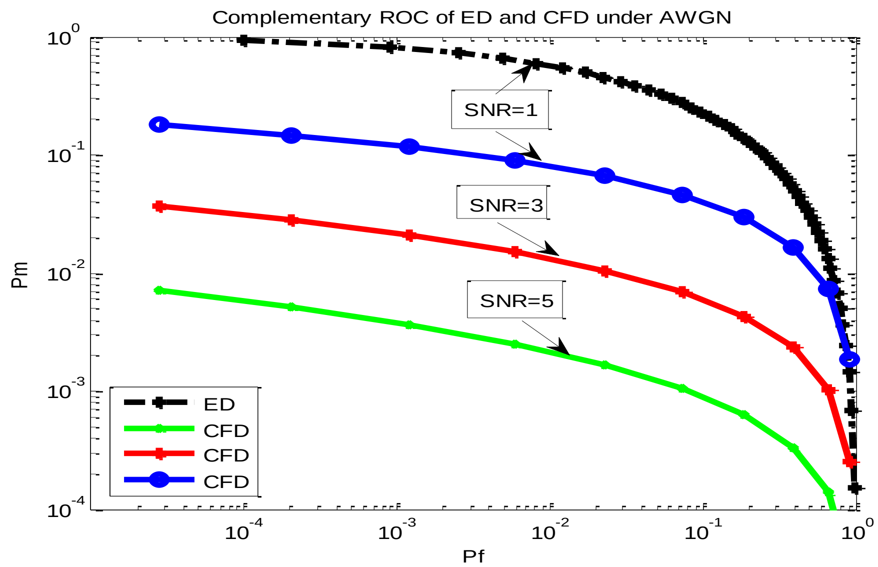


Fig. 5.5: Comparative results of ED and CFD

Fig 5.5 shows comparative results of Energy detection and Cyclostationary Feature Detection with complementary ROC curve between probability of miss and probability of false alarm for different values of SNR. In above plot, black dotted line represents ED and blue dotted line represents CFD for

SNR=1. It can be clearly observed that for same low value of SNR=1, $P_f = 10^{-2}$, P_m for CFD is reduced by 88.57% as compared to ED. Moreover CFD plots are also obtained for higher values of SNR=1, 3, 5 and it is observed that CFD gives better results as we increase SNR.

But as discussed above that limitation of CFD is that it senses for a very small range of Frequency so to overcome this problem a new technique is propose based on the combination of above two techniques and simulation results are discussed below.

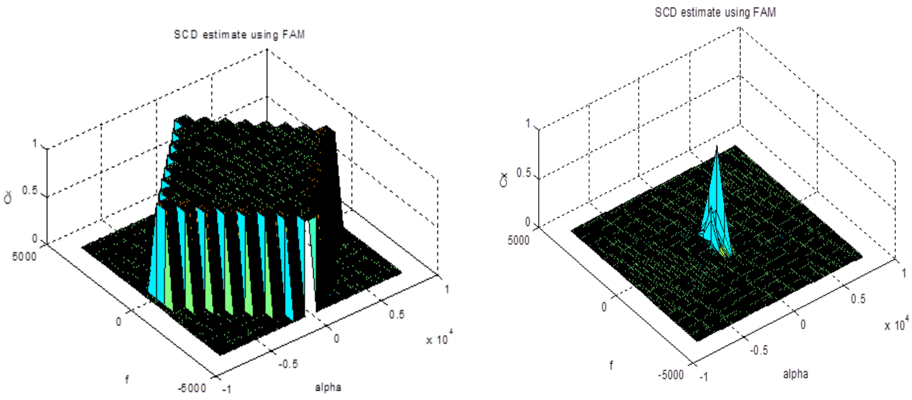
5.2 RESULTS FOR COMBINED TECHNIQUE

In this section two techniques are combined i.e ED and CFD to obtain better results compared to both the techniques. This technique is implemented using FAM algorithm. Firstly, the simulation results obtained for the combined technique are compared with that of Cyclostationary Feature Detection with the help of 3D plot obtained for following simulation parameters shown in Table-I:

TABLE-I: SIMULATION PARAMETERS

Parameter	Description
$f_s = 8192\ Hz$	Sampling Frequency
$\Delta f\ = 512\ Hz$	Desired Frequency Resolution
$\Delta\alpha$=16	Desired Cyclic Frequency Resolution

Above table shows value of three parameters i.e Sampling Frequency, Desired Frequency Resolution and Desired Cyclic Frequency Resolution which are assumed for ASK signal. These values are used to calculate Cyclic Spectrum of the combined plot as shown below:



SCD estimate using FAM for combined technique **SCD estimate for CFD**

Fig.5.6 Comparative results of Combined Technique and CFD

It can be clearly observed in Fig. 5.6 that combined technique is able to detect the same signal for quite a wide range of frequency as compared to CFD.

In order to carry out a comparison between the proposed combined technique and energy detection (ED), simulations are carried out in AWGN environment for the case $\delta^2 = 1$ and L=1. The results indicate that better performance can be achieved in proposed combined technique compared to the conventional energy detector as shown in Fig. 5.7.

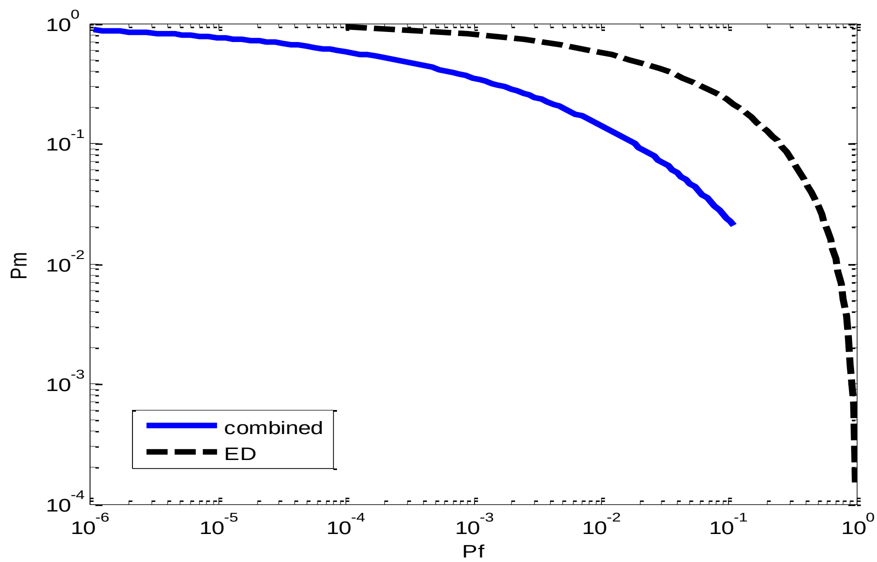


Fig. 5.7 Comparison of Energy detection and combined technique

Complementary ROC curve shows plot of energy detection with dotted black line and combined technique with solid red line. As shown in graph for $P_f = 10^{-2}$, probability of miss is reduced by 98.33 % by using combined technique which again proves that proposed technique is better than CFD (which reduced probability of miss by 88.57%).

CHAPTER-6
CONCLUSION & FUTURE SCOPE

CONCLUSION

To effectively utilize the wireless spectrum Cognitive Radios were introduced which utilizes the unused spectrum in the wireless channel. The most essential aspect of a cognitive radio system is spectrum sensing and various sensing techniques which it uses to sense the unused spectrum. In this work, in order to sense spectrum effectively two methods are discussed namely Energy Detection and Cyclostationary Feature Detection. Each of these techniques has their own shortcomings which have been overcome by proposing Combined Technique. Energy detection technique is very easy to implement but it cannot distinguish different PUs and SUs. Moreover, ED underperforms in low SNR. This is shown with the help of ROC curve in Fig.5.2 where different curves are plotted for different SNR=1, 3, 5. This problem is overcome by Cyclostationary Feature Detection where cyclic spectrum of the signal is calculated. However, CFD is complex and time consuming but shows better results than Energy Detection. Simulation results are obtained for individual techniques i.e. Energy Detection and Cyclostationary Feature Detection. Results obtained for ED shows that for 10% probability of false alarm, the probability of miss is 21% as shown in Fig.5.1whereas It has been clearly observed in Fig.5.5 that for same low value of SNR=1, $P_f = 10^{-2}$, P_m for CFD is reduced by 88.57% as compared to ED. But it is observed in Fig.5.4 that CFD senses the spectrum over a small range of frequency. In order to overcome the shortcomings of CFD, a combined technique has been proposed which as its name suggest combines above discussed two techniques to get better results compared individual techniques. This is supported with the help of simulation results shown in Fig.5.6 which shows comparative results of proposed technique and CFD. It has been observed that combined technique senses over a wide range of frequency as compared to CFD. Also ROC curve is shown in Fig.5.7 to compare the results of Combined Technique with ED. It has been observed that for $P_f = 10^{-2}$, probability of miss is reduced by 98.33 % by using combined technique which again proves that proposed technique is better than CFD (which reduced probability of miss by 88.57).

FUTURE SCOPE

1. Wavelet detection technique can be implemented for spectrum sensing.
2. Spectrum sensing can also achieve good results using cooperative sensing.

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