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SPECTRUM SENSING TECHNIQUES IN COGNITIVE RADIO: CYCLOSTATIONARY METHOD

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ABBREVIATIONS

3GPP	3rd Generation Partnership Project
ADC	Analog to Digital Convertor
AGC	Automatic Gain Control
AM	Amplitude Modulation
AMDSB	Amplitude Modulation Double Side Band
AMSSB	Amplitude Modulation Single Side Band
AP	Access Point
ASK	Amplitude Shift Keying
AWGN	Additive Wight Gaussian Noise
BPSK	Binary Phase Shift Keying
BS	Base Station
CMOS	Complementary Metal Oxide Semiconductor
CP	Cyclic Prefix
CPE	Consumer Premise Equipments
DAC	Digital to Analog Convertor
DSA	Dynamic Spectrum Allocation
DSM	Dynamic Spectrum Management
DSP	Digital Signal Processor
DVB	Digital video Broadcasting
FAM	FFT Accumulation Method
FCC	Federal Communication Commission
FFT	Fast Fourier Transform
GPS	Global Positing System

ISI	Inter Symbol Interference
ITU	International Telecommunication Union
LNA	Low Noise Amplifier
LOS	Line of Sight
MAC	Medium Access Control
NTIA	National Telecommunication and Information Administrations
OFDM	Orthogonal Frequency Division Multiplexing
OSI	Open System Interconnection
PDAs	Personal Digital Assistants
PHY	Physical Layer
PSD	Power Spectral Density
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
QPSK	Quadrature Phase Shift keying
QTI	Quadratic Time Invariant
RKRL	Radio Knowledge Representation Language
RSA	Radio Scene Analysis
SCF	Spectral Correlation Function
SDR	Software Defined Radio
SIR	Signal-to-Interference Ratio
SNR	Signal-to-Noise Ratio
SQPSK	Staggered Quadrature Phase Shift Keying
SSCA	Strip Spectral Correlation Algorithm
TPC	Transmit Power Control
UHF	Ultra High Frequency

UWB	Ultra Wide Band
VHF	Very High Frequency
WPAN	Wireless Personal Area Network
WiFi	Wireless Fidelity
WiMAX	Worldwide Interoperability for Microwave Access
WLAN	Wireless Local Area Network
WSCS	Wide Sense Cyclostationary Process
WWRF	Wireless World Research Forum

ABSTRACT

Cognitive Radios promise to be a major shift in wireless communications based on developing a novel approach which attempt to reduce spectrum scarcity that growing up in the past and waited to increase in the future. Since formulating stages for increasing interest in wireless application proves to be extremely challenging, it is growing rapidly. Initially this growth leads to huge demand for the radio spectrum. The novelty of this approach needs to optimize the spectrum utilization and find the efficient way for sharing the radio frequencies through spectrum sensing process.

Spectrum sensing is one of the most significant tasks that allow cognitive radio functionality to implement and one of the most challenging tasks. A main challenge in sensing process arises from the fact that, detecting signals with a very low SNR in background of noise or severely masked by interference in specific time based on high reliability. To overcome this limitation spectral analysis has been implemented successfully to detect the presence or absence of target signals in communication systems, especially cyclic spectral analysis based on cyclostationary method it can also extract significant information from the incoming target signal.

This thesis describes the fundamental cognitive radio system aspect based on design and implementation by connecting between the theoretical and practical issue. Efficient method for sensing and detecting are studied and discussed through two fast methods of computing the spectral correlation density function, the FFT Accumulation Method (FAM) and the Strip Spectral Correlation Algorithm (SSCA). Several simulations have been performed to show the ability and performance of studied algorithms.

KEYWORDS:

Cognitive Radio, Spectrum Sensing, Cyclostationay method, Spectrum Sharing, Sensing Methods, FAM method and SSCA Algorithm.

1. INTRODUCTION

Wireless applications are a broad and dynamic field that has evolved and growing rapidly, wireless is everywhere. Formulating stages of increasing interest in wireless application proves to be extremely challenging since it is driven by markets. The growth of the wireless application, leads to huge demand for radio spectrum which is grow up in the past and expected to increase in the future. As the number of wireless application increase the risk of interfering with other users increase especially if they use the same band in a specific location. From this view spectrum scarcity has arisen for new services and application. Nevertheless the extensive main portions of the available spectral resources have already licensed to a primary users and large portion of this assigned spectrum is utilized periodically and vary in different locations. This has opened door to a new technology is “Cognitive Radio” that enables to use the spectrum in a dynamic manner. Cognitive Radio address the problem of deficient utilization demonstrated in many frequency bands allocations. The concept is that, cognitive radio networks sense the spectral environment and adapt the transmission parameter to enhanced utilization of the spectrum by reuse the available spectrum without harmful interference with primary users or other cognitive radio networks rather than fixed allocations. While spectrum utilization is accumulated on specific portions however huge amount of the spectrum remains unutilized.

Sensing the spectrum environment for the purpose of reuse the available spectrum introduces big technical challenges which attracts a great deal of research. First is concentrating on software defined radio and second concentrating on signal processing and communication technology. Moreover sensing the spectrum is the key part for implementing functionality of cognitive radio networks. Therefore the objective of my thesis is to analyze and explore the spectrum sensing algorithms, focusing on cyclostationary method by studying efficient estimating methods and bridging between theoretical and practical aspects through several simulations.

1.1. Spectrum Availability Problem

The electromagnetic radio spectrum is natural resource which is regulated by government. Since the increasing demand for wireless connectivity and current crowding application stimulate the regulatory agencies to be ever more powerful in preparing new ways to utilize spectra. However, it is communally believed that there is a spectrum scarcity at the frequencies below 3GHz that can be used economically for wireless application. Conventional spectrum allocation aspect was based on specific band assignments designated for particular service, under this static frequency allocation wireless systems are adjusted according to this fixed spectrum assignments, bandwidths and operating frequency, with adapt transmitted power based on the environments that limits their coverage area. Due to these limitations most wireless communication systems are designed with sophisticated modulation, coding, and multiple antennas or other technique to achieve the best spectrum efficiency within the fixed assigned bandwidths as illustrated by the National Telecommunication and Information Administration's (NTIA) chart. Figure 1 indicates overlapping allocation in most frequency bands and a high degree of spectrum utilization which supports the scarcity concept.

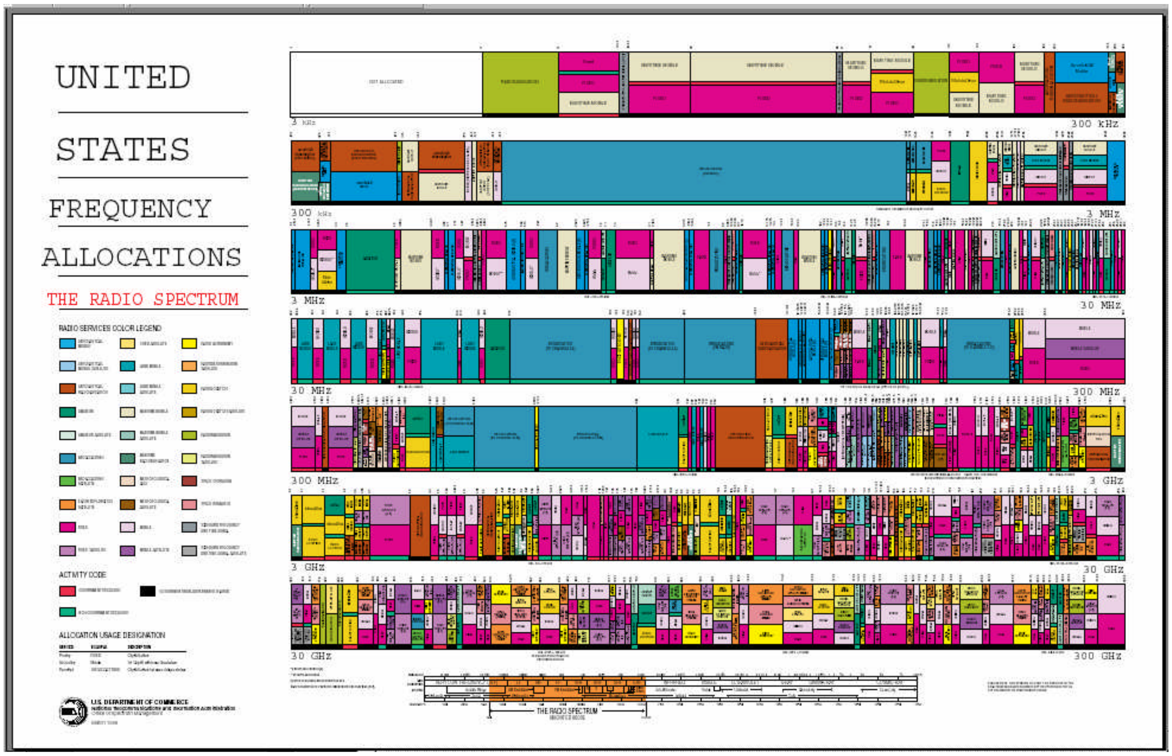
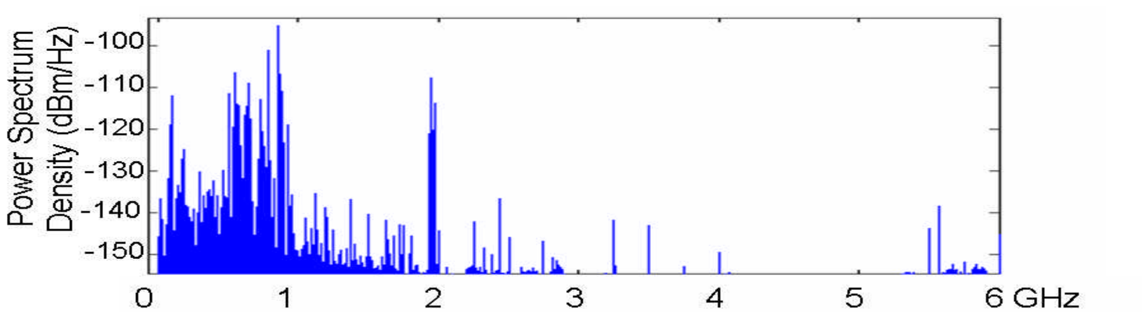


Figure 1. The NTIA frequency allocation chart (NTIA 2003).

However the current spectrum allocation are faced with increasing interference for some radio systems (e.g., cell phone and WiFi) that limits network capacity an scalability, while they are continually improving. Moreover with this current spectrum allocation it is evident that there is no available spectrum bandwidth for future wireless systems or enhance network capacity for existing one. (Cabric etc 2006).

Intuitively, increasing of wireless systems that expected to rise in the future according to the Wireless World Research Forum (WWRF), by the year 2017 seven trillion wireless devices will be in use by seven billion people most of these devices are short range communication (WPAN, WLAN), average 1000 devices per person (Fitzek & Katz 2007: 6-7).

From implementation point view, the rapidly increase of the wireless systems and applications also poor allocation of the spectrum in which that encourage the scarcity mindset. Consequently actual measurement of the spectrum utilization taken in downtown Berkeley indicate the many assigned frequency bands are occupied infrequently and not in every location. Figure 2 illustrates the typical spectrum utilization, based on that allocation the usage of the spectrum is crowded on certain portion of the spectrum approximately 30% below 3 GHz while a significant amount of the spectrum in low utilization 0.5% in the 3 to 6 GHz frequency band. The Figure shows the (PSD) of the received 6 GHz wide band signals allocated for a span of 50µs samples at 20 GS\s (FCC 2002).



Freq (GHz)	0~1	1~2	2~3	3~4	4~5	5~6
Utilization(%)	54.4	35.1	7.6	0.25	0.128	4.6

Figure 2. Measurement of 0-6 GHZ spectrum utilization in downtown Berkeley (Cabric etc 2006)

Actually, measurements have been taken in the same location Berkeley downtown location by Federal Communication Commission (FCC) in which that illustrates there is a significant variation in utilization of the assigned spectrum. That variation range from 15% to 85% depends on the operating frequency band and geographical location as shown in Figure 3. According to this inefficiency utilization arises from fixed allocation process, which assigns the complete rights to a frequency band to a primary user. Although the primary users are poorly utilized these available limited spectrum recourses.

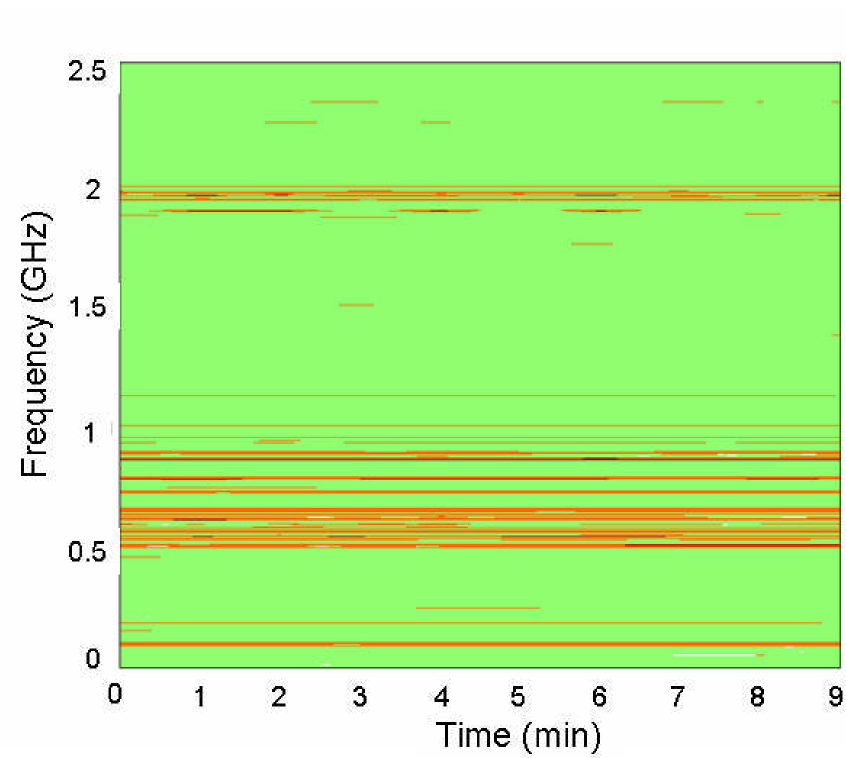


Figure 3. Temporal variation of the spectrum utilization (0-2.5GHz) in downtown Berkeley (FCC 2002)

Therefore, to overcome this problem based on make spectra available for use by secondary users, new sharing concept has been introduced. First approach is the simplest sharing concept based on operates over Ultra Wideband (UWB) with a hard restriction on the transmitted power level to guaranty that no harmful interference causes to the primary users. However, the (UWB) approach did not recognize the existence of the White space in the spectrum utilization. Hence Its application are limited for only few meters (personal area networks).

Second approach is to sense the spectral environment over a wide band frequency (Cognitive Radio) and exploit this information to provide a wireless communication links meet the user communication requirement. Both these techniques are providing a significant shift from concept that assigned frequency bands must kept out of interfere and cannot reused it (Cabric etc 2004).

1.2. Introduction to the Artificial Cognition

The sciences of artificial systems that exhibit intelligent capabilities were independently developed by researcher from Russia and U.S., on the 60's and 70's. Despite, within around 25 years had been ignored. A several recent research papers are interesting with such work started to appear around 1995 and had been increasing. The main purposes of these papers are to imitate some function of brains. It is obvious to understand that the humans and animals have brains are for survive, live, and solve every day's problems, learn by doing.

The brain is highly complex information processing systems in which that it capable to compute faster than the fastest digital computer. Moreover, brain knowledge's are built based on its ability to learn from experiences and extracting relevant information from the environment developing own rules. Actually knowledge and experience are cumulated over time (Gudwin etc 2005).

In general, "artificial cognition: is massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use". Intuitively, by imitating some function of brain such as knowledge and store the acquired knowledge also based on the above definition artificial cognition looks like the brain in those behaviors.

Knowledge refers to increase awareness of their location, networks, users, moreover immediate environment in doors, heating, air conditioning, lighting, thermal, audio and video sensor, this lead to high degree of environment sensing in which that make the device human centric information services located behind the limited location awareness to high level environment awareness. This high level information from all different sensors and experiences are gathered and stored in memory.

Memory is key part in such system. For instance, in digital computer if you want to recall some thing need to up load data from disk to memory. In artificial cognition system need to put that system partially into the state which has prior knowledge based on it was in that state at previous time on the other hand to perform a solution what we call artificial cognition system it need to develop a paradigms match on the current state of the system, stimulate the system in to the predicted next state (predicted from the some of all past experiences), and repeat the cycle (Keene 1995).

An artificial cognition system has three key components: representation, reasoning, and learning as illustrated in Figure 4.

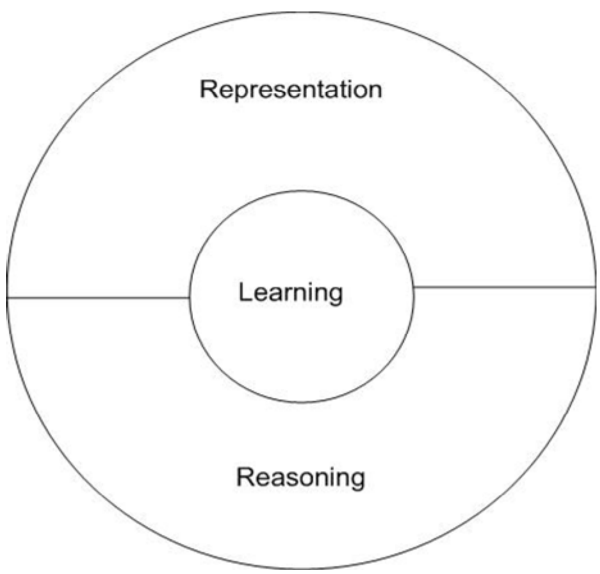


Figure.4 Illustrating the three key components of an artificial cognition system (Haykin 1999)

First, *representation*: The most intensive feature needs to create standard language to exchange knowledge about a problem domain and the solution of the problem to enhance the flexibility of wireless communications. As regards exchanging knowledge between network and a terminal handset can be illustrated in this example, if the network wants to ask "How many distinguishable multipath components are you seeing?" Two problems facing the system. First presenting the question requires standard language from the network. Second the answer is located in the internal structure of the handset which has no knowledge about it. Also it has no standard language to prepare the answer. Joseph Mitola explains how to enhanced flexibility and the robustness of personal wireless service through a novel language is (RKRL) Radio Knowledge Representation language (2000).

Second, *reasoning:* In general it defines the system capability to address wide, different types of problems and provide an optimum solution based on its ability to explicit and implicit information known to it in which that can be used by a control mechanism to determines and select the efficient operation for a specific problem. In many cases uncertainty in the experimental knowledge led to use a probabilistic reasoning procedure.

Third, *learning:* The most significant property within machine learning includes supervised and unsupervised approaches to extracting knowledge from environment to improve its performance based on learning. Supervised technique requires a dataset to which they have to adapt and acquired the machine learn based on what they have already been identified. Unsupervised technique, a new clustering of data require algorithm to extract knowledge, this gives raise the possibility to find a new relation between datasets, resulting found previously unknown skills and knowledge by entity lead to self learning (Haykin 1999 ; Loula etc 2007).

Therefore cognitive radio increases the awareness of larger environment and embeds machine learning techniques that improve its performance.

1.3. Cognitive Radio Overview

Cognitive Radio is a novel technology that significantly extends user support functionality by make the software functionality available for various classes of adaptivity which enable users, network operators, spectrum regulator, to enhance performance much more than before with a fixed application radios. Historically, the term cognitive radio was coined by Mitola in the first doctoral dissertation published in 2000, in this dissertation Mitola describe the point that how the wireless personal digital assistants (PDAs) and the related network could be sufficiently computationally intelligence about the radio resources and the related software functionality to detect a user communication needs and provide radio resources with wireless service meet best of the user demand through a software defined radio (SDR)(1999).

Thus, cognitive radio is intelligent as much as it can select the best and cheapest service for radio transmission like if we are at university and we want to send E-mail, there are several networks available for use, cognitive radio automatically select the cheapest and best (university network) it is free for use based on learning from the previous state, moreover it can predict about the current transmission status or soon available another resources.

As a result cognitive radio can be defined as, "the smart radio which has the ability to sense the external environment, learn from the history and make the intelligent decision to adjust its transmission parameters according to the current state of the environment" (Fette 2006).

From this definition two main characteristics of the cognitive radio can be describe. The key characteristics of cognitive radio operation are cognitive capability and reconfigurability in which that simply implemented in software supported by (SDR) development.

Cognitive capability: refers to the ability to continuously sense, extracting information from the radio environment to independently detect the presence of the primary user through this process. Thus different sensitivity and rate of sensing are required to capture the temporal and spatial variations in the radio environment and avoid interference to potential primary users or other cognitive network in which that makes radio spectrum sensing the most challenging research problem. Through this sensing process a significant portion of the spectrum are unutilized in a certain time at a specific location has been identified and make it available to exploit by unserviced secondary users.

Reconfigurability: exhibit software control of the radio give advantage to a single system to operate under multiple configurations, providing flexibility over variety of modulation techniques, wideband and narrowband operation and transmission security function meet the best user communication demands supported by its hardware design (Akyildiz 2006).

As regards the fundamental issue of cognitive radio is to get unutilized spectrum in certain time and specific location through cognitive capability and reconfigurability as illustrated in Figure 5 and make it available for secondary users by two concepts.

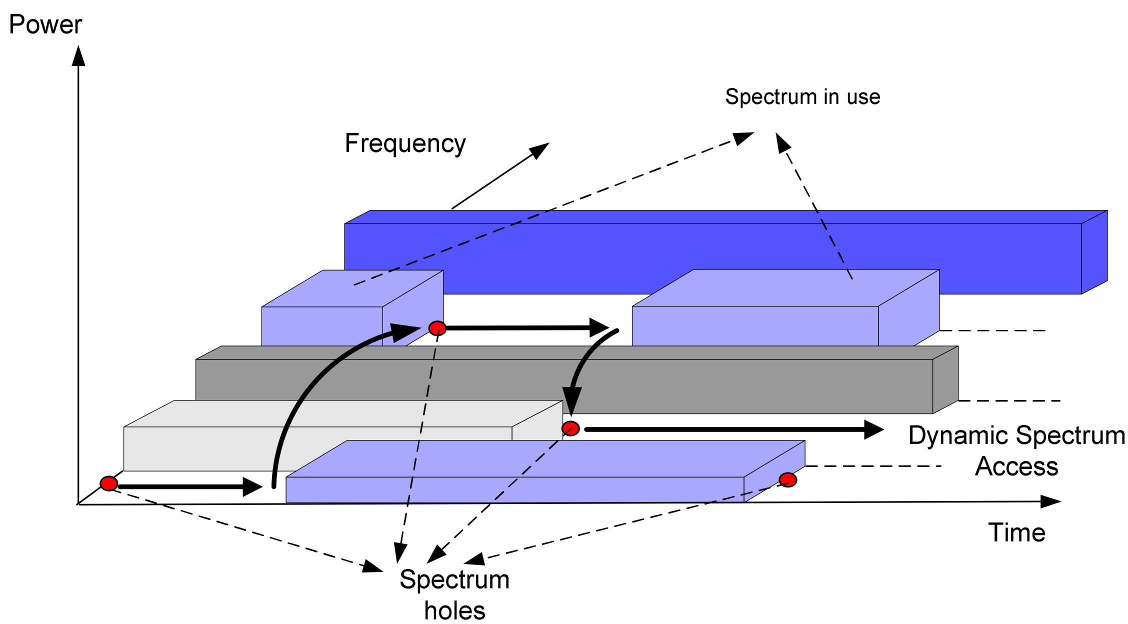


Figure 5. Spectrum whole concept (Akyildiz 2006)

First, since not all the licensed spectrum are utilized all the time in every location cognitive radio search for those target which is referred as spectrum hole or white space, and when suddenly primary user claim the assigned band cognitive radio move to another spectrum hole if it is possible or switch-off searching for another opportunities.

Second, the cognitive user share the same spectrum band and modifying its own transmission parameters in such away they do not yield any harmful interference with licensed user. Consequently the sensing and implementing of spectrum holes proves big technical challenges based on two classes. First is concentrating on software define radio and second concentrating on signal processing and communication technology (Cabric 2008).

1.4. Main Tasks in Cognitive Radio

Cognitive Radio offers a paradigm shift in the way that the radio spectrum are regulated and sheared. Since cognitive radios are secondary users which they do not have prior right in to any frequency bands to occupy and their communications are strictly depending on the presence of the primary users. As a result, cognitive radio networks must sense a wide frequency bands which spans multiple primary users bandwidths and execute frequent measurement of primary user's activity through spectrum sensing. Both of the real time measurement and the external word monitoring are obtained by the following list of primary tasks:

- Monitor the external radio environment by allowing each cognitive radio receiver to continuously sense its local environment.

- Adapt the performance based on learning from the environment to statistical variations in the incoming stimuli.

- Cooperation between multiple cognitive radios in the way that provides the best communication links requirements in a self organized manner.

- Share the available resources among the competing cognitive radios in a fair manner, and control the communication processes.

- Learn from these sequence tasks and built its own experience.

From reconfigurability point view cognitive radio looks naturally to software defined radio (SDR) to implement these tasks and from capability side view looks to signal processing and machine learning procedures for their implementation. In general we can capsulate the primary tasks in the three main tasks as fallows.

- Radio scene analysis (RSA), which includes, estimates of interference temperature, detect spectrum holes and predict modelling for the state.

- Channel identification, which enhanced spectral utilization.

- Dynamic spectrum management (DSM) and transmit power control (TPC), which is seen when cognitive radio attempts to access the white space or when cognitive radio share the licensed band with the primary user by adapting its transmission parameters based on the receiver environment observation, feed back stimuli.

From the cognitive signal processing cycle shown in Figure 6 it is evident that the first two tasks are implemented in the receiver and the third task is implemented in the transmitter (Haykin 2005).

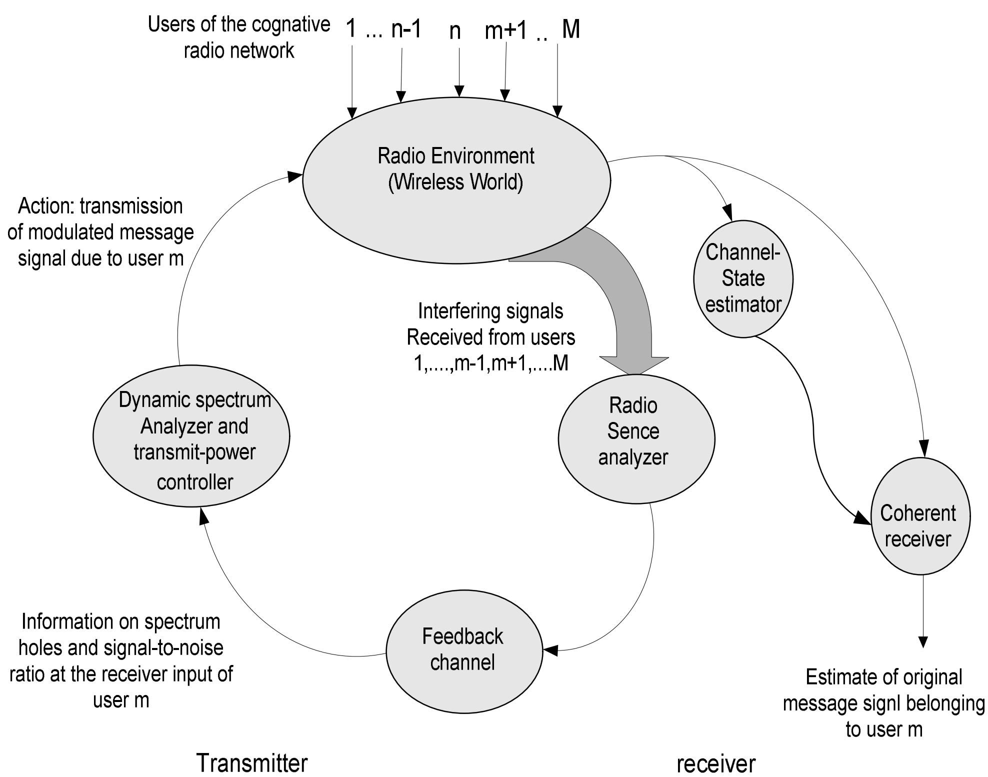


Figure 6. Basic signal processing cycle for user m in cognitive radio network (Haykin 2005)

For harmonically working between the transmitter and the receiver it is obviously need a feedback channel to pass significant information about the RF receiver environment, spectral state and the performance of the forward link. Clearly, cognitive radio is a closed loop feedback control system shows a promise to achieve magnitude improvement in system flexibility rather than system with fixed frequency allocation (Hossain 2007: 1-7).

2. Background of cognitive radio

Wireless communications are accomplished with three main entities such as signal, physical hardware and its functionalities which complement each other and evolved since the invention of the radio transmission by Gugliemo Marconi. The primitive devices have very simple signaling process such as analog hardware and limited functionality which the communication devices transmitter need to encode the information from the source into proper electronic representation and transmit through a channel. While the receiver must recover the transmitted signal although the channel distorts the RF signal, adds noise and many distorted replicas of the original signal.

Simply the process in the receiver is the reverse what had been done in the transmitter as depicted in the Figure 7 (Mitola 1999).

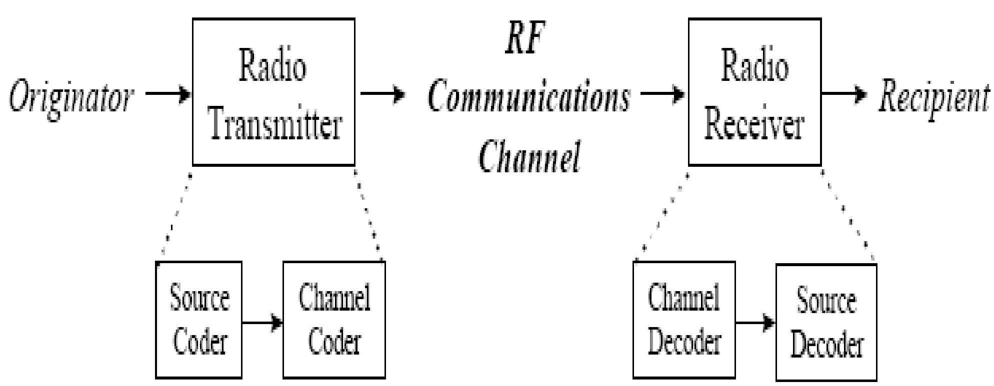


Figure 7. Traditional Model of a Radio Communication System (Mitola 1999)

In terms of implementation, primitive communication systems are significantly evolved, different signaling methods have been invented and different wireless communication standards have been added and developed. Furthermore hardware technology evolved widely by transition from analog hardware to digital hardware followed by developing of the software defined radio (SDR) structure and virtual hardware which under development. Most of these sophisticated technologies are considers to support three major capabilities that rise in cognitive radio.

- Enhanced spectrum utilizations in a dynamic manner.
- Optimization of the network resources and make a flexible interface with a wide variety of networks.
- Make a robust interface with high layer and provide resources meet best on demand.

The growing interest in cognitive radio lead to many technology have come together to drive cognitive radio technology. At the beginning the major contribution which have made significant development in cognitive radio that the developing of digital signal processing DSP techniques by convert analog signal process to digital signal process on the other hand developing of software tools that would eventually converge with the DSP to enable efficient representation of the DSP techniques.

Another crucial development that the semiconductor industry which evolved to the point that enhanced the radio communication performance, reliability, flexibility by implementing the digital function in semiconductor rather than analog function with large separate components lead to less expensive, more reliable and less power (Fette 2006: 1-25).

Consequently, it has been clear that some mechanism of learning should be embedded to cognitive radio to achieve machine learning and related methods to improve cognitive behavior. Also focus has been on exploring the various technique of language to express knowledge and to understand knowledge by exchanging information between the user and the device based on environments awareness. Moreover developing of the variety computer networking techniques such as wired Ethernet and Internet which have a wide benefit. Also extend packets destination through wireless ad-hoc network based on intermediate node serve as repeaters to their destination in ad-hoc network topology (Dinalankara 2008).

Fortunately, all of these techniques are cumulate at the cognitive radio area as illustrated in Figure 8. All are support the users communication demand based on their applications built on the top of the SDR.

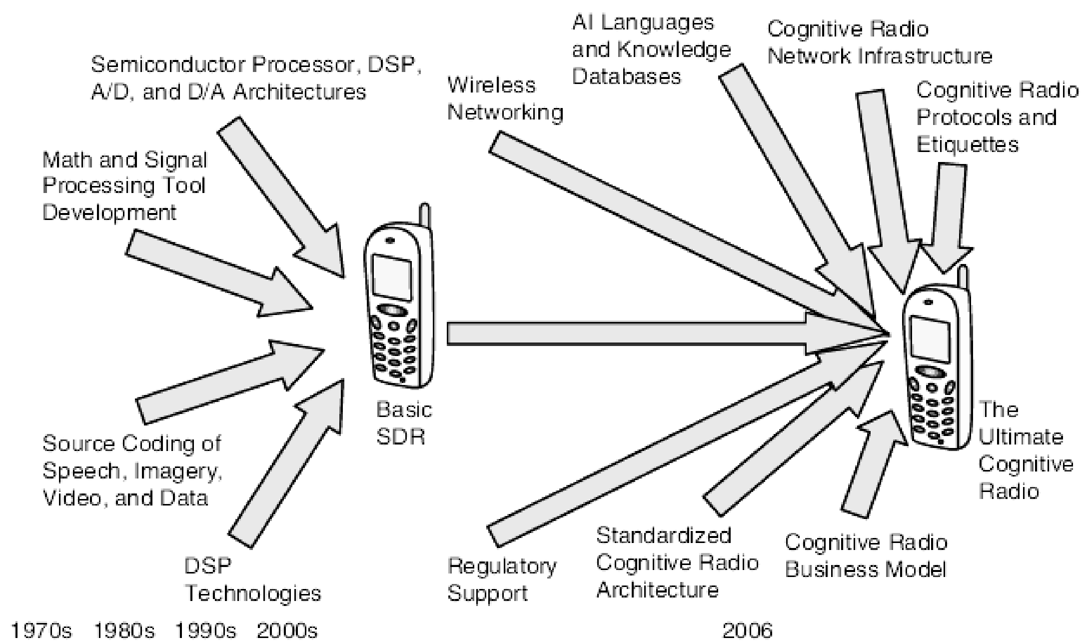


Figure 8. Technology time line (Fette 2006)

2.1. Software Define Radio (SDR)

In conventional radio systems were designed to communicate using one wireless standard lead to two groups with different type radio were not able to communicate due to the different operation parameter. While the demand for the integration of several wireless standards and applications into the same wireless device as a result the functionality of this devices increase and they become more and more sophisticated.

For instance the cellular personal communication at first developed to provide voice communication however current cellular phones have multi functionality such as digital communication systems, Global positioning systems (GPS), Bluetooth, digital camera, games, and music player etc. Moreover the quality of service (QoS) requirements is continuously enhanced by the provider to meet the best user demands. As a result based on these rapid developments and improvements software programmable radios need to be adding to the wireless devices which it has flexible architecture to provide a global seamless connectivity and enhance the interoperability issue based on its implementations (Sadiku & Akujuobi 2004).

The initial purpose of the SDR is to replace hardware analog component where the radio can implement only single or very limited group of the radio functionalities with programmable devices in which the same radio tuner or processors able to operate with many different bandwidths over a wide range of frequencies also implement many kinds of modulation and realize multi wireless standards with multiple access technologies.

From implementation point view, the benefit of this approach that the device able to deal effectively with various situations and decrease cost based on reducing electronic circuit components. Furthermore, the existing software can be updated and developed with new version based on demand. As regard SDR is invented to be a promising technology for interoperability, global seamless connectivity, multi standard and multimode issue (Scaperoth etc 2005).

Once more, adaptivity in cognitive radio is the one of the fundamental characteristic where the radio parameters (frequency, power, modulation and bandwidths) can be adapted based on the radio environment, channel condition, user's situation and geolocation. As regards avoiding of use application associated with fixed analog circuits and components by implementing SDR in which that can provide very flexible intelligent radio functionality. Therefore one of the main component in the designed cognitive radio systems is SDR, also SDR is the core enabling intelligent functionality for cognitive radio see Figure 9 (Arslan & Celebi 2007).

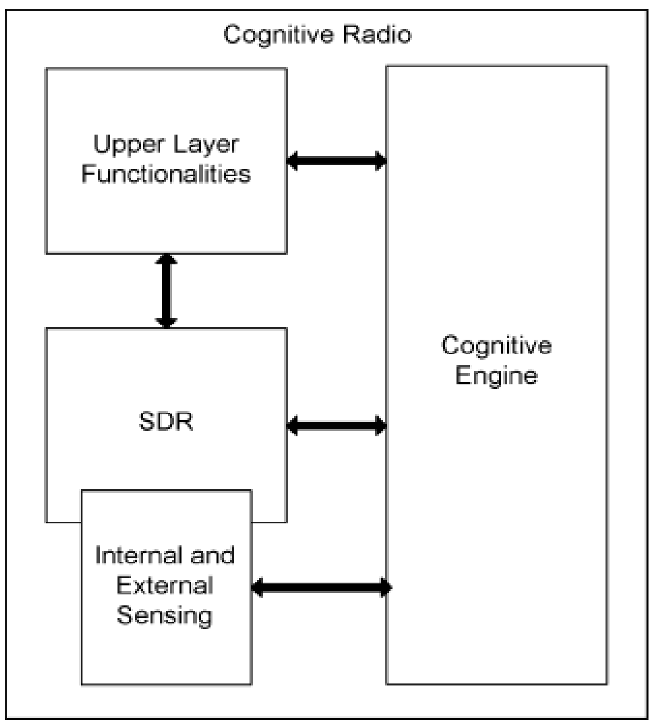


Figure 9. The illustration of relationship between SDR and cognitive radio (Arslan & celebi 2007: 109-144)

Figure 9 shows one of the simplest conceptual models in which illustrates the relation between cognitive radio and SDR. Moreover it built around SDR that support one of the common definition of the cognitive radio "A cognitive radio is an SDR that is aware of its environment, internal state, and location, and autonomously adjusts its operation to achieve designated objectives". This model fits a previous cognitive radio definition that the cooperative of cognitive engine, SDR, and other supporting component led to cognitive radio system and from cognitive engine's approach that responsible for enhancing and controlling SDR which is seen as black box for example when cognitive engine stimuli SDR to use specific modulation (e.g. QAM-16), Cognitive engine has no idea how the SDR implement this kind of modulation, except that the task has implemented.

Input parameters such as sensed or learned from the radio environment, user's context and channel condition. Stimulate SDR to achieve a best radio interface requirement for the user's applications based on available resources such as spectrum and power. Thus SDR representing a very flexible generic radio platform that capable to support operation with several different bandwidths over a wide range of frequencies by implementing different types of modulation and waveform formats (Scaperoth etc 2005).

SPEAKeasy system was the first successful implementation of the SDR for the U.S Navy's allows digital hardware to communicate over a wide range of frequencies, modulation techniques, data encoding methods, cryptographic types and other communication parameters. It demonstrates the completely software programmable radio examined many aspects of software reconfigurable air interface implementation.

The basic SDR architecture depicts in Figure 10 groups the hardware in to three sections: RF section, IF section and baseband section. From the design perspective no hardware block in the architecture is specialized to any specific signal. The architecture places no limitation on the achievable signals it is operate in any given implementation which support some range of frequencies.

The RF front end includes of both transmission and reception processes. In transmit mode the fundamental task is to modulate the RF signal without introducing noise and avoid transmit at any frequency that might interfere with other users in the spectrum. On the other hand at the receiver mode the task is to capture and extract the target signal.

IF section consists from analog to digital converter (ADC) and digital to analog converter (DAC) for RF to digital and digital to RF. The last section at the receiver side is the baseband section which can be implemented by digital signal processor (DSP) to control the radio components (Saha & Sinha 2008).

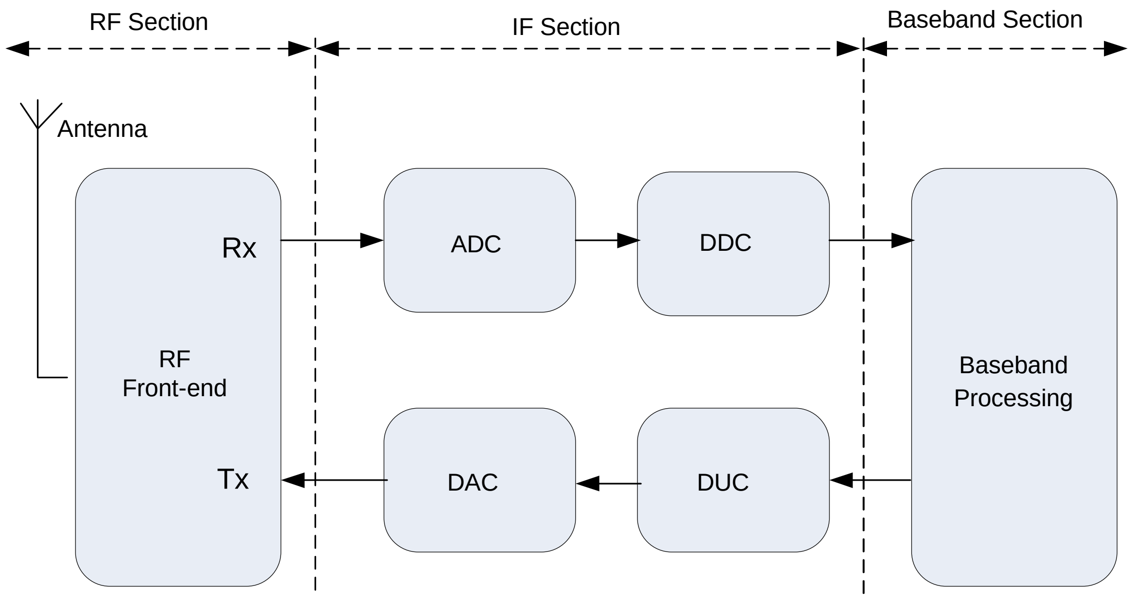


Figure 10. Architecture of a SDR (Saha & Sinha 2008)

2.2. Physical Layer

Recent study by FCC spectrum policy task force discover the scarcity of the spectrum specially in the bands bellow 3 GHz there is imbalance between spectrum scarcity and spectrum under utilization moreover there is a competition for the utilize of the spectra in those bands where the radio signal characteristics are more desirable (FCC 2002).

The promising radio technology “Cognitive Radio” are the key to solve such a problem by allowing more flexible utilization of the spectrum instead of current approach that the spectrum is regulated in the way that the primary users wireless systems are assigned fixed spectrum, operating frequencies and bandwidths, with strict on transmission power that reduced the coverage area so that most communication systems are designed to meet the best efficient utilizations of the spectrum within a fixed bandwidths which is assigned for primary users in advanced. Thus flexibility, mean that the radio is capable to dynamically sensing over a wide bandwidth and locating unutilized spectrum segments to serve secondary users, establish transmission link for communication that occupy the unutilized spectrum segments and adapt its transmission parameters in ways that cause no harmful interference to the primary users. The implementation of this new functionality is facing many challenges across all layers of cognitive radio systems design (Tang 2005).

The open system interconnection OSI was developed by International telecommunication Union ITU in which it is most basic form that divides system architecture into seven layers to be the standard for the most conventional communication systems. Physical layer defined the relation between the system and physical medium also to control access to the medium and transmission parameters. Additional physical layer functions are establish interface with upper layer data link layer through the handshaking protocol. Although the cognitive radio functionality are separate from the traditional radios. As a result, for implementing this new functionality in cognitive system it require to enhance the existing layers of conventional OSI with the unique cognitive functionality. First we start with cognitive function on the physical layer to realize the capability and the limitation for performing new functionality (Cabric 2004).

As regards, establishes this new functionality involves the design of different analog and digital circuit as well as signal processing in order to detect unoccupied spectrum over all available degrees of freedom time, frequency, and space in which requires an RF front end capable to operate over wideband frequency agility to identify frequency bands currently available for transmission. Also high speed analog to digital converter A/D and based band processor to implement real time spectrum measurements algorithms for detection of primary user signal as depicted in Figure 11. In Addition spectrum measurement algorithms are based on primary user modulation type, emission power, frequency and temporal parameters. (Cabric 2005).

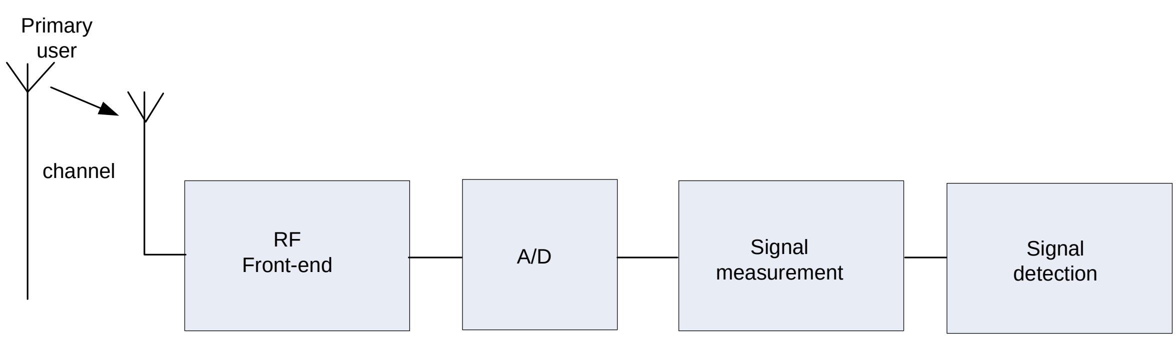


Figure 11. Cognitive radio receiver (Cabric 2005)

The challenges facing the spectrum sensing are. First, sufficient RF front-end meet the best sensitivity requirement for wideband signals detection. Second, accurately detecting of different types of primary user systems has weak signals in different propagation losses and interference with a very small probability of false detection. In the rest of this chapter we present the cognitive radio receiver sensitivity.

In order to continue explaining the physical layer functions, thus after identifying available spectrum opportunities by spectrum sensing process, cognitive radios should establish transmission links for communication in ways that achieved the best spectrum implementation and capacity while avoiding interference to primary user. Characteristics of these communication links are different from that in the traditional narrow band communication system.

There are several requirements that the communication links should performed. First, spectrum available for transmission could be separate over a wide frequency range, with variable bandwidths and band separations. More over the availability of these bands are characterized in a stochastic manner. Second, to perform optimal spectrum and power efficiency every cognitive radio estimate the quality of unused frequency bands in order to provide this information to higher layers with signal to noise measurements to be implemented for power emission and bit allocation. Lastly, different application might require different selection of frequency bands based on propagation characteristic or power. Figure 12 illustrates the top level architecture of a wideband transmitter.

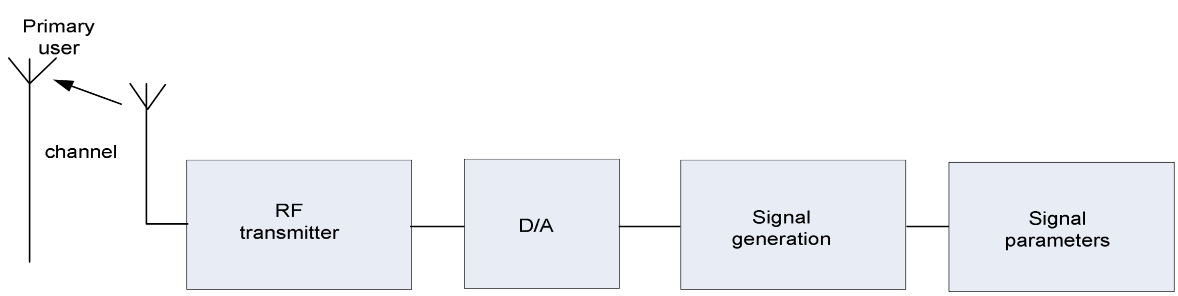


Figure 12. Cognitive Radio transmitter (Cabric 2005)

The main challenge is to synthesis the signal without external analog filters, adapt its transmission parameters occupied frequency and power emission in condition causing no harmful interference to any existing primary users.

2.2.1. Noise and Interference temperature

Nowadays, increasing of wireless systems that expected to rise in the future, lead to intensive use of the radio spectrum. Allocation of unused spectrum for new services or improves the bandwidth of the existing once based on new demand proves to be extremely challenging since most of the frequency bands of the spectrum are licensed and overlapped based on current regulation. Correspondingly greater application density, mobility and variability of RF radio emitters also increased flexibility in spectrum use by the users. As a result, interference becomes a significant issue and interference management has become more difficult.

Interference management required more than determining the degradation in the received radio signal it involves technical and economic tradeoffs. In economic point view, the license user need more selective receiver than sensitive to enhance interference management in a way that such receiver cannot effect very vast by adjacent channel interference. Despite it effect-cost based on communication systems design.

On the other hand, the rapidly developing technology and the cumulative emission of the unlicensed users also emitter types such as radio telemetry, cell phones and out-of-band primary license etc, might result in harmful interference and must be considered in practicable manner through a more quantitative standards reflect a real-time spectrum use measurements and provide users more certainty.

Currently transmitter centric is the wireless communication paradigm. The main idea behind this technique is to adapt the transmit power in away to not exceed agreed noise floor at the receiver which has particular distance from the transmitter. Despite the noise floor is the cumulative level of radio emissions on a particular frequency at a specific location which it is random in the way that cannot be predicted in advanced. Moreover, the instant noise can be increase due to new interference from new source, make a huge degradation in transmitted signal and decrease the coverage area. (Haykin 2007)

In 2002, the FCC introduces a shift from a current paradigm for assessing interference and submits the concept of *interference temperature* as a new quantity for quantifying and managing interference. The idea is to regulate received power based on real-time interaction between transmitters and receivers rather than transmitted power. Lead to a new metric to measure the cumulated RF power available at the receiving antenna per unit bandwidth called interference temperature. Regardless, one can use these measurements to establish maximum acceptable levels of interference in particular frequency band and at a specific location. Different levels might be set for each band depends on the RF environment of these bands and the tolerance level of that service (FCC 2002).

Moreover, the interference temperature limit at the receiving antenna gives the a accurate measure for the permissible level of RF interference in specific frequency band, any transmission from other devices at that band which increase the noise level above the interference temperature limit is considered to be harmful interference for the licence users. Thus the cognitive radio controller might adapt its operation parameter through reducing emission power in order to stay in the same frequency and share the band with licensed users without effecting primary user operation. Move to different frequency band if it is possible. Or switch of and scan to locate an opportune time to transmit.

While interference temperature aim to share bands between licensed and unlicensed users in condition that, at particular band in which the interference temperature is not exceed a specific level, other users could operate at that band. Thus interference temperature provides the limitation of reuse the specific band as a maximum cap on the potential RF energy that might introduced in that band. This could provide a robust dynamic spectrum allocation DSA for cognitive radios networks (Haykin 2005).

In cognitive radio network, secondary users operating in licensed frequency bands would be capable to make a real time measurements for RF environment, and adapt there transmission parameters in such away that avoid exceed the interference temperature limit (T□) with this model illustrated in Figure 13 spectrum allocation become more flexibility and robustness.

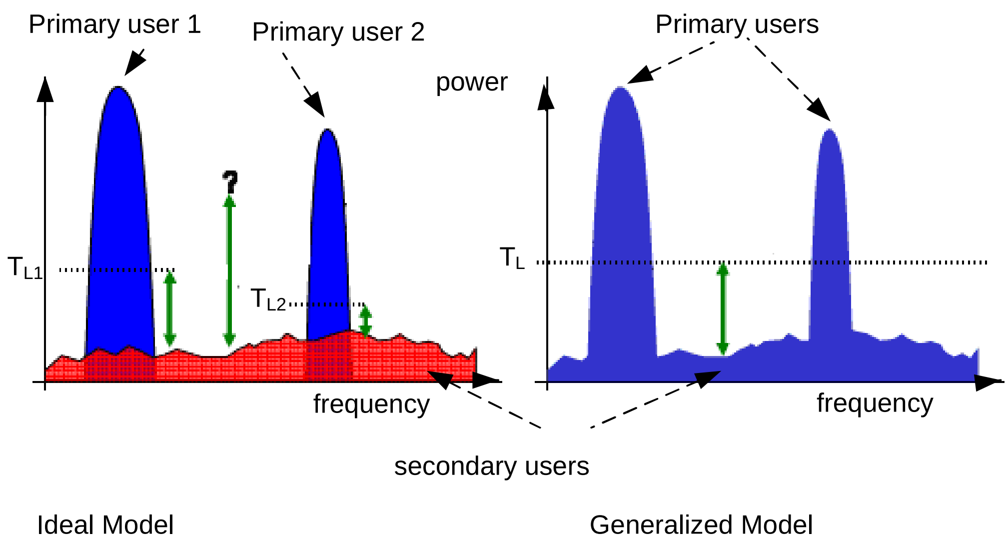


Figure 13. Ideal and Generalized of the interference temperature model (Clancy 2007)

The concept of interference temperature is the same as noise floor in which it measured in degrees Kelvin unit as explained in the equation.

$$T_I(f_c, B) = \frac{P_I(f_c, B)}{kB} \tag{2.1}$$

It is a measure of the average interference power in Watts centred at f_c and divided by bandwidth occupied by the interference multiplied by Boltzmann's constant (1.38×10^{-23}) Joules per Kelvin degree.

In the ideal interference temperature model as illustrates in Figure 13, licence users assign interference temperature limit based on its receiver environment, thus there is different thresholds level. Further, unlicensed users operate on a centre frequency f_c with bandwidth B overlaps with n licence signals with a strict condition that do not exceed interference temperature limit in which it assigned in advanced by licence users.

$$T_I(f_i, B_i) = \frac{M_i P}{kB_i} \leq T_L(f_i) \qquad \forall 1 \leq i \leq n \tag{2.2}$$

Note the constant M_i is fractional value between 0 and 1, representing a multiplicative attenuation based on fading and bath loss between the unlicensed transmitter and licence receiver.

In the generalized interference temperature model based on Figure 13, the fundamental issue is that the system has no knowledge about RF environment and cannot distinguish between the licensed user and the interference. Thus in that case of uncertainty the system should assign the interference temperature level to entire frequency range rather than where the licence signals are detected.

$$T_I(f_c, B) = \frac{M \quad P}{kB} \leq T_L(f_c) \tag{2.3}$$

Notice, all the emission constraint is in terms of unlicensed transmitter parameters, since there is no knowledge about licence receiver RF environment (Clancy 2007; Bing & Lili 2009).

As regards to maintain the interference temperature in way that not exceeds the interference threshold causes harmful interference to the licence receiver, noise floor should widely monitored to determine and adapt the opportunity of new source of interference appear over interest band at specific location.

2.2.2. Receiver Sensitivity

In traditional communication systems, a quantitative measure of the minimum signal level that can be detected for a target signal with specific modulation scheme is denoted by receiver sensitivity. While in cognitive radio systems the front-end is used to detect wide range of signals and modulation schemes, thus such metric dose not exists. Moreover, spectrum sensing requires the detection of a weak signals in background noise were the power level are so low in a way that they fall below the receiver noise floor in condition that the probability of miss detection is very small. Under these situations, cognitive radio system requires high sensitive receiver from the antenna to detector circuits with a minimal signal to noise ratio degradation and signal distortion (Cabric 2005).

In order to provide efficient spectrum utilization, cognitive radio systems must be able to detect wide spans of the spectrum includes multiple licenses users through these new types functionality added to cognitive radio receiver. Lead to all front-end circuits should be wideband to be able to detect a different RF radios presented at the antenna includes signals from close and widely separated sources in which their operating at vast different power levels and channel bandwidth. In addition high speed sampling requirement analog-to-digital converter A/D and digital signal processing technique to be utilized to perform measurements for detection of licence users. As a result, the large dynamic range becomes the main challenge since it requires high linearity circuits and high resolution A/D converter also digital signal processing and network cooperation techniques in order to meet such challenging requirements.

The fundamental issue of the cognitive radio receiver is to perform reliable detection of primary users, since licence user systems require protection even in worst case scenarios also to increase spectrum capacity utilization by introduce the dynamic spectrum allocation DSA schemes. Thus cognitive radios must have highest degree of sensitivity and flexibility than traditional radios. Figure 14 illustrate an architecture of a wideband RF front-end capable of simultaneous sensing of several GHz wide spectrum.

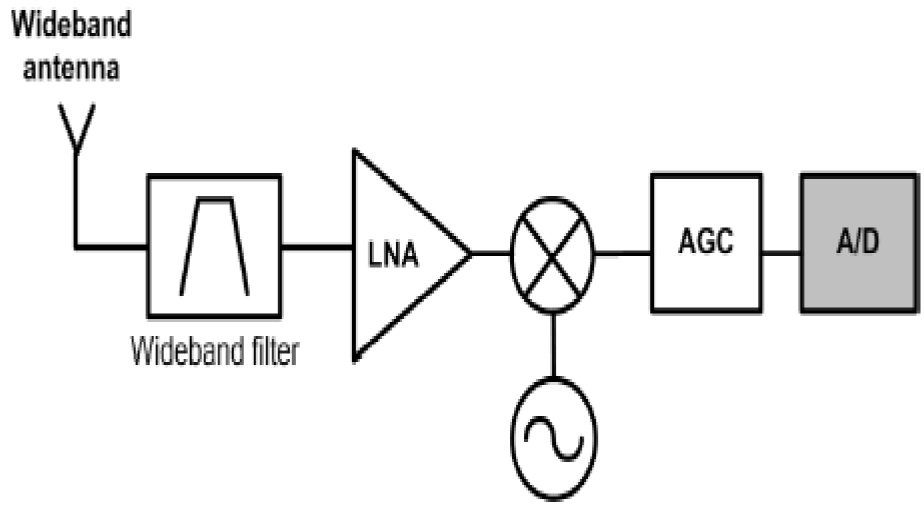


Figure 14. Wideband cognitive radio RF front-end (Cabric 2005).

This architecture is commonly proposed for software defined radios. At the beginning, cognitive radio sensing antenna should provide wideband reception with minimal signal loss. Another critical design for amplifiers and mixers is to keep the linearity across entire dynamic range further require high precision and high speed A/D converter. In this discipline, built for detecting and processing weak signals, thus it would be necessary to reducing the strong in-band licence users which have no benefit to detect. Therefore, to solve the strong signals problem would be achieved by filtering these signals in frequency, time and space domains.

First, in frequency domain filtering approach, fixed filter are used to provide frequency selectivity for the input signal in traditional radios. However, cognitive radios have a wideband implementation thus strong signals can be located anywhere in the frequency band. Therefor cognitive radios require bandpass and bandstop filter with restriction that high centre frequency narrowband with large out-of-band rejection and tuning ability. Tunable bandpass filters are implementing to channel selection and reduction of out-of-band interference, in which might be to complex to implement.

Second, filtering in time domain can be achieved by selective cancellation or subtraction of strong signals from the incoming signals and this process can be done by defined a strong interfering signal first, and then reconstruct it and subtract from the receiving signals. As result week signals can be defined too as illustrates in Figure 15. Essentially, the linearity problem has to be solved in the reception process ideally at the LNA and mixing stages. This guide thinking to the third method for filtering (Cabric etc 2004)(Cabric & Broderson 2005).

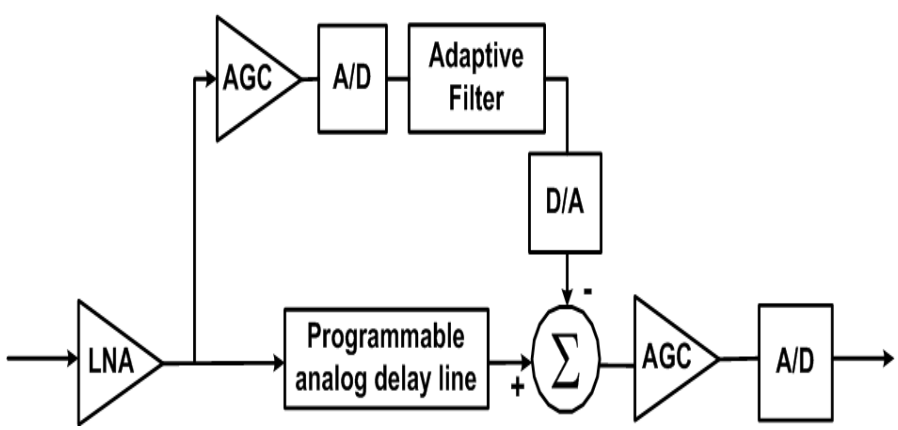


Figure 15. Time domain analog interference cancellation system (Cabric 2005).

Lastly, filtering in the spatial domain is based on using multiple antennas. This idea on multiple antenna channels detecting and identifying that spatially received signals occupy a limited number of directions or spatial clusters. Commonly, selective and adaptive signal reception is achieved through beamforming techniques. In terms of implementation, signals received from multiple antennas must be combined. After combining stage there is only one receiver branch and one A/D converter. At the antenna multiple analog processing could be done to redact dynamic spectrum range before amplifying by automatic gain control AGC circuits for the best utilization of the number of bits in the A/D converter.

The proposed architecture could be designed as a phase antenna array coefficients are computed in the digital back-end fed back to analog phase shifters which then adapt the gain and phases pf the antenna elements. Clearly, there is an additional hardware complexity involved in the proposed architecture despite analysis shows that spatial filtering techniques could relax requirements for the implementation of RF wideband sensing front-end as illustrates in Figure 16 (Poon & Brodersen 2005).

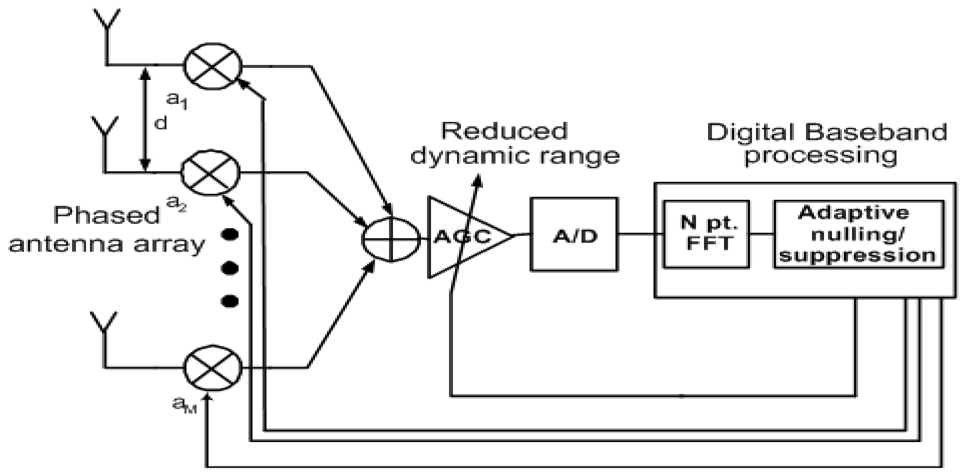


Figure 16. Phase antenna array for spatial filtering (Cabric & Robert 2005).

In the final stage-implementation digital signal processing techniques should be utilized after reliable reception and sampling wideband signal to further increase radio sensitivity and processing gain.

2.2.3. Receiver Structure (OFDM)

The spectrum is scarce resource as recent studies illustrate that a large portion of the assigned spectrum is used infrequently. Cognitive radio based on OFDM radio is new paradigm in wireless communication that provides promise for efficient utilization of spectrum by sensing their environment, learning and adapting to satisfy the immediate demand of the upper layer, network, and the radio environment.

One of the main challenging tasks for cognitive radio is to sense the environment to adapt and plan future action to improve communication quality meet best user demands. To achieve and implement this functionality a novel conceptual physical layer based on highly flexible and adaptable need to be executed. A special case of multicarrier OFDM techniques are becoming paramount in current and future wireless communication (e.g. WiMax, WiFi, DVB TV and 3GPP etc). It has the ability of fulfilling the aforementioned requirements also provide efficient utilization of the spectrum by enabling unlicensed users to share the license spectrum. Moreover shaping capabilities, subcarrier power can be used to shape the signal into desired mask. Together make OFDM the best candidate techniques for cognitive radio systems Figure 17 shows the block diagram of the OFDM receiver (Lei & Chin 2008).

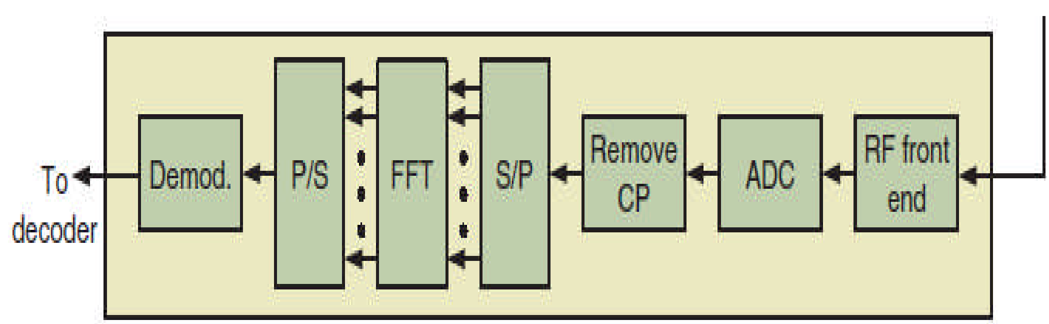


Figure 17. Block diagram of OFDM receiver (Arslan 2007).

The configurations of the blocks represent the inverse actions done at the transmitter. At first by the RF front-end the incoming signal is passed through a band-pass noise rejection filter and down-converted to baseband signal. Second, the baseband signals are then sampled and digitized using analog to digital converter. Third, forward the digitized signal to cyclic prefix remover and serial to parallel block. Forth, retrieve the signal by using fast Fourier transform block in which it converts the symbol to frequency domain. Lastly, the parallel to serial converter, demodulation block, deinterleaved and decoded to obtain the transmitted signal. Simplified baseband model of the received symbols can be written as.

$$Y(k)= H(k)\, X(k) + W(k) \tag{2.4}$$

Where Y(k) is the received symbols on the (k)th subcarrier, H(k) is the frequency response of the channel on the same subcarrier, X(k) is the transmitted symbols on the (k)th subcarrier and W(k) is the additive noise plus interference sample which is usually modelled as Gaussian random variable with zero mean and variance (σ_w^2).

In the following, we identify the advantages of OFDM in which it play an important role in realizing cognitive radio concept. Naturally, the incoming signal arrives to the receiver antenna either Line-of-sight (LOS) or Non-line-of-sight. As result such channel with different delays referred to as multipath channel in which it make (ISI) and frequency-selective fading which causes a significant degradation of system performance.

The problem of frequency selective fading has been overcome by using OFDM. The idea is to send the wide-band signal over many parallel and orthogonal lower-band signals. Hence, we have flat fading channel. In OFDM to avoid ISI, symbol duration are extended by repeat of the end of the symbol at the beginning of each symbol in what is known as cyclic prefix (CP) and it must be longer than long delay. In the implementation point view the OFDM frequency selective fading is avoided by increasing the number of subcarriers lead to decreasing of the subcarriers spacing and can be considered as group of narrow band signal in which that avoid using equalizer in the receiver.

While each radio performs spectrum sensing, in OFDM system converting from time domain to frequency domain is achieved inherently by using FFT. Thus the power spectral density can be scanned without any extra hardware to identify the available spectrum holes or to share the frequency band with the primary user in the way that can be done by using simple hypothesis testing as it illustrates next in chapter three.

The simplest approach to share the spectrum without interfering with the primary users is based on served restriction on transmit power levels OFDM systems can provide such flexibility. After identifying the operating frequency band, choosing the desirable subcarriers in the way that can be shaped to fit into the selected band mask. The main parameters of an OFDM system that can be adapted to shape the signal spectrum are number of subcarriers, emission power, pulse-shaping filter and subcarriers that make interference to license user are turned off.

In addition, OFDM systems have a higher resolution for fixed bandwidth by increasing the number of subcarriers. Despite OFDM technique is not a multi-access method it can be combined with other existing multiple accessing methods to be able to access the available channel by multiple users Figure 18 shows OFDM based cognitive radio system (Arslan 2007)(Hossain & Bhargava 2007).

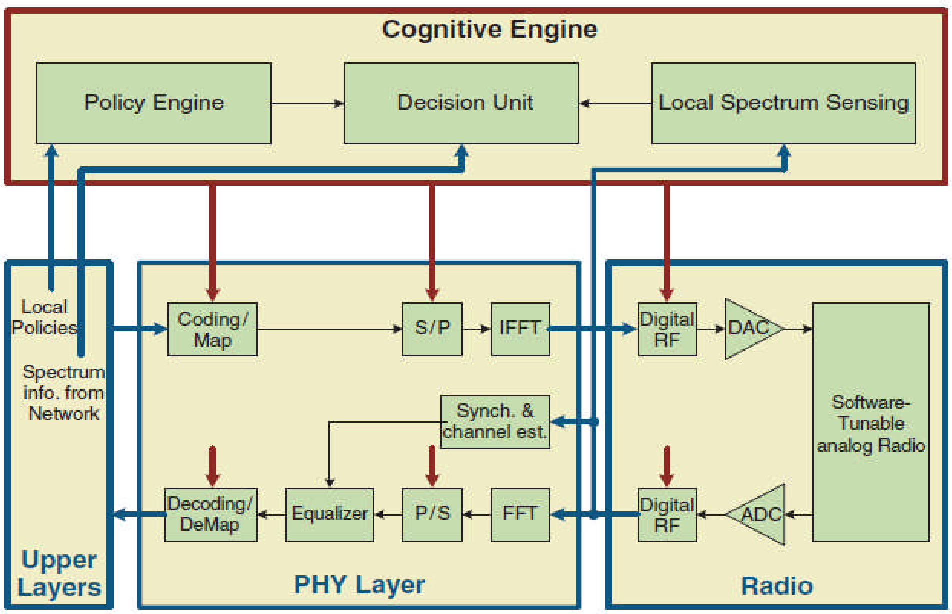


Figure 18. OFDM-based cognitive radio system block diagram (Arslan 2007).

2.3. Cognitive Cycle

The next step in understanding cognitive radio intelligent functionality requires definition of cognition cycle. Cognitive networks are developing towards small, smart personal devices in which it can share the spectrum with minimal coordination and infrastructure. This development is driven by software defined radio technology in which that provide high adaptability and flexibility. Add intelligence to the personal devices in the way that combined in a cognition cycle, in which that allows the personal devices to aggregate information about the local environment "learn" and make decision "act" based on their transmission parameters and possible access methods (Mitola 2000).

Clearly, in the first doctoral dissertation on cognitive radio in 2000 and in cognitive radio architecture published book (Mitola 2006), Joseph Mitola, in both publication he described the cognition cycle, mentioned to smart radio that has capability to sense the environment learn from the history to be able to take the intelligent decision to enhance the performance of wireless communication by adjusting the transmission parameter based on new current state of environment depicted in Figure 19, cognition cycle.

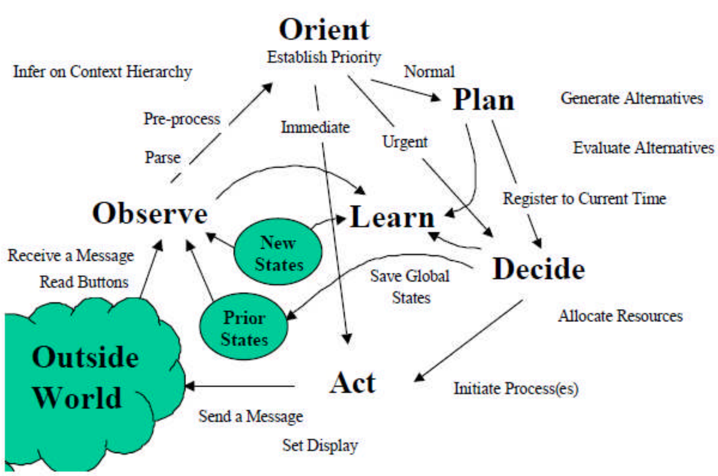


Figure 19. Simplified cognition cycle (Mitola 2006).

Moreover, this kind of cognition cycle requires to continuously sense the environment ’’observe” collect information and extract it from experience, analysis the prior knowledge, compare it with the current state to predict the future state, “orient” itself by make a computation for the significant observations, determining priorities in the way that might be take action initiate immediately as a reactive stimuli response behaviour, make plans, able to decide and take right action selects among the candidate plans based on machine learning.

Since cognitive radio has sleep and prayer period in which that support machine learning, “act” initiates the selected process based on attracting with the environment in which it operates. Most of these tasks are implemented during the wake period, reception of new stimulus based on sensing lead to initiate new cognition cycle (Mahmoud 2007: 148-202).

On the other hands the development towards smart networks requires further motivated to support a novel spectrum management policy concept by implementing tasks such as, observe the radio environment, adapt the performance, cooperation among users, share the available resources and learn to achieve self experience.

In the final stage implementation of these tasks are to solve the spectrum scarcity and to approach towards efficient utilization over the available radio spectrum which has crowded application below 3GHz as depicted in Figure 2, and to provide a high flexible wireless communication among multiple networks by controlling the communication process.

2.4. IEEE 802.22 The First Regional Area Network Standard

Within cognitive radio technology, it will be possible to enhanced spectrum allocations also new secondary market is created on the wireless applications. Consequently, there is an evidence that regulators is considering a paradigm shift on the spectrum allocation policy by allowing shared use in TV broadcast bands. The technology is being developed by IEEE 802.22 standard group in which that addressing the critical issues of interference protection set by the base station also designing network architecture. This technology proved a first step to toward truly dynamic spectrum access and opening of other licensed for spectrum sharing (Hwang etc 2008).

Clearly, IEEE 802.22 WRAN wireless rural area network is the first standard aimed at using cognitive radio technologies to support unlicensed users in the VHF/UHF TV broadcasted bands from 54MHz to 862MHz providing wireless broadband access to area of 17-30 km or more up to 100km and the minimum peak throughput achieved in down stream will be equivalent to a rate 1.5 Mb/s and 384 kb/s in the up stream in which that supporting videoconferencing service, insuring that no interference to the incumbent operation TV broadcasting and low-power licensed devices such as wireless microphones.

The advantageous of selected TV bands for providing such services are first, lower spectrum frequencies have favourable propagation characteristics second, it has been shown that many TV channels are poor utilization of the spectrum third, operator based on 802.22 standards in TV band will be second user lead to lower cost for providing a more affordable services. The 802.22 system indicate a fixed point-to-multipoint network in which a base station manages its own cell and controls the medium access of a number of associated Consumer Premise Equipments CPE.

In order to illustrate WRAN IEEE 802.22 Table 1 tabulates the typical feathers compared to IEEE 802.16e. Its frequency operation is unused TV channel as shown in Table 1. These frequencies are referred to as white space in which there is a time component since it is unused frequencies or unused fragments of time, if the availably changes, the 802.22 network must adapt its emission parameters as fast as possible in a way that not to cause harmful interference to licensed users.

Table 1. IEEE 802.22 features compared to IEEE802.16 (Stevenson etc 2009).

	IEEE 802.22	IEEE 802.16e
Air interface	OFDM	OFDMA, OFDM, Single Carries
Fast Fourier transform	Single mode(2048)	Multiple modes (2048, 1024, 512, 128)
OFDM channel profile (MHz)	6, 7, or 8 (according to regularity domain)	28, 20, 17.5, 14, 10, 8.75, 7, 3.5, 1.25
Burst allocation	Linear	Two dimension
Subcarrier permutation	Distributed with enhanced interleave	Adjacent or distributed
Multiple-antenna techniques	Not supported	Support multiplexing, space time coding, and beamforming
Superframe/frame structure	Support a superframe structure based on groups of 16 frames size 10ms	Super frame is not supported. Supported frame size 2, 5, 10, 0r 20 ms.
Coexistence with incumbents	Spectrum sensing management, geolocation management, incumbent databse query, and channel management.	Not supported.
Self-coexistance	Dynamic spectrum sharing	Master frame assignment
Internetwork communications	Over-the-air coexistence beacon or over-the IP-network.	Over-the-network (primarily)

There are two methods that can be used by 802.22 to protect the licensed user based on environment awareness. First, geo-location database in which 802.22

network has database of licensed transmitter that can be used to determine the availability of the channel for reuse by 802.22 networks. Second, spectrum sensing in which that 802.22 network continuously sensing the radio environment and identifying the occupied channels by licensed users in the way that modifies its operation frequency based on the availability of the spectrum hole.

A distinctive feature of 802.22 WRAN as compared to existing IEEE 802 family is the extended coverage area up to 100 km as shown in Figure 19 WRANs has a much larger coverage range than existing networks. Due to this enhancement afforded by the use of these lower frequencies several technical challenges appear based on its implementation and design.

This new radio functionality involves the design of the systems architecture in order to meet challenging for the 802.22 PHY and MAC layers, flexibility and adaptability requirements and wide band agility. PHY layer need to offer high performance, thus in order to obtain a flat fading channel the number of subcarrier in OFDM would have to exceed two thousand in which that might increase cost and complexity. Also PHY need to support multi types of modulation and coding techniques to provide high flexibility since CPEs have various distances from the base station and operate in different SNR quality.

Another critical requirement for implementation of cognitive devise based on 802.22 PHY layer are transmission power control, frequency agility which arise from the fact that 802.22 is secondary user operates in spectrum where incumbents have to be protected. Further, BS serves a large area thus different cyclic prefix are defined as 1/4. 1/8. 1/16. and 1/32 of symbol duration to absorb varies channel delay, beyond 30 km MAC layer will absorb additional propagation delays through intelligent scheduling to overcome such cases.

Finally, the advantages of the 802.22 is to define a technology that not only provides its own intended services, nevertheless it guarantees the existing incumbent services abele continue to be provided (Cordeiro etc 2005) (Stevenson etc 2009).

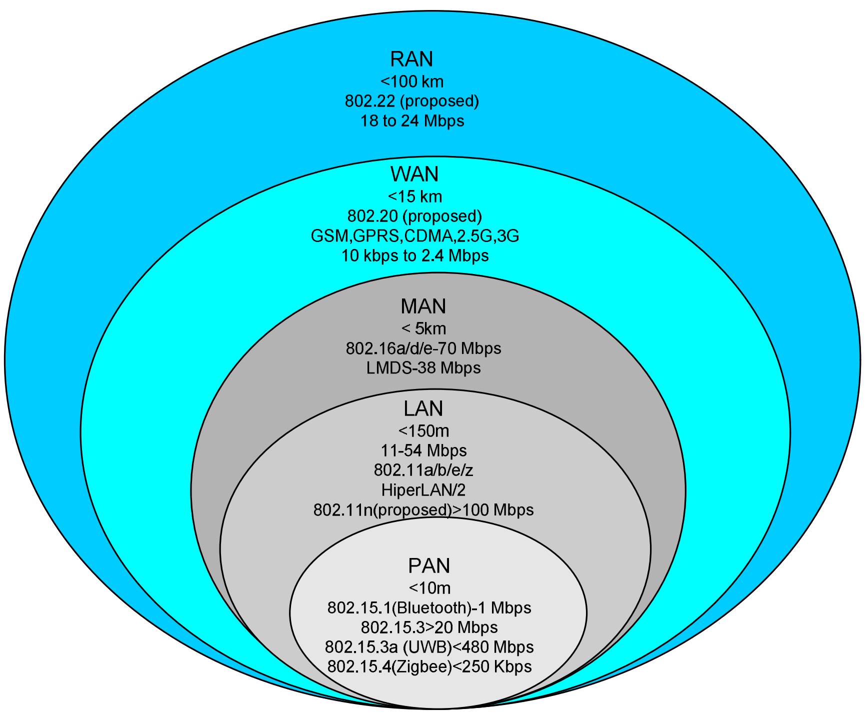


Figure 20. 802.22 wireless RAN classification as compared to other popular wireless standards (Cordeiro etc 2005).

3. Spectrum Sensing Algorithms

As presented in chapter one that frequency spectrum of the wireless communication is inefficient utilized due to conventional frequency allocation policy. Several bands are heavily utilized such as those bands used by cellular phone, while many other bands are rarely utilized as depicted in Figures 2-3 . From this observation and the increasing demand of spectrum for wireless communication based on new services or enhanced the existing application, efficient spectrum management schemes are needed.

This has prompted the regularity to different paradigm that open licensed spectrum to unlicensed user in the way that allowed secondary user to opportunistically transmitted in the available spectrum hole. The basic idea that secondary user needs to identify available spectrum resources that unutilized by primary user and establish a link that ensure to not harmfully interfering with primary users (Höyhtyä 2007).

In order to efficiently utilize the available spectrum holes. Protect primary user from harmful interference. Spectrum holes should be reliably identified through all dimensions frequency, time, and space. A set of choices that may be implemented for this goal are depicted in Table 2.

Table 2. Classification of white space identification methods (Ghasemi & Sousa 2008).

	Infrastructure Cost	Legacy Compatibility	Transceiver complexity	Positioning	Internet Connection	Continuous monitoring	Standardized channel
Database registry	High		Low	X	X		
Beacon Signal	High		Low	X			X
Spectrum sensing	Low	X	High			X	

The database registry and Beacon Signal choices charge the primary user systems in the way that current spectrum usage information is provided to secondary user. These informations are delivered by either registering to a centralized database in which it has all the relevant information for licensed system (e.g. system location, emission power and the expected duration of usage) within a secure connection. Or by broad casting the relevant information on regional beacons in which it has the advantage that avoids the need for internet access. Hence the first two choices required deployments in licensed system in which that conflicting with legacy primary users and effect-cost. Although, the secondary user transceiver still in simplified manner (Ghasemi & Sousa 2008).

In recent research that spectrum sensing has got more attention than other choices and has been considered as the key enabling cognitive radio functionality. Moreover guarantee that no harmful interference cause to the primary user. Due to their ability to autonomously sense and flexibility of reaction based on changes in spectrum usage by licensed user. Secondary user system informed with spectrum sensing in which that can offer new ways to solve the spectral crowding problem. In addition reliable sensing is the first and foremost task in cognitive radio systems (Brown 2005).

The sensing task is realized based on two stages, fast and fine sensing. From the fast sensing perspective, an energy detector simply measure the energy of the incoming signal in the specific band through the observation interval, and compare it with properly set threshold. Based on these measurements cognitive radio systems able to defined spectrum hole if the energy level is less than the set threshold. The main characteristics of the energy detector are low cost, simplicity in implementation. However the main drawback of the energy detector that it cannot differentiate between sources of incoming signals, especially at low signal to noise ratio.

In the fine sensing stage, based on knowing some features of licensed primary user signal which result in built-in periodicity, it requires more sophisticated and powerful algorithms in which that increase cost and complexity. On the other hand features detection allows cognitive radio to detect primary signal with particular modulation type in a background of noise and other modulated signals. From practical point view based on different situation and noise uncertainty a combination of different sensing techniques might be implemented in one receiver to enhance the detecting process (Cabric 2007).

The sensing performance can be improved by sensing the interest band for longer time in which that increase the signal processing gain. In Addition reliable sensing in condition of satisfactory protection of primary user requires from the secondary system to continue on periodically sense the interest band every (Tp) within utilization in case that a primary user may be appear in the band. The sensing period (Tp), represent the maximum time in which that the secondary user has no knowledge about the situation of primary user thus may causes harmful interfere if a primary user appear in the band in this period. Hence (Tp) determine the delay and the degradation in the (QoS) if the primary user access the band in that period. As regard regulator set the (Tp) period based on the type of the primary services, delay sensitivity therefore varies for each licensed bands such as in public safety band it should be very short, while for the TV spectrum long (Tp) and less frequent sense may be accepted since the utilization of the spectrum varies over long time period.

From the cognitive radio system perspective, sensing and transmitting process cannot be implemented simultaneously, thus an effective time for sensing and frequent sense should be minimized to meet the requirement of the cognitive radio in utilizing the available spectrum resources as efficiently as possible to increase system throughput and QoS.

Another crucial issue in sensing performance is sensing sensitivity. Clearly from the cognitive radio design system perspective, the degradation of the signal-to-interference ratio (SIR) at any primary receiver to below the set threshold (Γ) recognized as harmful interference. Consequently this threshold set by the regulator based on the robustness of each receiver toward interference and it is different from one primary band to another. Thus one can defined the interference range as the maximum distance between the secondary transmitter and primary receiver in which that still cause the harmful interference to the primary receiver. Thus interference range depends on both secondary transmitter location and primary receiver interference tolerance. As shown in Figure 21 (Ghasemi & Sousa 2008).

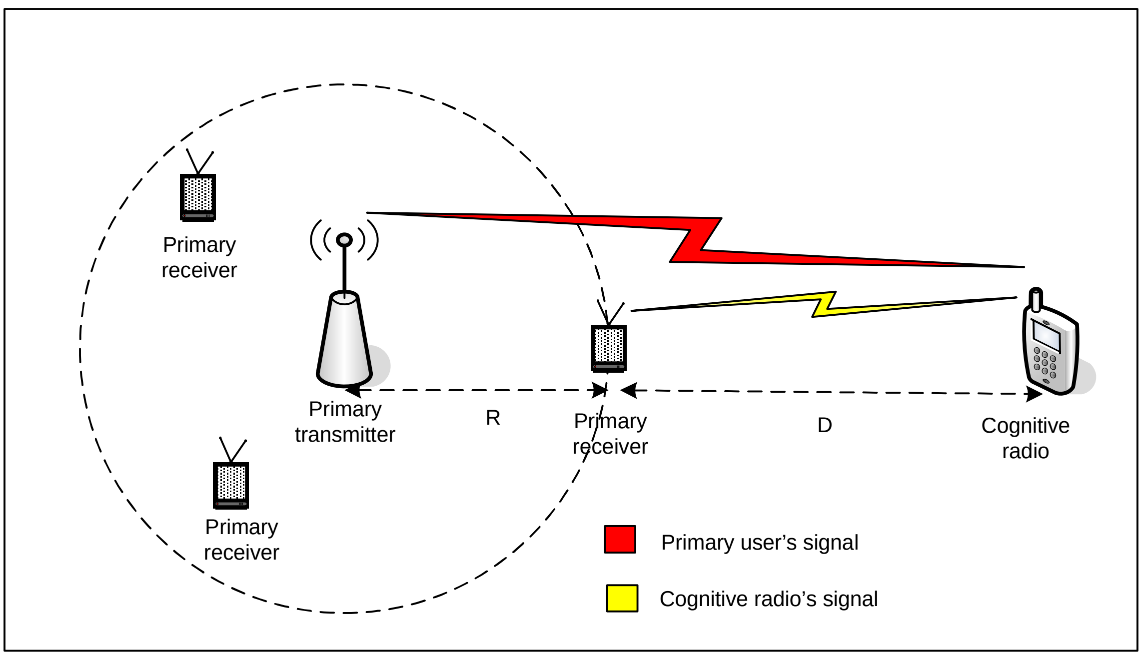


Figure 21. Interference range of a cognitive radio (Ghasemi & Sousa 2008).

From Figure 21, let (Pp) and (Ps) denote the transmit power for the primary and secondary users respectively and R the maximum coverage area of the primary base station therefore the interference range (D) can be determined by the following condition.

$$\frac{P_p \ L\ (R)}{P_s \ L\ (D)\ +\ P_b} = \Gamma \tag{3.1}$$

Where (P_b) represent the background noise at the primary receiver and (L) represent the total path loss caused by multipath fading and shadowing phenomena and it varies based on frequency characteristics and antenna gain parameters. Γ denote the signal-to-interference ratio threshold set by the regulator for particular band and not allowed to exceed.

Previous scenario shows that primary receiver operate in condition that insure protected from harmful interference even though it located at the edge of coverage area and not in side the interference range of the secondary user.

Clearly, spectrum sensing is a critical challenging for the secondary user receiver designs where reliability detecting of any active primary transmitter within the radios distance R+D operates in vary low SNR becomes a key design issue, to insure that no active primary receivers are operating within its interference range. Therefore detection sensitivity (γ_{min}), play a key role in reliable detection and can be defined as the minimum SNR that primary user can operate with and still protected from harmful interference, and represent in the following.

$$\gamma_{\min} = \frac{P_p L(D + R)}{N} \tag{3.2}$$

Where, (N) is the back ground noise power of the secondary receiver environment. Detection sensitivity can be evaluated based on parameters such as transmit power of primary user, signal-to-interference ratio and R should be set by regulator or relevant primary system. Thus from previous discussion spectrum sensing sensitivity requirements are defined by two parameters; minimum detectable signal strength SNR and probability of missed detection based on sensing this minimum SNR (Ghasemi & Sousa 2008).

3.1. Spectrum Sensing Challenges

One of the most critical issues on implementing cognitive radio system is to avoid harmful interference to primary user receivers. Since cognitive radios are secondary users of a primary user spectrum and sharing the spectrum between two parties have no need that the primary users to change their infrastructure. Therefore, cognitive radio system must make a reliable detection in the way that can be decided about primary user activity through the sensing process based on reception of primary transmitter signal.

In general, harmful interference can be defined as the operation of the secondary user in any setting lead to a single primary receiver suffers any service outage, based on that operation. As a result, primary user can ask the secondary user either to turnoff or to vacate the frequency band and wait for another opportunistic spectrum sharing. Consequently, harmful interference may be happened based on two scenarios.

First scenario, when primary user is using the frequency band and secondary user start operating in same frequency band in which that it may not be able to sense the transmitted signal of the primary user. This can be addressed as a hidden terminal.

Second scenario, secondary user operates in frequency band and it is free based on sensing process. While primary user start claims their frequency band however, secondary user may not be able to reliably detect the primary user. This lead to harmful interference to primary user, since secondary user may not vacate the frequency band as fast as possible and still continue operating in the same band.

From the above two scenarios we can define that several resources of uncertainties causes the difficulty in sensing the primary user signal. Since, sensing process should be implemented robustly even under the worst case channel condition. Usually miss detection caused by such uncertainties. In the next section we describe these uncertainties (Tandra & Sahai 2005).

3.1.1. Channel Uncertainty

From the cognitive radio receiver perspective, the difficulty in sensing primary user signal based on low received incoming signal strength at the secondary user receiver dose not mean that the primary signal is located out of the interference range of the secondary user. Since primary user transmitted signal decays with distance and sensing process becomes increasingly challenging based on that distance. Moreover other wireless channel effects such as multipath fading and shadowing in which that can significantly degrade the strength of the incoming signal that the secondary user receiver observe through sensing process. This lead to hidden primary user problem as shown in Figure 22.

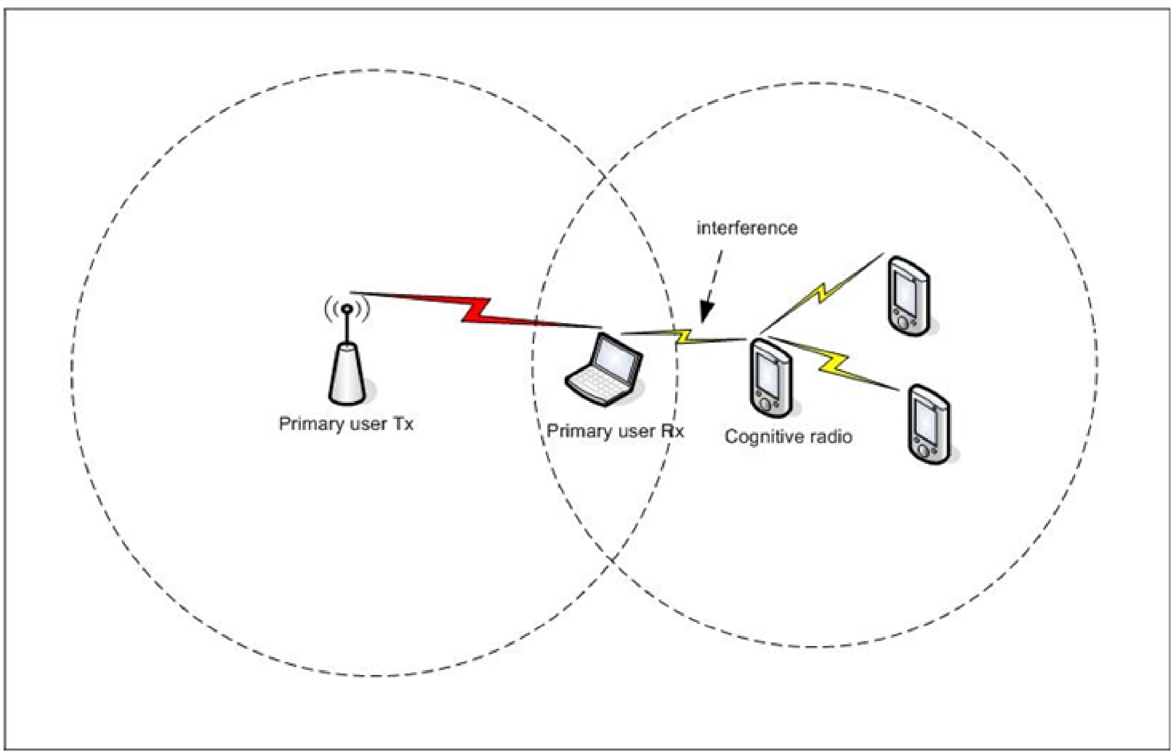


Figure 22. Illustration of hidden primary user problem in cognitive radio systems (Huseyin & Yucek 2007).

3.1.2. Noise Uncertainty

Naturally, in most communication system defining the noise as the combination of several independent sources, internal noise, such as thermal noise at the receiver cause by the electrical components, and external noise like the environment interference at the receiver based on undesired emission from adjacent networks. From Equation 3.1 in order to determine the detection sensitivity, noise power need to be known however, such knowledge practically is not available as noise could vary over time based on, temperature change, and environment interference. Thus In that case noise power need to be estimated to determine the detection sensitivity by the receiver in which it evaluated with the worst case assumption lead to weak signals might not be detected.

However the noise power are periodically estimates by the receiver in which tries to take a large number of samples, but still some residual uncertainty in estimating the noise variance. Thus require a more sensitive detector especially when simple energy detection is used in which a very weak signal below a certain threshold could never be detected. Moreover receiver cannot distinguish between signal and noise. While, on the otherhand feature-detectors are able to overcome this limitation as will be discussed later (Tandra & Sahai 2005).

3.1.3. Aggregate Interference Uncertainty

As cognitive radio deployment rapidly in future, it is more common multiple cognitive radio networks operating on the same band. Thus, spectrum sensing will be difficult based on uncertainty in the aggregate interference resulting from unknown number of secondary user systems and their locations. Practically aggregate interference may cause a harmful interference, however the primary user located out of interference range of cognitive radios networks. In this case need to more sensitive cognitive radio network in which that to be able to detect primary user located beyond its interference range.

In addition the required detection sensitivity should be determined based on the aggregation interference. In Figure 23 cognitive radio networks A and B located in the same coverage area thus they can detect each other in which they can reduce the aggregate interference based on their negotiation to claim the same band simultaneously. However other cognitive radio network C located further away still cannot detect and negotiate with the other parties and simultaneously transmit causing harmful interference to primary user receiver and other cognitive radio networks.

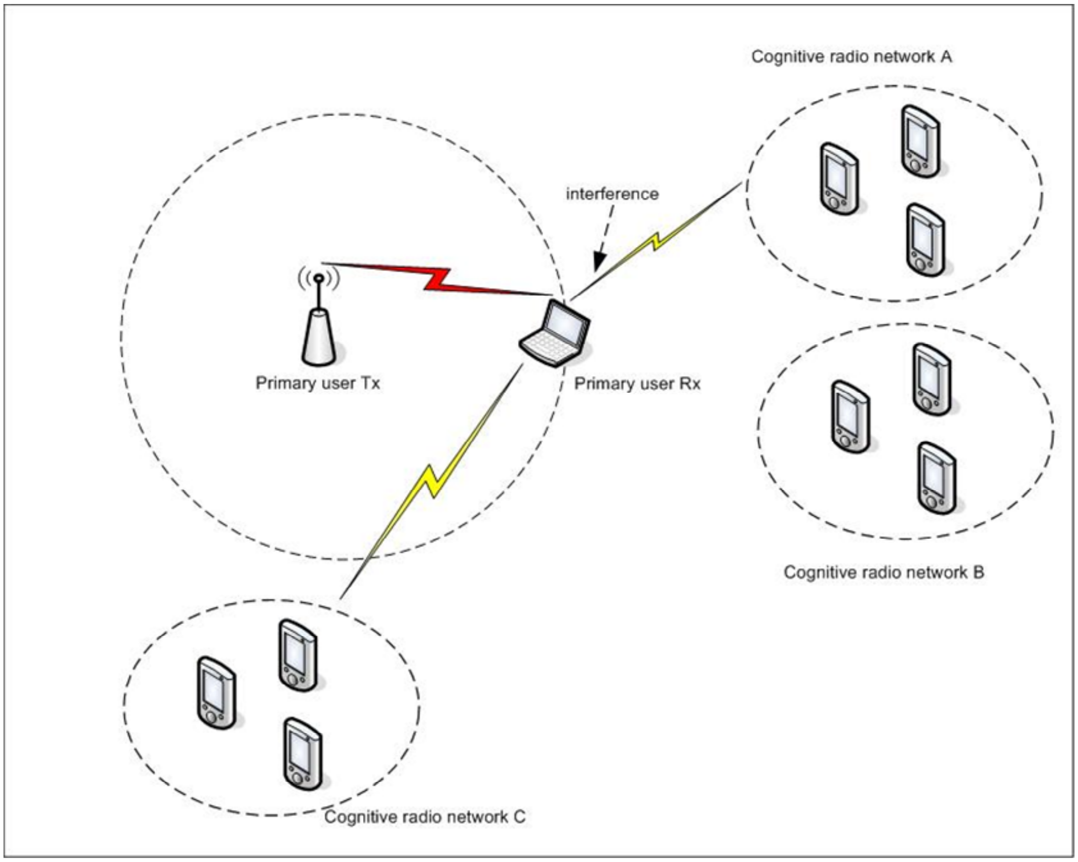


Figure 23. The operation of network A forces network B to move to another band; however, the aggregate interference of networks A and C may still be harmful (Ghasemi & Sousa 2008).

By increasing implementation cost, system-level coordination among different cognitive radio networks helps to overcome this uncertainty limitation. On the other hand there are some other challenges that need to be considered such as primary users that use frequency hopping or spread spectrum signalling, in which the power are distributed over a wider frequency bands still difficult to detect. In frequency hopping case in which that creates a significant challenging related to spectrum sensing process. However, by knowing the hopping pattern and achieving perfect synchronization to the transmitted signal, the problem can be partially avoided (Ghasemi & Sousa 2008).

3.2 Introduction to Sensing methods

Spectrum sensing is the first main task of the cognitive radio that enables to define spectrum availability which is the bases for the design, performance and practical usage of cognitive radio systems in the way that requires to implements all the available degrees of freedom such as time, frequency and space. Consequently, two subtasks can be derived from the main sensing task: occupancy sensing and identity sensing tasks.

First occupancy sensing in which that explained before, that able to identify unoccupied band "white spaces" free of RF interferes and partially occupied "gray spaces" with restriction of reuse based on avoid harmful interference to the primary user (Haykin 2005).

Second, identity sensing, in which that sensing is unique for cognitive radio system, based on ability to distinguish between the usage of the frequency band such as primary user and other network systems like second user cognitive radio systems. Identity sensing requires more complex and sensitive sensing methods (Cabric etc 2004).

In order to evaluate the performance of spectrum sensing algorithms different measurements can be implemented based on, bandwidth, resolution and real-time capability. From the bandwidth perspective, capacity of the cognitive radio systems can be enhanced by sensing a wide range of the spectrum. Further based on resolution in which that the smallest spectrum step can be defined based on the whole bandwidth range is quantized. Finally the real-time capability in which that the cognitive radio observes the environment and makes a decision to relevant emission parameters based on its real-time observation.

On the other hand within a wide band of sensing there could be several of primary users with different type of operation systems and traffic pattern. This scenario requires ability of using different algorithm for reliable sensing and implementing a proper spectrum shearing strategies. Thus spectrum sensing method can be classified as shown in Figure 24 (Wang etc 2008).

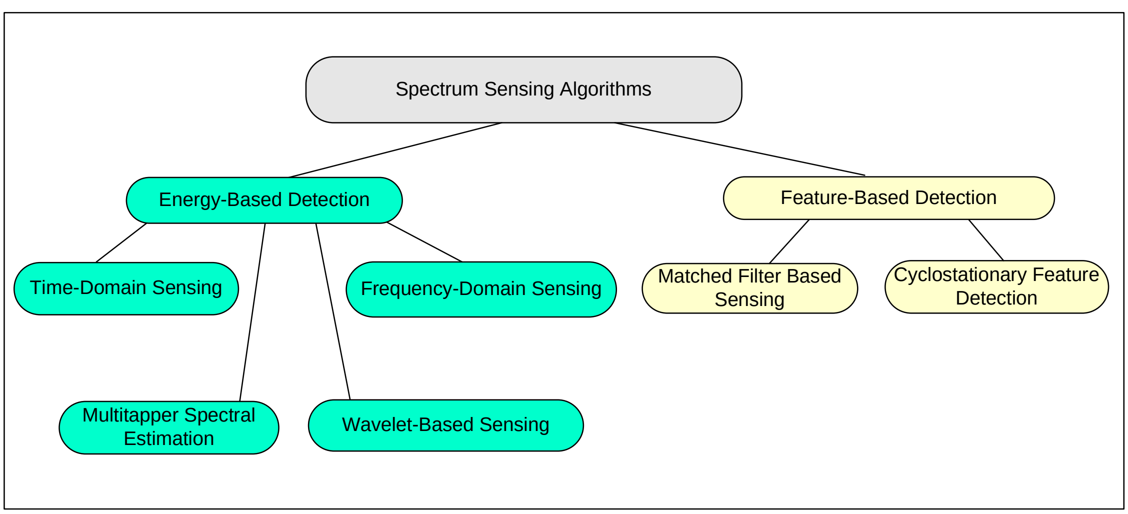


Figure 24. Spectrum Sensing Algorithms (Wang etc 2008)

Classification of the spectrum sensing method can be implemented into two submethods: energy based detection and feature based detection, both of them have advantages and disadvantages. The energy based detection can be executed in time and frequency domain. Normally in time domain, band pass filter is used for the interest frequency bands, and then the energy of the sampled signal is measured. On the otherhand, the time domain samples are transformed to frequency using FFT.

Furthermore, other energy sensing method such as Wavelet and Multitapper spectral estimation can be used for detection. Multitapper is good candidate for spectral sensing based on reducing the sidelobe leakage phenomenon by implements multiple orthonormal windows for spectral estimation.

The fundamental issue of energy based detection implementation is to measure a power spectral density (PSD) of the incoming signal based on selected frequency band in a specific area also to evaluate (PSD) in some fixed threshold to defined the existence of the primary users (Wang etc 2008).

Feature based detection methods can be divided in to two submethods; matched filter based sensing and cyclostationary feature detection Feature based method provides a reliable sensing based on its ability to detect the primary signal in very low SNR and differentiate between signals and noise (Haykin 2007).

The principle of the feature based detection is to correlate the incoming signal with the prior knowledge of the transmitting signal, thus it assumes that the receiver has some knowledge about the transmitting signal parameters. Matched filtering is the feature based detection method, which is implemented based on low pass filter (prototype filter). Filter banks are created by modulating the prototype filter to realize other bands. While an estimate of (PSD) is done by measuring the output power of each filter based on passing the input signal throw a bank filters (Boroujeny 2008). Another feature based detection methods are cyclostationary in which investigated in Chapter 4.

3.3. Energy Based Detection

The most basic method for detecting signals on the additive white Gaussian noise (AWGN) is the energy detector also known as radiometry or periodogram based on energy measurement. It is commonly used in spectrum sensing due to its low computational, sensing time and implementation complexities to perform real-time detection also it is more general technique since it requires minimum knowledge about the primary signal such as bandwidth and carrier frequency moreover it applies to any signal type.

The primary user signal detection can be formulated as an hypothesises testing problem which in classical hypothesises testing the goal is to distinguish between the null hypothesis and alternative hypothesis such as the following H_0 represent the null hypothesis states that no primary user is present and there is only noise in the observed spectrum band and H_1 represent alternative hypothesis indicates that primary user and noise are exists at the input of the receiver. In addition the performance is measured by a resulting pair of detection and false alarm probabilities (P_d, P_{fa}) (Lehtomaki 2005).

$$H_o : y[n] = w[n] \qquad n = 1,\ldots\ldots, N \tag{3.3}$$

$$H_1 : y[n] = x[n] + w[n] \qquad n = 1,\ldots\ldots, N \tag{3.4}$$

Where N number of samples represent the observation interval equivalent to the sensing time, y[n] is the received signal, x[n] is the transmitted signal from the primary user and w[n] is the additive noise, both signal x[n] and noise w[n] samples are modelled as independent Gaussian random variables with zero mean and variance σ_s^2 *and* σ_w^2 respectively. A decision metric ε(y) is a sum of N independent Gaussian random variable lead to its pdf follows chi-square distribution X_N^2 . The decision metric for energy detector is measure energy of the incoming signal over N samples is.

$$\varepsilon(y) = \sum_{n=1}^{N} y[n]^2 \tag{3.5}$$

$\varepsilon[y] >= \gamma_\circ$ decide primary signal present

$\varepsilon[y] < \gamma_\circ$ decide primary signal absent

Detection is performed based on the measured energy compared to a threshold γ°, There are several ways to set γ°, in case of spectrum sensing threshold γ° set to meet the required values of P_{fa} and P_d within the given number of samples N.

$$\gamma = N\sigma_w^2 + Q^{-1}(P_{fa})\sqrt{2N\sigma_w^4} \tag{3.6}$$

Frome Equation 3.6 indicates that threshold γ° depends only on the receiver noise. Then the detection probability and false alarm probability can be derived as

$$P_d = Q\left(\frac{\gamma - N(\sigma_w^2 + \sigma_x^2)}{\sqrt{2N(\sigma_w^2 + \sigma_x^2)^2}}\right) \tag{3.7}$$

$$P_{fa} = Q\left(\frac{\gamma - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right) \tag{3.8}$$

If the number of samples is not limited, the energy detector meets any given detection and false alarm probability. The minimum number of samples required by the detector is a function of received signal to noise ratio $SNR = \sigma_x^2 / \sigma_w^2$:

$$N = 2\left[Q^{-1}(P_{fa}) - Q^{-1}(P_d)SNR^{-1} - Q^{-1}(P_d)\right]^2 \tag{3.9}$$

Increasing N improves frequency resolution in which helps narrowband signal detection. However in the low SNR << 1 paradigm, number of samples require in which that energy detector could meets specified P_d and P_{fa} , approach to 1/SNR². This low scaling is characteristic for non-coherent detection (Lin & Zhang 2008).

From implementation perspective, First, analog implementation the main design are to optimally filter the incoming signal with bandpass filter (BPF) to select the interest bandwidth also to minimized the contribution of the adjacent band noise and interference lead to increase sensitivity. The filtered signal is squared and integrated over the observation interval. Finally, the output of the integrator, take the test statistic, by comparing with the threshold and decide either the primary user is present or absent.

Energy detection based on analog implementation require analog filter with fixed bandwidth Figure 25, in which that the system become inflexible for simultaneously sensing of narrowband and wideband.

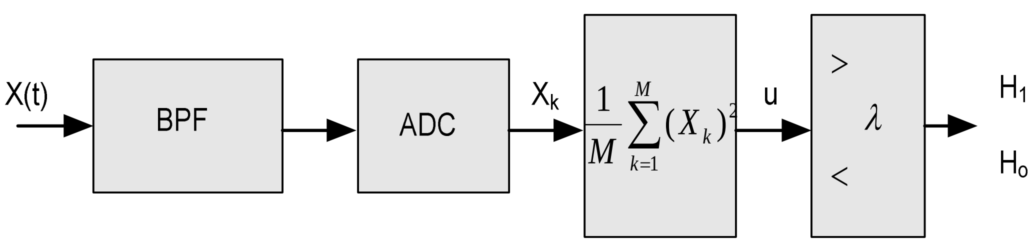


Figure 25. Narrow band architecture (Ye etc 2008).

Second, digital implementation offers more flexibility and provides the required resolution in frequency domain. This supports different band types and allows sensing multiple signals simultaneously by using FFT based spectral estimation. The processing gain depends on FFT size N and observation averaging time. The size of FFT is critical parameter, since increasing N enhanced frequency resolution and narrow band signal detection. On the other hand increases latency based on increase sensing time. In practical filed, balancing between complexity and latency in which that meet the desired resolution which achieved by using a fixed FFT size. Also, extending the average time lead to reducing the noise power. However based on non-coherent detection $1/SNR^2$ samples are required to meet a probability of detection constraint. Architecture for wideband energy detector is illustrates in Figure 26 (Höyhtyä & Hekkala 2007).

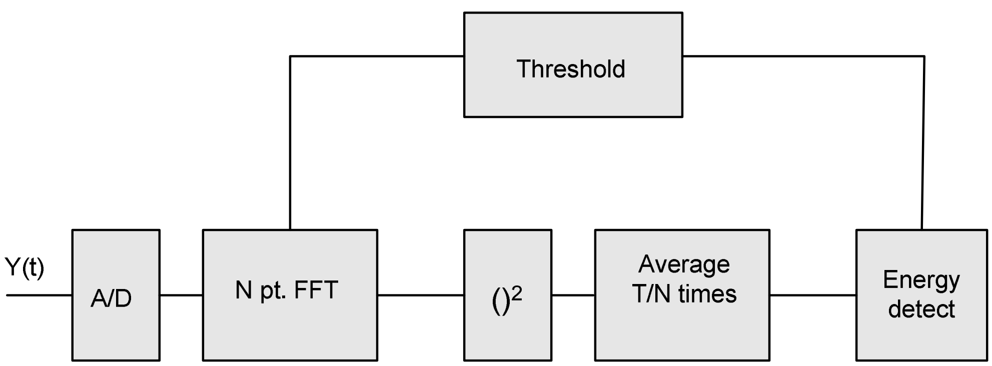


Figure 26. Digital implementation of wideband energy detector (Cabric & Broderson 2007).

The simplicity of energy detector based on implementations and architectures gives key advantages to be used widely. However there are several drawbacks of energy detector in which that reduce their simplicity.

First, set the threshold which is used for primary signal detection is highly susceptible to noise uncertainty, that result from internal noise (thermal noise) and external noise based on channel interference, shadowing and fading as we discussed earlier in which that vary over time. Thus it is difficult to set the threshold properly without knowledge of the accurate noise level and from the fact that when the probability of missed detection is very low, the probability of false alarms increase lead to poor spectrum utilization. While, low probability of false alarms result high missed detection probability, which increases the probability of interfering with primary user.

Even if the threshold would be set adaptively, any interference from in-band source appear would increase the aggregate noise and become particularly important when the detecting signal strength below the estimation error of the noise variance and the detection threshold is set high, resulting weak signal cannot be detected. Thus energy detector has a poor performance in highly negative SNR as illustrates in Figure (27) where signal below -20dB incrementally difficult to detect it and at -23dB signal cannot be detected based on sensing time duration.

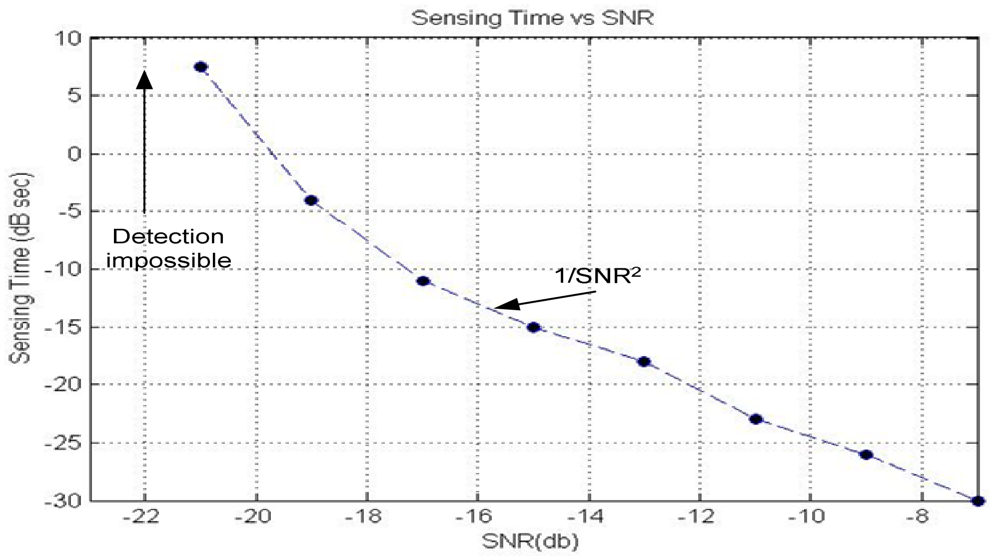


Figure 27. Performance of energy detector in negative SNR (Cabric & Broderson 2007).

Second, energy detector based on its implementation cannot differentiate between different type of signals such as modulated signal, noise, interference and other cognitive radio signal. Since it cannot identify interference it cannot cancel it based on benefit from adaptive signal processing gain. Thus, energy detector should deal with noise and other secondary user differently (Cabric & Broderson 2007).

Lastly, energy detector based on its implementation by monitoring energy level and selected frequency band, dose not operate for spread spectrum signals, and frequency hopping systems. In general, monitoring signal features such as modulation type, data rate etc, could enhanced detector robustness.

3.4. Feature Based Detection

From the signal detection techniques perspective, in order to be able to sense weak signals, cognitive radios should have better sensitivity than conventional radios, based on enhancing the detection probability by implementing robust sensing algorithm in which that able to achieve significant performance gain in the low SNR channel. A suboptimal method is cyclostationary feature based detection in which that built on the base concept that any communication signal has some kind of periodicity. Since the periodicity is typically introduced in the signal parameters such as carrier phase, pulse timing, or direction of arriving, kind of modulation, cyclic prefixes and coding. The receiver can exploit the information associated with incoming signal parameters to detect the random signal with a particular modulation type in a background of noise and other modulated signal (Höyhtyä 2007).

In addition, feature detection able to distinguish between the noise energy and modulated signal energy, since noise has no spectral correlation while modulated signals exhibit correlation between widely separated spectral components based on embedded spectral redundancy of signal periodicities. In Figure 28 block diagram of a cyclostationary feature detector which illustrates the implementation of a spectrum correlation function for the cyclostationary feature based detection.

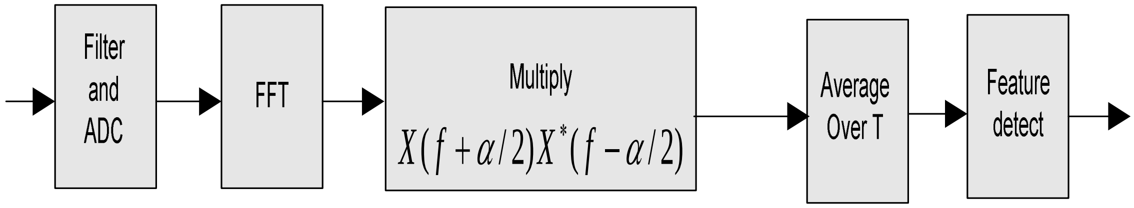


Figure 28. Implementation of a cyclostationary feature detector (Höyhtyä 2007).

Where the parameter (α) is the cycle frequency in which that represent the frequency separation of the correlated spectral components. Consequently, cyclostationary feature detector is more efficient, robust to noise uncertainty and needs less information about the primary signal. On the other hand feature detectors are more complex to implement also cyclostationary detectors need longer observation time to achieve reliable detection. Thus, implementing of short duration of spectral holes are inefficient compared with other sensing methods that needs shorter observation times. In chapter four we investigate cyclostationary sensing method that can improve radio sensitivity and detect primary user presence (Höyhtyä 2007).

The others feature based detection method is matched filter in which that required a prior knowledge of the primary user signal parameters at both physical and MAC layers, such as modulation type, pulse shaping and packet format which are stored in CMOS. The main advantage of matched filter detector is achieving high processing gain in less time based on coherent detection since 1/SNR samples are require to meet a proper probability of detection(Cabric 2004).

As regards matched filter is the optimum linear signal detector since it maximizes the output SNR. Even the main drawback, it needs to demodulate the incoming signal this process requires coherency with primary user signal by performing timing and carrier synchronization, even channel equalization. Thus the detection process becomes even more difficult when the matched filter detectors need to sense more than one primary user in which that require a dedicated receiver for every primary user class. Based on these facts, matched filter method is not proposed for the first generation of cognitive radios (Elmusrati 2009).

3.5. Cooperative Spectrum Sensing

Single cognitive radio may not have a clear vision for the spectrum based on its own sensing. Hence cooperative sensing based on combination of the spectrum information gathered from different cognitive radios and distributed among several cognitive radios located in the same area will enhanced the reliable detection and provide a clear vision for the spectrum occupancy. Therefore cooperative sensing is one of the techniques to improve the detection probability and reduce the sensing time in which that not always possible with a single radio sensing, due to the multipath fading, shadowing and local interference that mentioned in the primary user protection requirements in which are set by worst case channel condition resulting in highly negative SNR systems. Despite multipath is considered as negative effect, on the other hand the positive point is that the probability that all secondary users in the network will simultaneously experience the worst channel condition is extremely low based on the variance on location and independent realization at different time.

Consequently, in cooperation sensing the channel diversity increase the probability that there are several radios in a good channel condition which can provide reliable sensing that increase the robustness of the network without imposing higher sensitivity requirement on individual cognitive radios (Mishra etc 2006).

Figure 29 illustrate a scenario that one secondary user has favourable channel condition and able to detect the primary transmitter for the whole network.

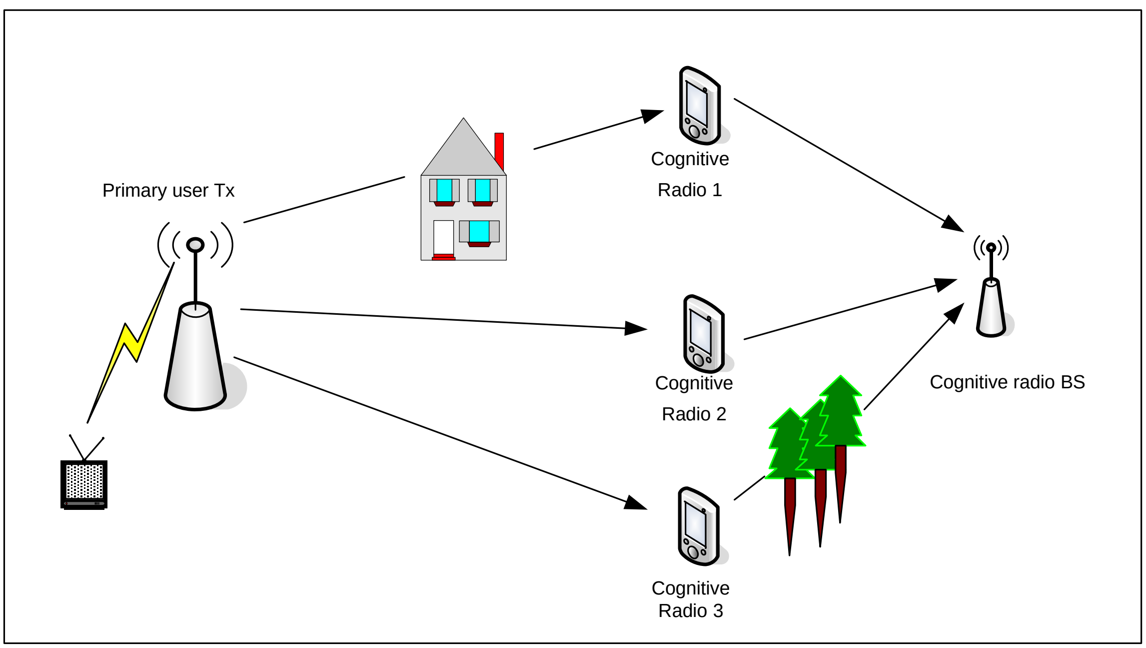


Figure 29. Cooperative spectrum sensing in shadowed environment (Ben Letaief & Zhang 2007).

Recently, cooperative spectrum sensing is one of the main research directions in cognitive radio spectrum sensing, also the benefits and proposed implementation of the cooperative sensing are discussed in several papers, especially on achieving diversity gains based on increase the probability of detection in bad channel condition and reduce sensing time also decrease the outage probability (Yu etc 2007).

In general, there are three steps to execute cooperative spectrum sensing. First, each cognitive radio has physical layer sensor in which that independently can perform a local spectrum measurements based on its observation and for low bandwidth control channel it is realistic to assume that the cognitive radio exchange their final binary decision 1-bit (H_0 or H_1) rather than long vector of long data to minimize the communication overhead, for simplicity we analyse energy based sensing.

Second, in centralized sensing the hard binary sensing results are forwarded from all cognitive radios to a common central receiver which is known as access point (AP).

Third, at the common receiver all the hard decision are gathered and combined together according to “OR” logic operation to make the final decision for all cooperating radios at specific area which are monitoring the same frequency band. This decision should be broadcast to all cognitive radios. Thus any cognitive radio in a favourable channel condition detects the primary user signal the whole network will take that decision. This cooperative spectrum sensing is referred to as *decision fusion* (Ben Letaief & Zhang 2007).

An alternative form of cooperating sensing based on distributed sensing in the sense that cognitive radio networks have no requirement for a backbone infrastructure, each cognitive radio simultaneously sense the spectral environment and then share the information based on its local observation among other cognitive radios located in the same area. Finally they make their own decision about the spectrum opportunities.

In order to quantify the gain obtained by cooperative sensing techniques need to characterize their benefits through improvement of overall probability of the detection and through of reduced sensing time. Next we analyze the theoretical framework of the indoor cognitive radio network to define these gains.

Let (M) represent the number of cooperating users in the cognitive radio network, as mentioned before in cooperation steps each cognitive radio sense its local environment through energy based detection for simplicity also we assume that all (M) users are experience independent and identically distributed (path loss, shadowing and multipath fading) with the same average SNR. Recall from paragraph 3.3 each cognitive radio implements hypothesis testing.

$$y_i[n] = \begin{cases} w_i[n] & H_0 \\ h_i x[n] + w_i[n] & H_1 \quad i=1,\dots,M \end{cases} \tag{3.10}$$

Where h_i denote the wireless channel condition from primary user to the cognitive radio receiver included (path loss, shadowing and multipath) in which that the path loss can be neglected for the small network and the effects of local interference are merged with noise. While the main source of cognitive radios diversity in such case is shadowing. Thus the probability of detection and false alarm can be determined based on all cognitive radios perform sensing over the same period, implement the same threshold γ for detection are shown in equation 3.7 and 3.8 respectively assuming that all cognitive radios experience the same noise $\sigma_{w,i}^2 = \sigma_w^2$ for all i.

In the final stage by combining the M cognitive radios measurements with "OR" operation in which that all measurements are independent and decides H_1 if any of the total M individual decision is H_1. Then probabilities of detection and false alarm for the cooperation scheme which is denoted by $(Q_d \text{ and } Q_{fa})$ respectively are increases monotonically with the numbers of cooperative radios M as shown in the fallowing equations (Ye etc 2008).

$$Q_d = 1 - (1 - P_d)^M \tag{3.11}$$

$$Q_{fa} = 1 - (1 - P_{fa})^M \tag{3.12}$$

Where $P_d \text{ and } P_f$ are the individual probabilities of detection and false alarm respectively. Figure 30 illustrates that in the typical indoor environments cooperative cognitive radios achieve a significant improvement in terms of reliable sensing that cooperation among five cognitive radios improve the detection probability from 60% to 95% based on that result cooperation in spectrum sensing is one of the main solutions to efficiently utilize the available spectrum opportunities (Ghasemi & Sousa 2005).

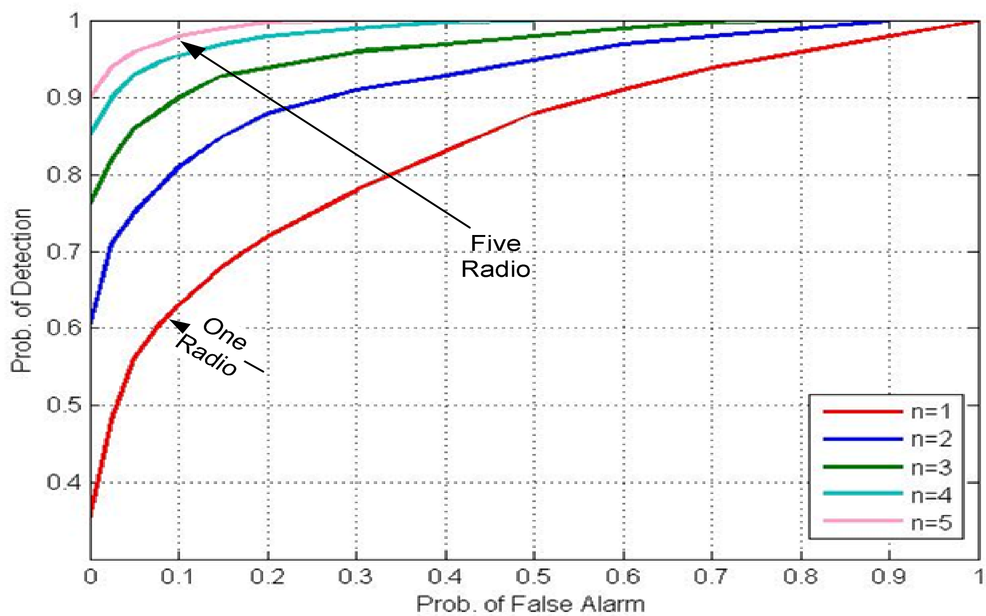


Figure 30. Measured P_d versus P_{fa} using cooperation of widely separated radios in indoor environments (Cabric 2008).

Apparently, cooperative sensing improves the probability of detection that allows network to relax with sensitivity of the cognitive radio detectors requirements. That relax can be interpreted as from implementation point view reduce the hardware cost and complexity and introduce some flexibility in terms of access policies. Also decrease the required sensing time to detect the primary user compared with individual cognitive radio detector in which that illustrated in Figure 31 and 32 (Ghasemi & Sousa 2008).

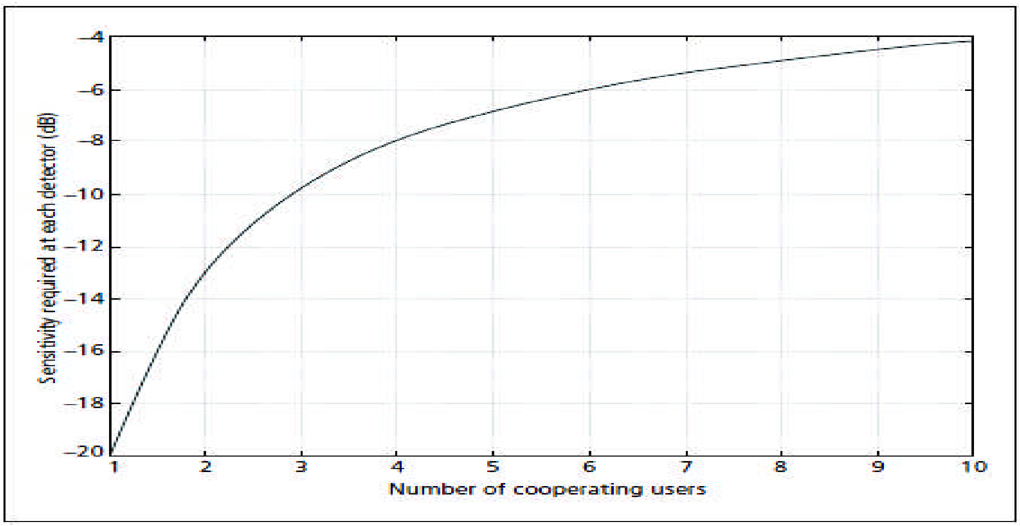


Figure 31. Required sensitivity of individual cognitive radios to achieve an overall detection sensitivity of -20 dB under Rayleigh fading vs. the number of cooperating users (Ghasemi & Sousa 2008).

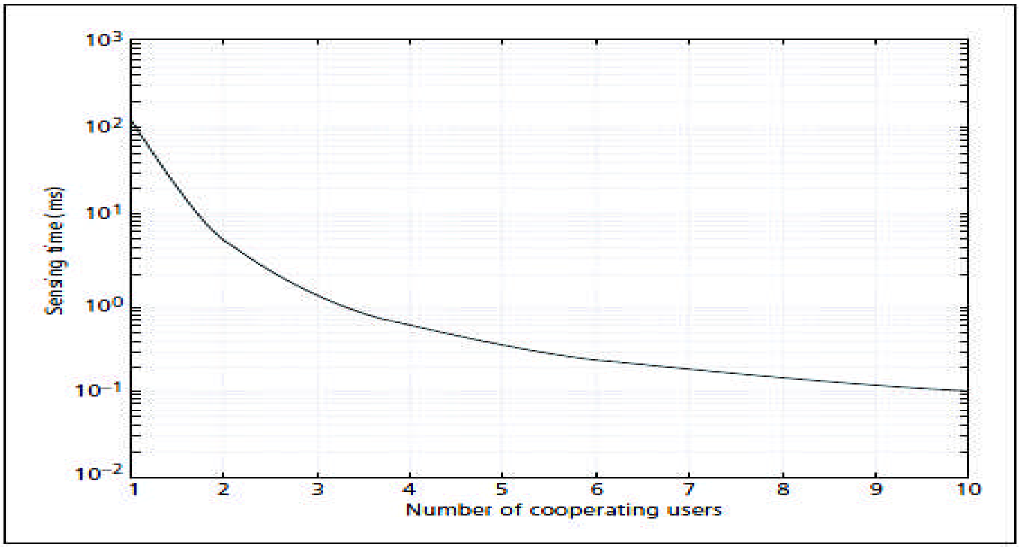


Figure 32. Cooperation-processing trade-off Rayleigh fading (Ghasemi & sousa 2008).

Another approach for improving the probability of detection is the ability to implement multiple antennas at sensing receiver instead of cooperation to minimize the network overhead. The main drawback of using more than one antenna is that increase complexity and cost of the cognitive radios. In conventional wireless systems the combination of the received signal from multiple antennas in one device will enhance the received SNR. This technique is more effective in Rayleigh channels where modelling in multipath dominated environments.

The idea behind using multiple antennas is to exploit the phenomenon of multipath diversity in which that requires separating the adjacent antennas larger than $\lambda/2$ where λ represent the wavelength of a carrier frequency. Figure 33 illustrates Qd vs Qf where two antennas improve the network detection probability by 10% and four antennas by 25%. While adding more than four antennas no benefit will achieved based on the limited number of degrees of freedom (Cabric 2008).

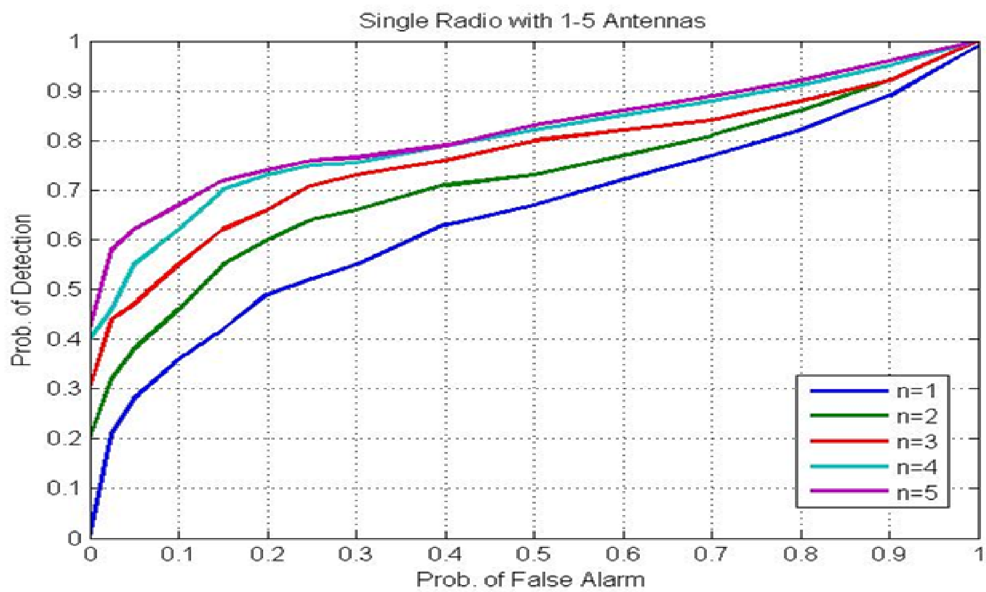


Figure 33. Measured P_d versus P_{fa} using multiple antennas (Cabric 2008).

3.5.1. Limitation in Cooperation Processing

In previous discussion we explored the enhancement in spectrum sensing performance based on cooperation among cognitive radios in which that it is proportion with number of cooperative cognitive radios. Also the required sensing time per individual cognitive radio can be reduced due to that achievable gain.

However the network overhead generally increases with the number of cooperative cognitive radios based on the increased amount of data that needs to be exchanged between cognitive radios and the AP. Therefore network determine the required number of cooperative cognitive radios and balancing between processing and cooperation to minimize the load and latency in which that scalable with the number of cooperative cognitive radios.

Another crucial issue in the cooperation sensing implementation is the cognitive radios reliability in which that unreliable sensing from any cognitive radios may significantly degrade the performance of network utilization based on prevent cognitive radio from accessing a white space by sending false report to the AP. Also sensing based energy detector cannot differentiate between primary and cognitive radios transmission. Thus all cognitive radios in the specific area should stop transmission when energy sensing take place and perform a synchronous sensing. In this case additional silent time is added, leads to decreasing in time operation period and reduces the effective system throughput. Finally, improve individual sensing methods and design of efficient trust management system in cognitive radio network may overcome these challenges.

4. Cyclostationary Method Analysis

The mean new features added to WRAN systems is the implementation of cognitive radio techniques. Recall from Chapters two and three that the fundamental task of cognitive radio is spectrum sensing based on its functionality of finding the empty frequency band. The conventional methods are radiometry in which it tends to false detection since it only measure the signal power that highly susceptible to changing in the interference or noise level.

However modulating signals are characterised as cyclostationary in which it defined as a wide sense cyclostationary signal or process in condition that the mean value and autocorrelation are periodic that will be discussed mathematically through the rest of this chapter. The robust signal detection and pattern matching based on signal classification algorithm involving cyclostationarity of signals. Moreover the extracting information can then be used for detection of a random signal having a particular modulation type in a very low SNR called cyclostationary feature based detection method. It offers a nice trade off between generality and robustness (Xu etc 2008; Ye etc 2007).

Most modulated signals although, are constructed from massage signal that is random, time varying stationary process and sinusoidal carrier wave that is deterministic and predictable. The final modulated signal is neither stationary nor deterministic, it is cyclostationary based on the periodicity.

Consequently, modulating signals such as, telemetry, radar, sonar system and communication signals exhibit periodicity. Since the periodicity is typically introduced in the signal parameters such as sinusoidal carrier phase, pulse timing, or direction of arriving, kind of modulation and coding etc. These periodicities in the signal format can be exploited by the receiver to achieve much more gain in terms of improvements in performance for detecting and defining the target signal in a background of noise and other modulating signal. However all these associated significant information are ignored by energy signal detector as we explained earlier.

Therefore random signal should be modelled as cyclostationary based on a single characteristic named spectral redundancy in which that constitute from three properties shared among most modulated signals. First, regenerative periodicity means that spectral lines can be regenerated from the signal by using a nonlinear quadratic transformation. Second, the resulting autocorrelation function exhibit periodicity indicating second order cyclostationarity. Third, correlation property between the signal components in distinct spectral bands. Most of these properties have a different manifestation for different modulating signals in which that can be used to perform signal processing tasks based on detecting and estimating of the highly corrupted modulated signals (Gardner 1991).

From the cyclostationary signal processing perspective, to make a distinction between primary user modulated signal and noise or other secondary user. A definition of cyclostationary signals, which are characterized by mean and autocorrelation function that are periodic in time are implemented to achieve a spectral correlation function SCF. The spectral correlation function characteristic of the cyclostationary signals provide a highly rich frequency domain that can be used to implement the sensing task, by detecting a unique cyclic frequency of different modulated signals.

Moreover, some information can be extracted such as carrier frequency, chip rate through defining the unique cyclic frequency. Also spectral correlation function achieves the best possible robustness with respect to random noise and interference. Figure 34 illustrates the cyclostationary sensing procedure for limiting bandwidth WRAN systems to reduce the computational complexity for its implementations.

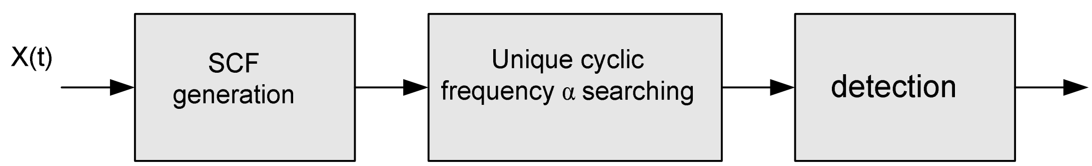


Figure 34. Cyclostationary signal detection procedure.

Three stages illustrates in this procedure. In the first stage SCF for the incoming signal is regenerated based on sensing wide spectrum. Then in the second stage the unique cyclic frequencies are defined. Last decision are made based on searching cyclic frequency procedure, the three stages are explained in the following.

First stage from Equation 4.1 the spectral correlation function can be calculated in which that follow the sequence instruction as illustrates in Figure 35.

$$\hat{S}_x^{\alpha}(f) = \frac{1}{\Delta t}\int_{-\Delta t/2}^{\Delta t/2} \frac{1}{T} U_T(t+u, f) V_T^*(t+u, f)\,du \qquad (4.1)$$

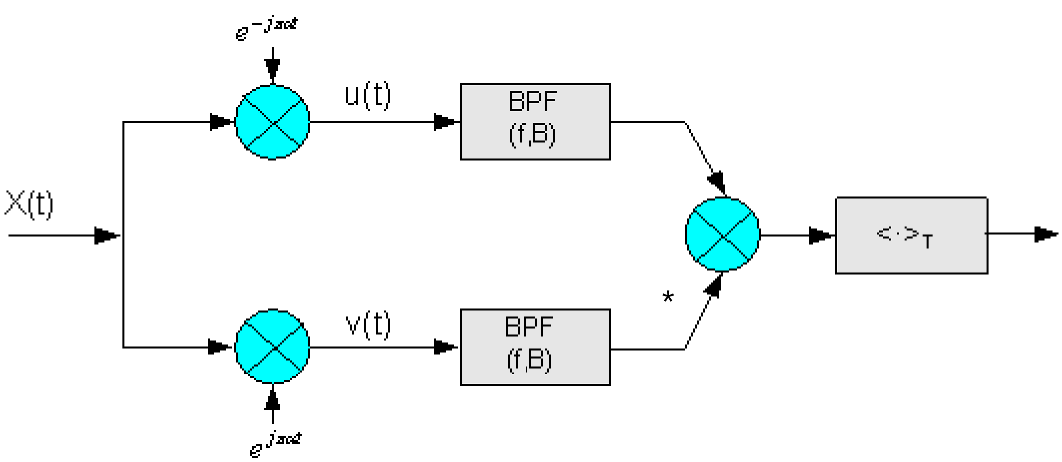


Figure 35. Spectral correlation function generation (Han etc 2006).

Where (*) denotes complex conjugation and $<\cdot>_T$ denotes the time-averaging operation. Both of the two frequency translates u(t) and v(t) of the incoming signal x(t) pass through the same set of band pass filters with centre frequency f and bandwidth B. Since we know the bandwidth of the incoming signal that we want to detect as in this example therefore the computational complexity is not as large as that of searching the whole frequency range.

Second stage, unique cyclic frequency searching. After we converting from hidden periodicity to the first order periodicity with associated spectral line located at the unique cyclic frequencies. The method is to detect the peak values in the frequency plan to define the cyclic frequencies as illustrates in Figures (41-55).

Third stage, detection decision. In order to detect the primary signal the threshold Γ is first calculated and it is a random value due to the random noise.

$$\Gamma = \max(I(\alpha)) / \sqrt{(\sum_{\alpha=0}^{N} I^2(\alpha)) / N} \tag{4.2}$$

Where $I(\alpha)$ is the magnitude at the frequency α and N is the noise.

Then the hypothesis testing is performed between ($H_\circ$ and H_1) as follows.

$$C_I \le \Gamma \qquad : Declare\ H_\circ \tag{4.3}$$

$$C_I > \Gamma \qquad : Declare\ H_1 \tag{4.4}$$

For the feature Extraction all (C_I) peaks greater than the threshold are encoded to one and the others are encoded zero. While, detecting the signal in the limited bandwidth as in our simple example the detection decision is made based on the searching result of the unique cyclic frequency. Thus no unique cyclic frequency indicates that there is no primary user signal in the band. Otherwise, the primary user signal exists in the band (Han etc 2006; Kim etc 2007; Gardenar 1991). In the next section we present the advantages of cyclostationary feature based detection method.

4.1. Advantages of Cyclostationary Method

Most of the wireless communication systems' signals can be characterized as cyclostatonary which exhibit underlying periodicities in their structures. These periodicities have a distinctive specific pattern in which that results from the correlation of the signal with the shifted version of it self by a specific value makes signal selectivity possible even at very low SNR. Due to the narrow frequency content along the (α) axis based on transferring from the second order periodicity to first order periodicity.

Consequently, cyclostationary, cyclic frequency and cyclic spectrum are arising from any periodically behaviour of the signal process. In addition richer information is preserves in cyclic spectrum domain such as frequency and phase representation of the incoming signal related to these periodicities. Thus, the analysis of the signal in the cyclic frequency domain give us that the power spectral density has features that overleapt, such as signals with different modulation types (BPSK, QPSK and SQPSK) have identical power spectral density function. Since their cyclic spectrum are highly distinct.

Moreover, from implementation perspective, the important point that interference and noise exhibit no spectral correlation in which that the spectral correlation of the noise is unique and large at cyclic frequency equals to zero comparing to other cyclic frequencies (Cabric 2004; Skinner etc 1994; Po 2009).

Clearly, in every process different primary user signals have different features, also the cyclic spectrum with its associated information can be used to enhance the accuracy and reliability of signal classification (Without need a priori knowledge of the primary user signal except rough information on signal bandwidth). For instance comfortably make a decision based on presence or absence of the primary user signal with a particular frequency at specific location in a very low SNR and able to differentiate between multiple received signals based on its modulation types in a background of noise and interferences.

From previous discussion, although cyclostationary based detection method exhibit many advantages, the computational complexity reduce its implementation based on the spectral components of two complex-valued signals are correlated in which that potentially large number of correlation computation.

On the other hand the growing interest in cyclostationary method leads to an increasing number of research papers in the recent years that several efficient cyclic spectral analysis algorithms have derived from the original methods introduced by Gardner. These approaches hold promise to solve complexity problem by reducing the number of correlation performed in cyclic spectrum estimation through limit the bandwidth of estimation and reducing the two dimensional space to be one dimensional that only estimate the cyclic spectrum values of ($S_x^{\alpha}(0)$) and the power spectral density PSD values of ($S_x^{0}(f)$). (Ye 2007; Roberts etc 1991; Gardner 1987; Gardner 1991).

4.2 .Mathematical Analysis: Deterministic Approach

In this section the statistical spectral analysis of experiential time-series in which it called cyclostationary time–series that arises from periodic phenomena will be discussed. This technique uses time averages contrary to the ensemble averages used in the probabilistic approach. The two techniques yield similar result based on as the time averaging tends to infinity the deterministic autocorrelation tends towards the probabilistic autocorrelation.

Recall from previous discussion that the mean and autocorrelation are calculated to reveal the cyclostationary of the signal in concentrate that they exhibit periodicity. Figure 36 shows the rectangular pulse sequence with different data form a and b even the transition of symbols for both signals are synchronised. Also the transition of all the symbols are occurring together in which that concentrate proves that the signals exhibit cyclostationarty with the fundamental period (T).

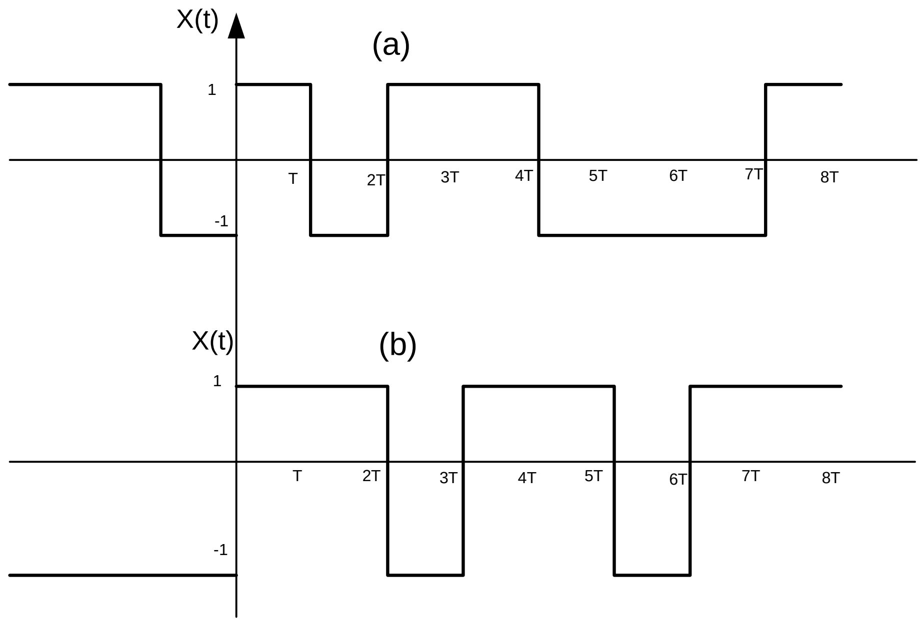


Figure 36. Two signals for calculation of the cyclostationary autocorrelation of rectangular pulse sequence.

Another example shows the technique for extracting periodicity from random data that it is called synchronized averaging. This technique illustrates in Figure 37. If the signal exhibit hidden periodicity in T_0 which is known then the signal can be partitioned based on the length of T_0 to disjoint adjacent segments and arranged vertically.

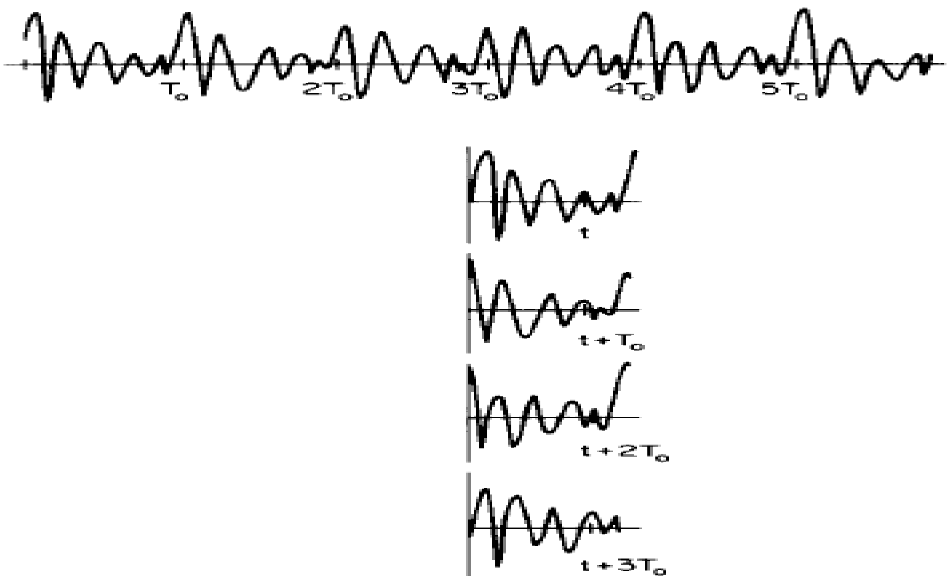


Figure 37. Synchronized averaging analysis (Gardner 1986).

Therefore the time-variant mean can be obtained within a period (e.g., t) by adding the time samples along the vertical line intersecting the point (t, $t \pm T_0$, $t \pm 2T_0$, $t \pm 3T_0$, …, $t \pm NT_0$). Thus the time-variant mean can be express.

$$M_x(t)_T = \frac{1}{2N+1}\sum_{n=-N}^{N} x(t+nT_0) \qquad (4.5)$$

Based on a total signal segment length of ($T=(2N+1)T_0$). Where N is an integer, T_0 is the cyclic period.

From the definition of cyclostationary by Gardner, the signal exhibit first order periodicity with frequency α if and only if the Fourier coefficient is not zero for any ($\alpha \neq 0$). We assume that the signal x(t) is periodic and can be expressed as.

$$x(t) = \sum_{-\infty}^{\infty} M_x^{\alpha} e^{i2\pi\alpha t} \tag{4.6}$$

$$M_x^{\alpha} = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t) e^{-j2\pi\alpha t} dt \tag{4.7}$$

In case of signal that do not give rise to spectral line based on the first order periodicity from signal process analysis in which that exhibit hidden periodicity that we are concerned with. We can define that signal as second order periodic or cyclostationary with period T ($\alpha \neq 0$) in which that exhibit hidden periodicity and can be converted into spectral lines (first order periodicity) through a stable quadratic time invariant (QTI) transformation of x(t).

$$y(t) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} k(u,v) x(t-u) x(t-v) du dv \tag{4.8}$$

Where the kernel function k(.,.) should be absolutely integrable to achieve a stable (QTI) transformation.

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} |k(u,v)| du dv \quad < \infty \tag{4.9}$$

Thus the condition to say that a time-series x(t) can be defined as a second order periodic cyclostationary signal with frequency (α) if and only if there exists some stable (QTI) transformation of x(t) into y(t) in which that y(t) exhibit first order periodicity that is foreign to x(t) with associated spectral line at f=±α.

Clearly, the autocorrelation is the lag product time-series x(t).

$$R_x(\tau) = < x(t + \frac{\tau}{2}) x(t - \frac{\tau}{2}) >_T \tag{4.10}$$

And can be seen that a time-series exhibit second order periodicity if and only if the autocorrelation exhibit first order periodicity for some lag values (τ).

Then the limit periodic autocorrelation can be obtained by applying the synchronized averaging to lag product time series.

$$R_x(t,\tau) = \lim_{N \to \infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x(t + nT_0 + \frac{\tau}{2}) x(t + nT_0 - \frac{\tau}{2}) \tag{4.11}$$

This function is periodic as we mentioned earlier and can be expressed as Fourier series.

$$R_x(t,\tau) = \sum_{\alpha} R_x^{\alpha}(\tau) e^{i 2 \pi \alpha t} \tag{4.12}$$

The Fourier coefficient which is called limit cyclic autocorrelation is that

$$R_x^\alpha(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} x(t+\frac{\tau}{2})x(t-\frac{\tau}{2})e^{-i2\pi\alpha t}dt \qquad (4.13)$$

Where α=m/T_0

From that we can say the time-series x(t) exhibit second order periodicity with the frequency (α) if and only if the limit cyclic autocorrelation exist and not identically zero as a function of (τ).

$$R_x^\alpha \neq 0 \quad \text{for } \alpha \neq 0 \qquad (4.14)$$

In addition, from Equation 4.13 there is another interpretation to the limit cyclic autocorrelation. Indeed it represents the conventional cross-correlation of the two complex valued frequency shifted versions for the real time-series x(t) as

$$\begin{aligned} u(t) &= x(t)e^{-i\pi\alpha t} \\ v(t) &= x(t)e^{i\pi\alpha t} \end{aligned} \qquad (4.15)$$

Thus from (4.15) we can express equation (4.13) as

$$\begin{aligned} R_x^\alpha(\tau) &\equiv R_{uv}(\tau) \\ &= \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} u(t+\frac{\tau}{2})v^*(t-\frac{\tau}{2})dt \end{aligned} \qquad (4.16)$$

And each cyclic autocorrelation based on Wienner relation has its frequency domain counterpart

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-i2\pi f t} d\tau$$
$$which \qquad S_x^{\alpha}(f) = S_{uv}(f) \tag{4.17}$$

This is called limit cross spectral density or limit cyclic spectral density of x(t). It can be thought as the density of correlation between the two spectral components at frequencies (f+α/2 and f-α/2). Moreover it can be interpreted as conventional autocorrelation and called spectral correlation function (SCF) that express as

$$S_x^{\alpha}(f) = \frac{1}{\Delta t} \int_{-\Delta t/2}^{\Delta t/2} \frac{1}{T} U_T(t+u, f) V_T^*(t+u, f) du \tag{4.18}$$

The spectral correlation function or cyclic spectrum is two dimensional transformation complex valued in which that a time-series x(t) exhibit second order periodicity through the cyclic frequency (α) if and only if there exists correlation between spectral components of x(t), located at frequencies separated by amount of (α) for appropriate values of (f) such as (f+α/2 and f-α/2).

In order to measure the strength of second order periodicity cyclostationary in a time-series x(t) a limit correlation coefficient for the two spectral components with the frequencies (f+α/2 and f-α/2) can be implemented in which that called spectral autocoherence of x(t) that give a result value either zero or one.

$$C_{uv}(f) = \frac{S_{uv}(f)}{[S_u(f)\,S_v(f)]^{1/2}} \equiv \frac{S_x^{\alpha}(f)}{[S_x(f+\frac{\alpha}{2})\,S_x(f-\frac{\alpha}{2})]^{1/2}} \tag{4.19}$$

Where $C_x^{\alpha}(f) \equiv C_{uv}(f)$

Consequently, time-series with spectral autocoherance equal to one means that it is completely coherent with a maximum amount of cyclostationarity with the cyclic frequency (α) and spectrum frequency (f). Or it equals to zero in which that interpreted as it is completely incoherent and exhibit no cyclostationarity with a cyclic frequency (α) and spectrum frequency (f)(Skinner 1994; Gardner 1986a; Gardner 1986b; Gardner 1991). In the next section we present the cyclostationary probabilistic approach.

4.3 Mathematical Analysis: Probabilistic Approach

Since cyclostationarity is a result of some form of repetitive operation such as sampling, scanning and multiplexing in which that introduce some statistical parameters that vary periodically with time. In addition these periodic parameters are introduced in the signal format advisedly, and preserved significant information. As a result it can be used for detection of random signal in a background of noise and interferences within rough information related to the target signal.

Consequently, recall from the definition of the cyclostationary, the wide sense cyclostationary signal or process can be interpreted in which that their statistics mean and autocorrelation are periodic. The probabilistic approach analysis can be implemented based on ensemble averaging, for theoretical work is easier than time averaging and depends on the periodicity presented within the signal format. Ensemble can be defined as an imaginary set of an infinite number of random samples to be time translates of the signal or process. The important point is similarities and differences between these different instances should be realized. The first order cyclostationary process (mean) is a periodic function of time,

$$E\{x(t)\} = E\{x(t + nT_0)\} \tag{4.20}$$

Where period (T_0) is related to underlying periodicity in cyclostationary signal, (t) is arbitrary real time, n is an integer. From Equation 4.21 the expected value of the process exhibit periodicity within (T_0) and can be presented based on the definition of the Fourier series that every periodic signal has a discrete spectral representation as,

$$E\{x(t)\} = \sum_{k=-\infty}^{\infty} m_k e^{i2\pi (k/T_0)t} \tag{4.21}$$

Where the Fourier coefficient can be represented as,

$$m_k = \frac{1}{T}\int_0^T E\{x(t)\}e^{-i2\pi(k/T_0)t}dt \tag{4.22}$$

Which represent the cyclic mean of frequency (k/T□). From equation (4.21) the expected spectrums of the first order cyclostationary signal with nonzero cyclic mean. Dirac impulses are the whole or part of this spectrum in which that can be detected optimally by linear FFT based detection receiver which is optimal for additive sinusoidal signals in a white noise environment detector.

In order to define a random process x(t) as second order cyclostationary, autocorrelation function should be periodic as (Gardner 1974).

$$R_x(t,\tau) = E[x(t)x^*(t-\tau)] = E[x(t+nT_0)x^*(t+nT_0-\tau)] \tag{4.23}$$

Where the subscript x of $R_x(t,\tau)$ indicate that the autocorrelation is for the signal x(t) and represented as a function of two variables (t and τ). The parameter (τ) is the lag between the two signals. From Equation (4.23) the expected value of the lag product exhibit periodicity based on the fundamental period (T_0). As a result it can be represented by the Fourier series which is called periodic autocorrelation function,

$$R_x(t,\tau) = \sum_{\alpha} R_x^{\alpha}(\tau)e^{i2\pi\alpha t}dt \tag{4.24}$$

Where (α=k/T_0) for k is an integer. The Fourier coefficients which is called cyclic autocorrelation function is depends on the lag parameter (τ) and can be represented as,

$$R_x^{\alpha}(\tau) = \frac{1}{T}\int_0^T R_x(t,\tau)e^{-i2\pi\alpha t}dt \tag{4.25}$$

From Equation 4.25 cyclic spectrum is the Fourier transforms of the cyclic autocorrelation and can be estimated based on the Wienner relations and represented as,

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau)e^{-i2\pi f\tau}d\tau \tag{4.26}$$

In Addition it is also called spectral correlation function based on the representation as a density correlation between two spectral components separated by (α) as in Equation 4.18.

As a result, to say wide sense cyclostationary process WSCS, it requires satisfying both Equation 4.20 and 4.23. Note that stationary noise and interferences have no spectral correlation only at α=0 as illustrated in Figure 38 (Gardner & Franks 1974; Gardner 1974; Skinner etc 1994).

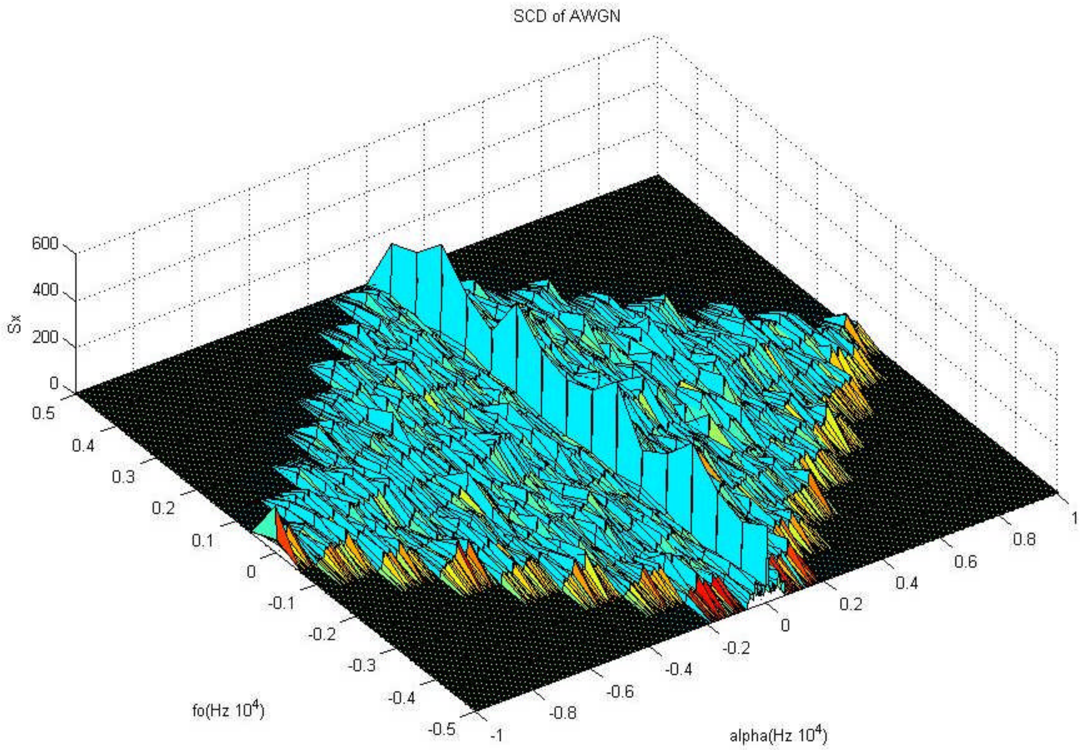


Figure 38. Spectral Correlation Function of the AWGN noise.

4.4. Simulation Scenarios

Recall that different primary user signals have different features. In addition the distinctive features of the signals can be seen easily in frequency domain rather than time domain in which that can be used for detecting the presence of the primary users. Simple example is a sinusoidal signal embedded in noise. It cannot be defined by just looking at its time-domain. However the same signal can easily recognized in frequency domain if SINR is large enough.

Moreover in frequency domain the correlation between signal and the frequency-shifted versions of it can be determined. It is called the cyclic autocorrelation function. As a result the cyclic spectrum through the Fourier transform of the cyclic auto correlation function can be determined and interpreted as localization of the correlation in frequency domain. It can be implemented to detect the target signal.

In practice two methods can be used to accomplish this goal. One is called the FFT Accumulation method FAM, and the other is Strip Spectral Correlation Algorithm SSCA. Both methods are based on modifications of time smoothed cyclic cross periodogram as defined (PO & TAKADA 2001).

$$S_{xyT}^{\alpha}(n,f) = \lim_{N=\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} \frac{1}{T} X_T(n, f+\frac{\alpha}{2}) Y_T^*(n, f-\frac{\alpha}{2}) \qquad (4.27)$$

Where $X_T(n,f+\alpha/2)$ and $Y_T(n,f-\alpha/2)$ are the complex envelopes of narrow band bandpass components of the signal x(n) and y(n) also called complex demodulates and can be computed in the following way:

$$X_T(n,f) = \sum_{r=-N'/2}^{N'/2} a(r) x(n-r) e^{-i2\pi f(n-r)T_s} \qquad (4.28)$$

$$Y_T(n,f) = \sum_{r=N'/2}^{N'/2} a(r) y(n-r) e^{-i2\pi f(n-r)T_s} \qquad (4.30)$$

Where a(r) is a data tapering window of length T=N'Ts , Ts is the sampling period and N' is the number of first FFT Transform.

The two methods are implemented to calculate the correlation of the signals and represented in graphs by computer simulation in MATLAB. Signals are generated with appropriate modulation type and pulse shape, with random data and performing the cross correlation using a finite simulated signals. Next section we described in details of those two methods (PO & TAKADA 2001).

4.4.1. FFT Accumulation Method (FAM)

From this method, the SCF of the incoming signal can be estimated by implementing Equation 4.27 based on at first determine the complex demodulate of x(n), y(n) through the Equation 4.28 and 4.29 by means of a sliding N′-point FFT, followed by a downshift in frequency to baseband. Then the product sequences between each one of them and the complex conjugate of the others are formed.

For optimal and efficient estimation, the N′ point FFT is hopped over the data in blocks of (L) samples (Channelization), by means of decimating $X_T(n,f)$. The value of decimation factor L was chosen to be (N′/4) to allow for a good compromise between maintaining computational efficiency and minimizing cycle leakage and cycle aliasing. Also the value of N′ is calculated based on the desired resolution in frequency (Δf) implemented in the algorithm and to be power of (2) equal to or larger than the number given by Equation 4.31 to avoid using zero-padding based on using the FFT algorithm and to take advantage of it as follows:

$$N' = \frac{f_s}{\Delta f} \tag{4.30}$$

In order to perform the time smoothing a second P-point FFT is implemented after the product sequences is formed. The value of (P) is calculated based on the desired resolution in cyclic frequency ($\Delta\alpha$) and to be power of (2) equal to or larger than the number given by Equation 4.32 to avoid using zero-padding based on using the FFT algorithm and to take advantage of it as follows:

$$P = \frac{f_s}{L\Delta\alpha} \tag{4.31}$$

Essentially, Figure 39 illustrates the implementation of the FAM method.

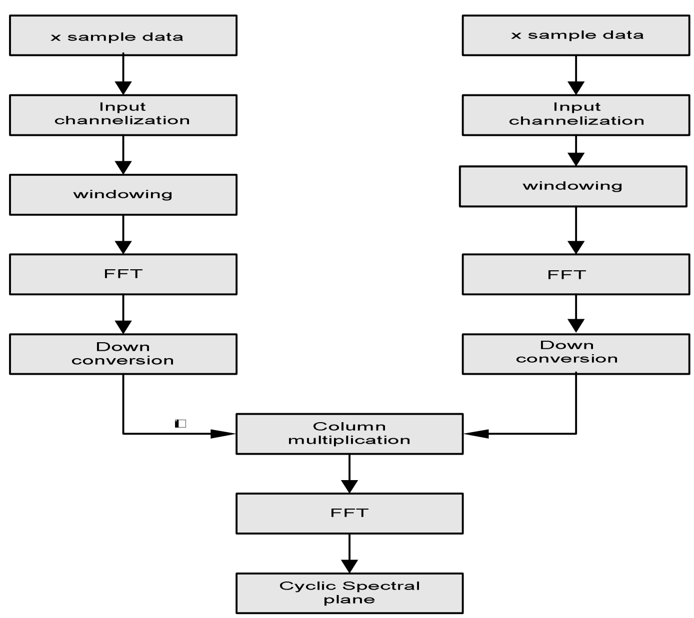


Figure 39. Implementation of the FFT Accumulation Method (Ge & Charles 2008).

The inputs required to estimate the spectral correlation density function are the signal, the sampling frequency (fs), the desired frequency resolution (Δf) and the desired resolution in cyclic frequency ($\Delta\alpha$) (Ge & Charles 2008) (Roberts etc 1991).

4.4.2. Strip Spectral Correlation Algorithm (SSCA)

As stated earlier, the complex demodulate is calculated for one of the signals branch based on the same process that what is done for the FAM method. After the complex demodulate is calculated, it is directly multiplied by the complex conjugate of the other branch of the signal. Then, the second step is the time smoothing to the resultant signal is implemented based on an N-point FFT transform and the estimation of the spectral correlation density function is achieved. Where N is the total number of signal points (N=P *L).

The deference in sampling rate between the complex modulate (fs/L) and x[n] is overcomes by means of a process called replication in which that executed by holding the value of each complex demodulate sample for (L) samples. Figure 40 illustrates the implementation of the (SSCA) and the required inputs are the same as in the (FAM) method (Roberts etc 1991).

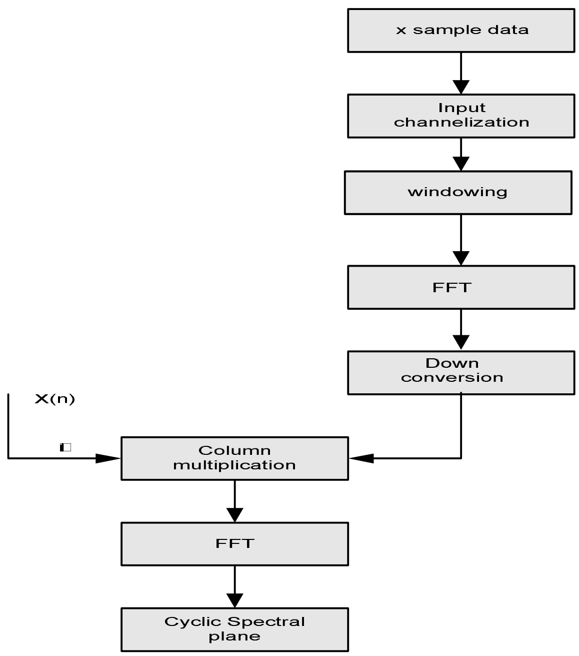


Figure 40. Implementation of the (SSCA) (Ge & Charles 2008).

4.5. Simulation Results

In this section we present the experimental result based on implementation of the FAM and SSCA to the several analog and digital modulated signals, also compare the resultant SCD function in which it is obtained as output from those methods with the theoretical results.

Three figures are used to present the estimated SCD function. The first figure is a surface plot to illustrate the magnitude of the SCD function with the coordinates (f) and (α). The second figure is two dimensional contour plot in which that allows a better top view to the position of the features in frequency plane with coordinates

(f) and (α). The third figure is a two dimensional slices of the SCD function with (f) and (α).

4.5.1 Analog Modulated Signals

- Lets at first consider the Sinewave signal:

$$p(t) = \cos(2\pi f_c t) \tag{4.32}$$

Where (fc) is the carrier frequency in Hz. The (SCD) function for this Sinewave and from the signal processing theory is given:

$$S_x^{\alpha}(f) = \begin{cases} \frac{1}{4}[\delta(f + f_c) + \delta(f - f_c)] & \alpha = 0 \\ \frac{1}{4}\delta(f) & \alpha = \pm 2 f_o \\ 0 & others \end{cases} \tag{4.33}$$

All details of all derivation are given in (Gardner 1986).

Figures 41-43 illustrates the results for the signal as fc= 2048 and the sampling frequency fs= 8192. Equation 4.33 leads to the following result:

$$S_x^{\alpha}(f) = \begin{cases} \frac{1}{4}[\delta(f-2048)+\delta(f+2048)], & \alpha = 0 \\ \frac{1}{4}\delta(f) & \alpha = \pm 4069 \end{cases} \qquad (4.34)$$

Based on theoretical result and Equation 4.34 we expect to obtain peaks at f=±2048Hz for α=0 and at α=±4096 Hz for f=0 in which that agree with the achieving experimental results illustrates in Figures 41-43.

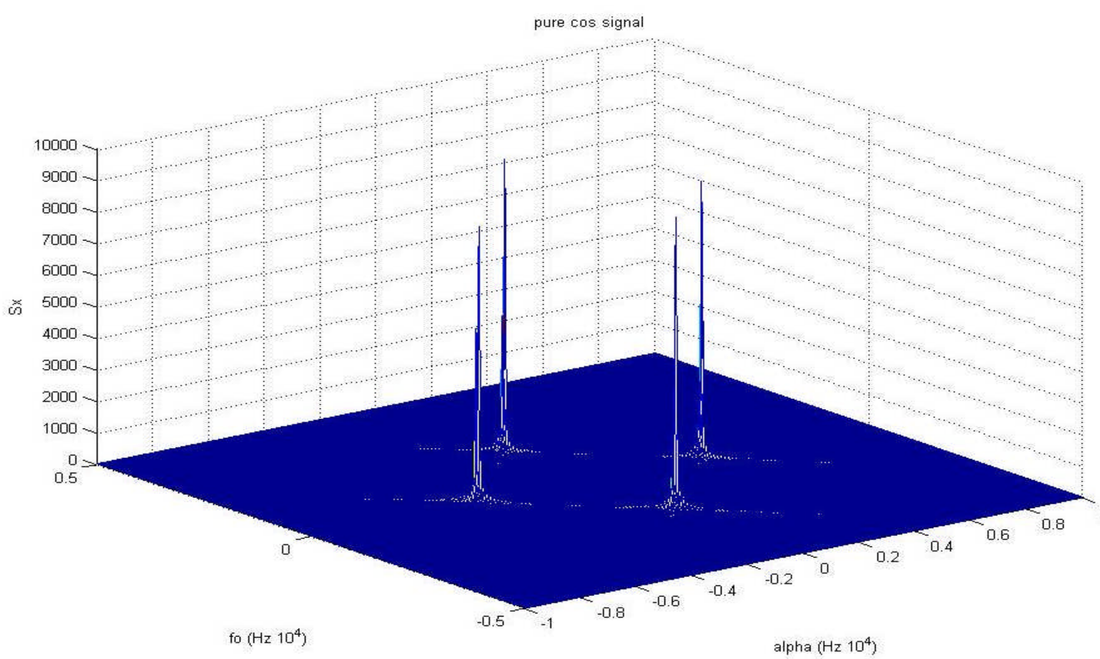


Figure 41. Surface plot of the SCD estimate magnitude for cos wave with the following parameters: Δf= 64Hz, Δα=32Hz, fc=2048Hz, and fs=8192Hz.

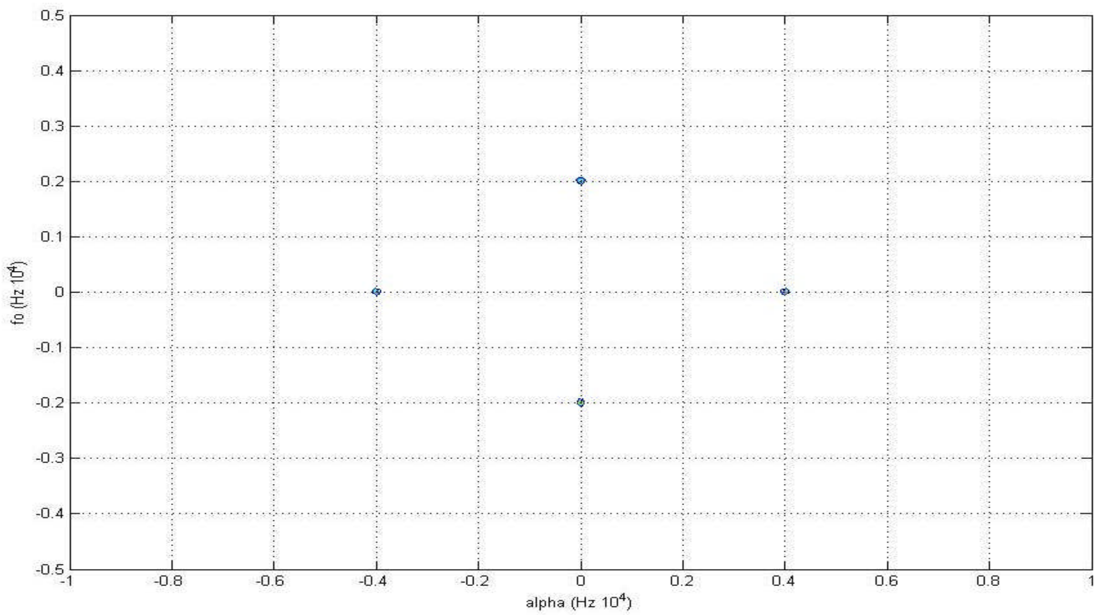


Figure 42. Contour plot of the SCD estimate for cos wave.

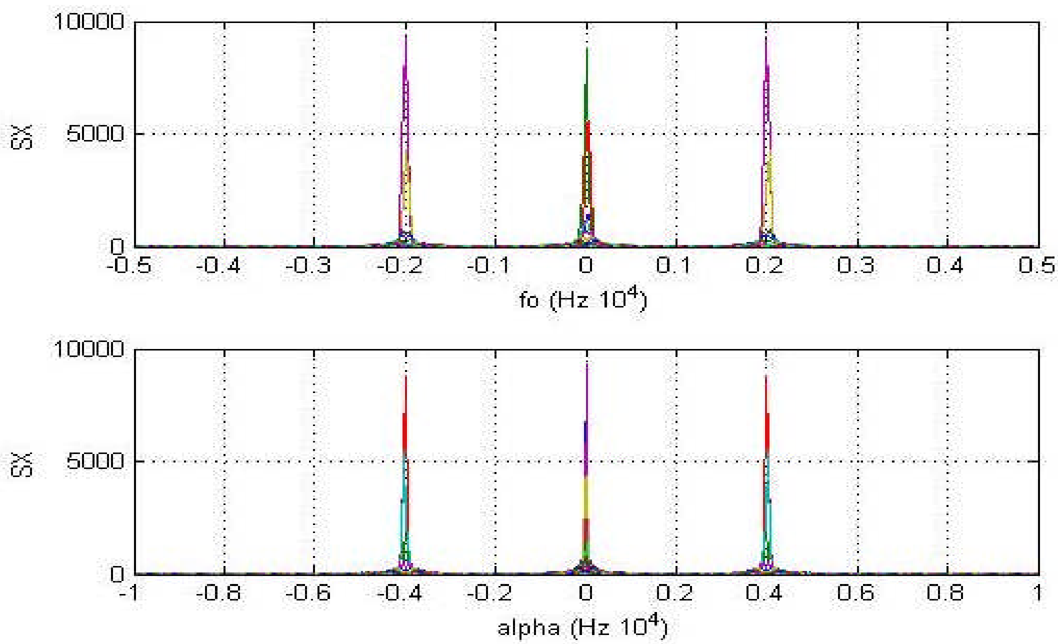


Figure 43. Plots of the SCD estimate magnitude for cos wave.

- Amplitude Modulation Single Side Band signal (AMSSB)

Let's estimate the SCD function for the AMSSB. Assume a massage signal as a tone to show the exact frequency of the massage fa= 512Hz such as (a(t)=cos(2*pi*fa*t)) and fc=2512Hz thus the signal and the SCD function are:

x(t)=a(t)p(t) (4.35)

Where p(t) is given in Equation 4.32 . We may describe the AMSSB as the result of passing DSBSC signal through the ideal BPF.

$$S_x^{\alpha}(f)=\left\{\begin{array}{ll}\frac{1}{8}[\delta(f-f_o+f_a)+\delta(f+f_o-f_a)] & \alpha=0\\ \frac{1}{8}\delta(f)e^{\pm i2\phi_o} & \alpha=\pm 2(f_o-f_a)\\ 0 & others\end{array}\right\} \quad (4.36)$$

So according to Equation 4.37 we expect to obtain peaks at f=±2000Hz for α=0, and at α=±4000Hz for f=0, in which that agree with the achieving experimental results in Figures 44-46.

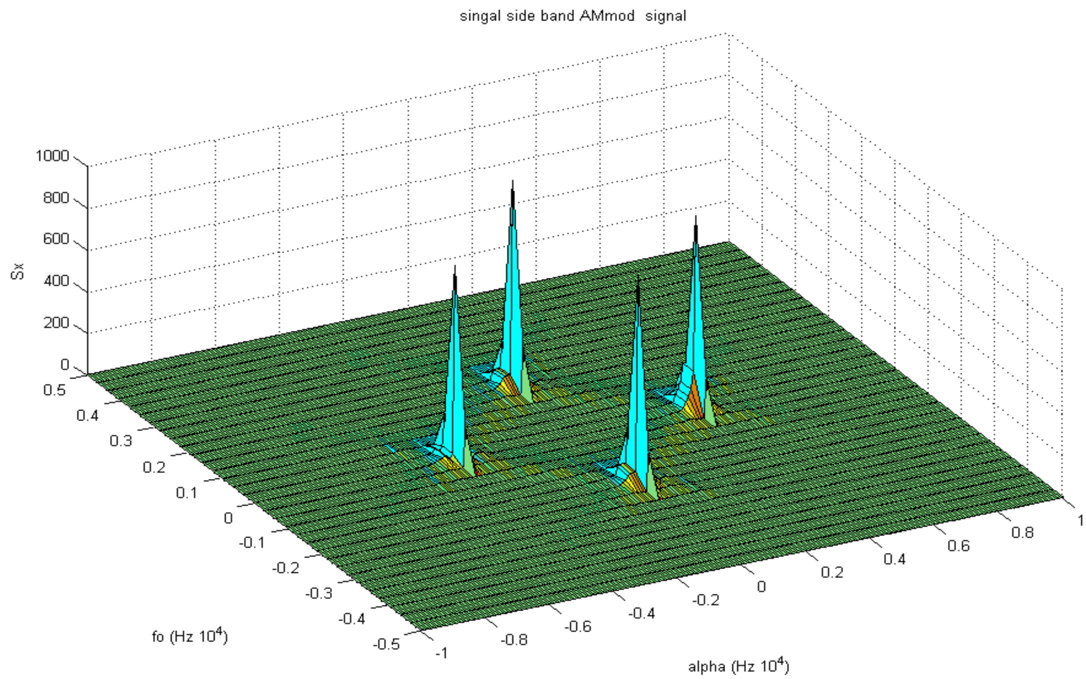


Figure 44. Surface plot of the SCD estimate magnitude for AMSSB with the parameters: Δf=256, Δalpha=64, fc= 2512, fa= 512, fs= 8192.

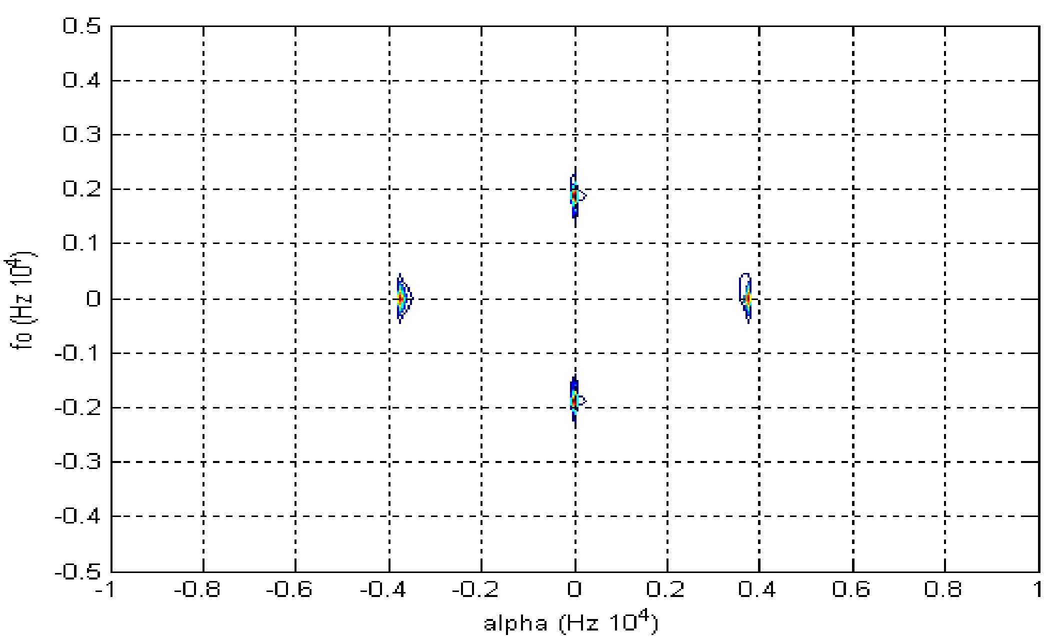


Figure 45. Contour plot of the SCD estimate for AMSSB.

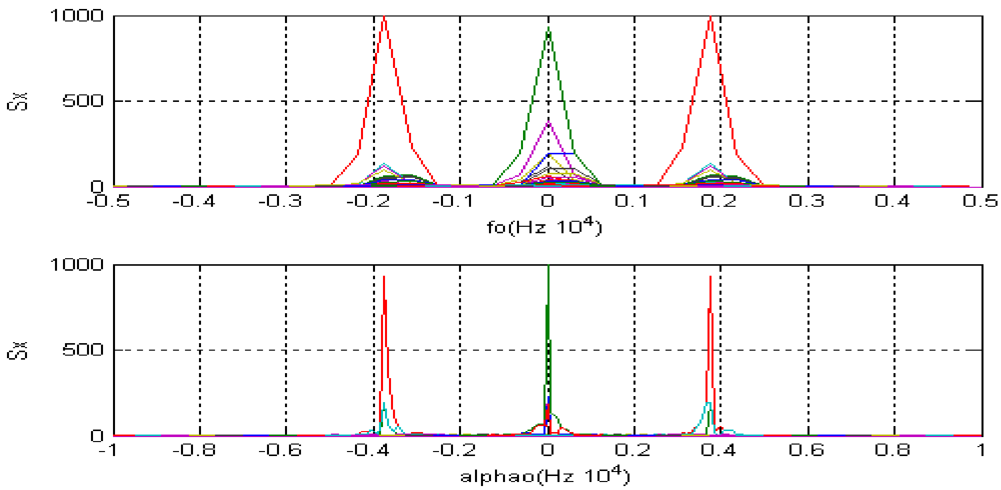


Figure 46. Plots of the SCD estimate magnitude for AMSSB.

- Amplitude Modulation Double Sideband signal (AMDSB)

Now, let suppose that x(t) is an amplitude modulation double sideband as given:

$$x(t) = \cos(2\pi\ f_a t).\cos(2\pi\ f_o t + \phi_o) \tag{4.37}$$

The SCD function for the (AMDSB-SC) is given as:

$$S_x^{\alpha}(f) = \begin{cases} \frac{1}{16}[\delta(f - f_o - f_a) + \delta(f - f_o + f_a) + \delta(f + f_o - f_a) + \delta(f + f_o + f_a)], & \alpha = 0 \\ \frac{1}{16}[\delta(f - f_o) + \delta(f + f_o)], & \alpha = \pm 2 f_a \\ \frac{1}{16}\delta(f)e^{\pm i2\phi_o}, & \alpha = \pm 2(f_o - f_a) \\ \frac{1}{16}[\delta(f - f_a) + \delta(f + f_a)]e^{\pm i2\phi_o}, & \alpha = \pm 2 f_o \\ \frac{1}{16}\delta(f)e^{\pm i2\phi_o} & \alpha = \pm 2(f_o + f_a) \end{cases} \tag{4.38}$$

Thus the result SCD obtained for an (AMDSB-SC) when the fa=1012Hz, fc=2048Hz, fs=8219Hz, Δf=256 and Δα=32

$$S_x^{\alpha}(f)=\left\{\begin{array}{ll}\frac{1}{16}[\delta(f-1036)+\delta(f-3060)+\delta(f+1036)+\delta(f+3060)], & \alpha=0\\ \frac{1}{16}[\delta(f-2048)+\delta(f+2048)], & \alpha=\pm 2024\\ \frac{1}{16}\delta(f), & \alpha=\pm 2072\\ \frac{1}{16}[\delta(f-1012)+\delta(f+1012)], & \alpha=\pm 4096\\ \frac{1}{16}\delta(f) & \alpha=\pm 6120\end{array}\right\} \quad (4.39)$$

Consequently, Equation 4.39 shows that we have four peaks at f=±1036Hz and f=3060Hz, for α=0, four peaks at f=±2048Hz, for α=±2024Hz, two peaks at f=0, for α=2072Hz, four peaks at f=±1012Hz for α=±4096Hz and two peaks at f=0 for α=±6120Hz, in which that agree with the achieving experimental as illustrates in Figures 47-49.

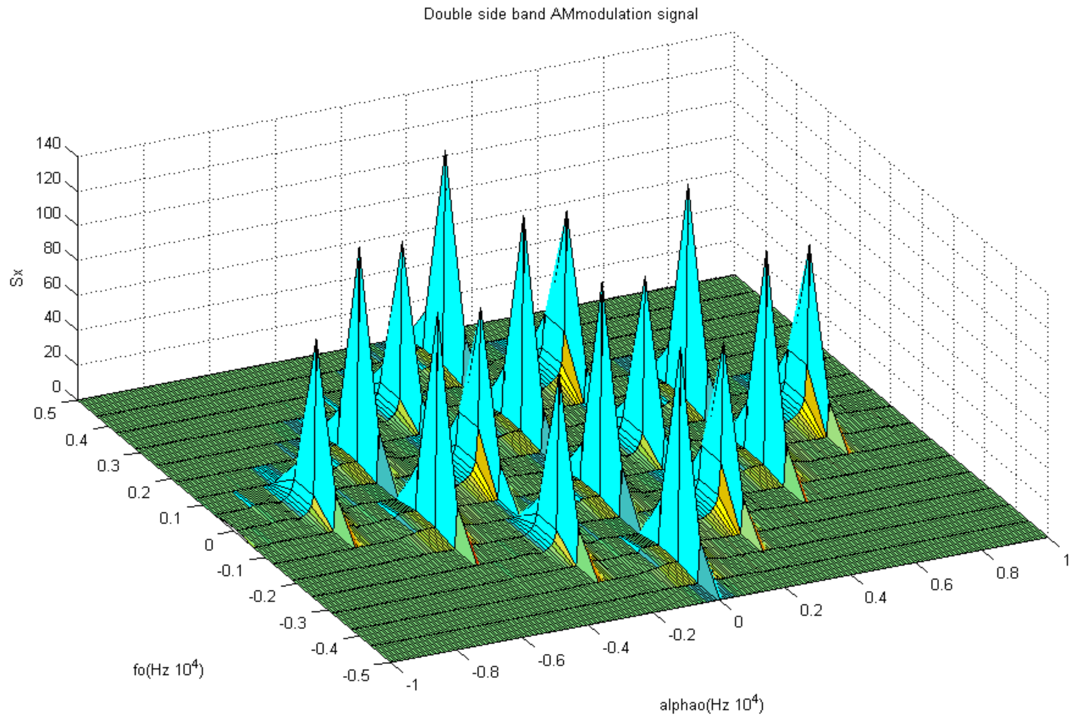


Figure 47. Surface plot of the SCD estimate magnitude for AMDSB-SC with the parameters: Δf=256, Δalpha=32, fc= 2048, fa= 1012, fs= 8219.

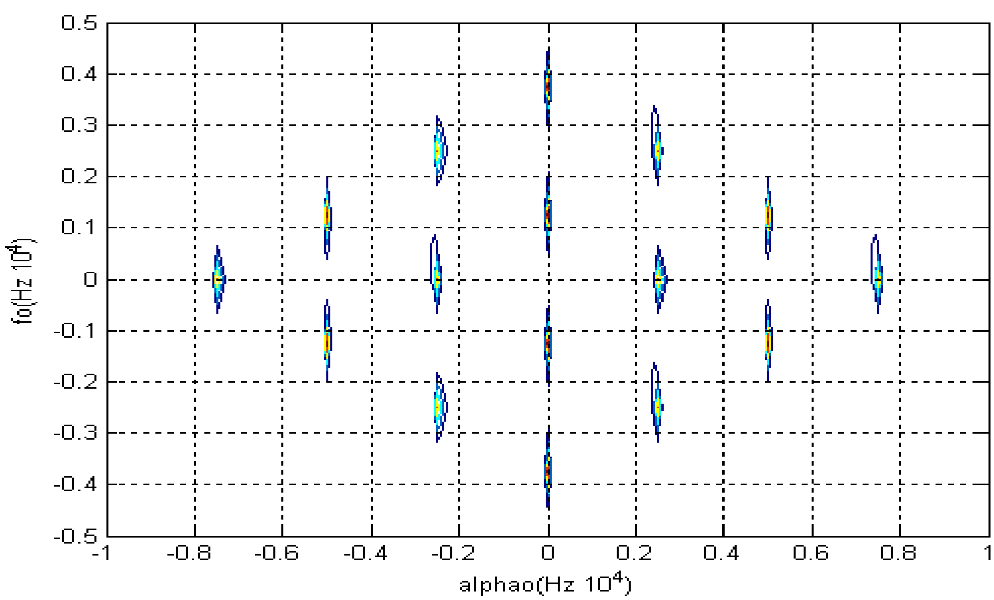


Figure 48. Contour plot of the SCD estimate for AMDSB-SC.

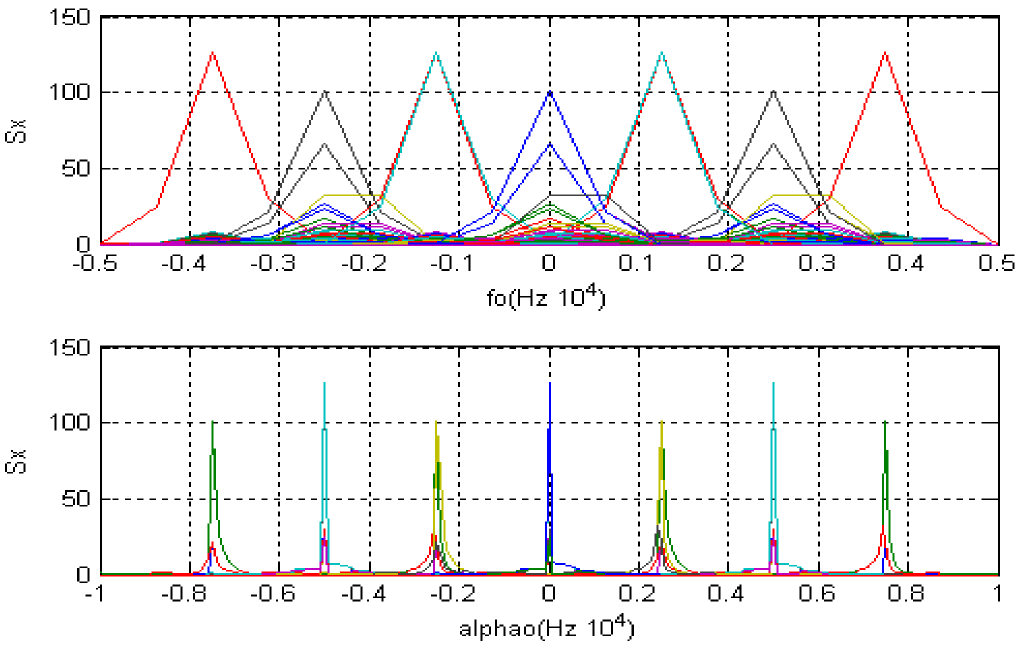


Figure 49. Plots of the SCD estimate magnitude for AMDSB-SC.

4.5.2. Digital Modulated Signals

- Amplitude Shift Keying (ASK)

The signals with modulation ASK is simply AM signal as follows:

$$x(t) = a(t)\cos(2\pi f_{\circ} t + \phi_{\circ}) \tag{4.40}$$

Where a(t) is the amplitude massage with a M-array PAM signal as:

$$a(t) = \sum a_n q(t - nT_\circ - t_\circ) \qquad \text{Where } a_n = \pm 1 \tag{4.41}$$

Leads to the SCD function for ASK signal:

$$S_x^\alpha(f) = \frac{1}{4T_\circ}\begin{Bmatrix} [Q(f + f_o + \alpha/2)Q^*(f + f - \alpha/2)S_a^\alpha(f + f_o) \\ + Q(f - f_o + \alpha/2)Q^*(f - f_o - \alpha/2)S_a^\alpha(f - f_o)]e^{-i2\pi\alpha t_o} \\ + Q(f + \alpha/2 + f_o)Q^*(f - \alpha/2 - f_o)S_a^{\alpha+2f_0}(f).e^{[-i(2\pi[\alpha+2f_o]t_o+2\phi_o)]} \\ + Q(f + \alpha/2 - f_o)Q^*(f - \alpha/2 + f_o)S_a^{\alpha-2f_o}(f).e^{[-i(2\pi[\alpha-2f_o]t_o-2\phi_o)]} \end{Bmatrix} \tag{4.42}$$

And for full duty cycle rectangle pulse, we have

$$q(t) = \begin{cases} 1, & |t| \le T_o/2 \\ 0, & |t| > T_o/2 \end{cases} \tag{4.43}$$

And there for the Fourier transform for q(t) is:

$$Q(f) = \frac{\sin(\pi f T_o)}{\pi f} \tag{4.44}$$

The SCD function for the M-ary ASK signal x(t) given by Equation 4.42 are the same as for the BPSK. Thus the simulation results are the same and illustrates in Figures 53-55.

- Binary Phase Shift Keying (BPSK) Signals

The signals with a PSK are simply a phase modulated (PM) carrier such as:

$$x(t) = \cos[2\pi f_o t + \phi(t)] \qquad (4.45)$$

Where the phase φ(t) is a digital PAM signal as:

$$\phi(t) = \sum a_n q(t - nT_o - t_o) \qquad \text{Where} \quad a_n = (0, \pi) \qquad (4.46)$$

Figures from 50-52 shows the SCD function for the baseband BPSK signal representing baud rate related correlation.

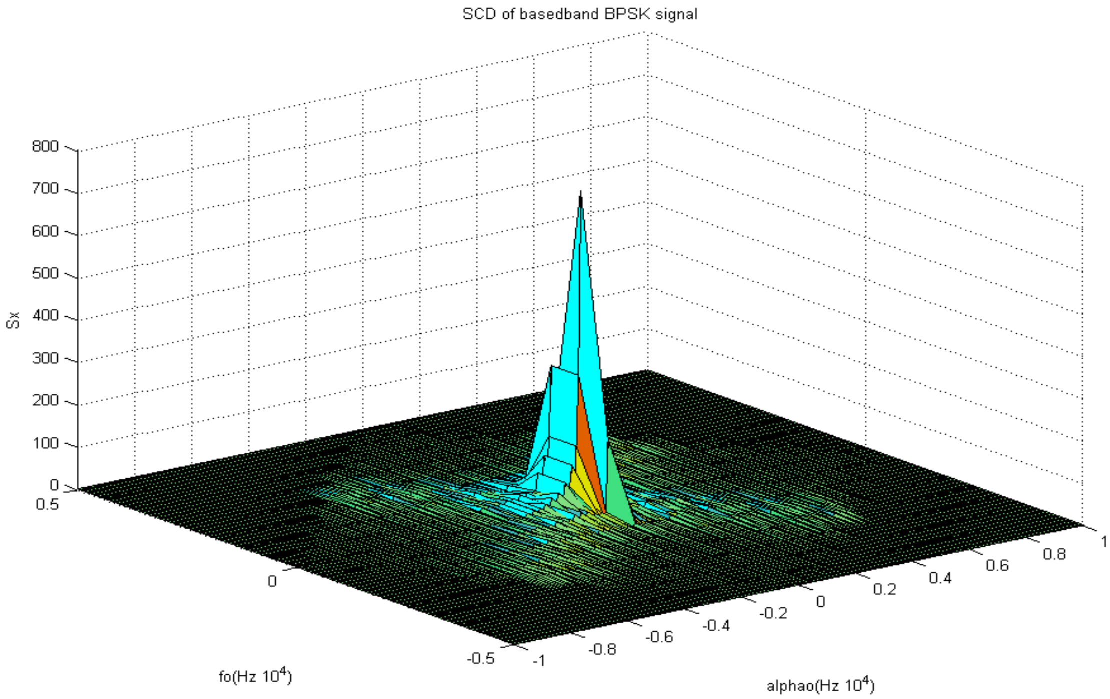


Figure 50. Surface plot of the SCD estimate magnitude for the baseband BPSK with the parameters: Δf=512, Δalpha=64, br= 1000, fs= 8192.

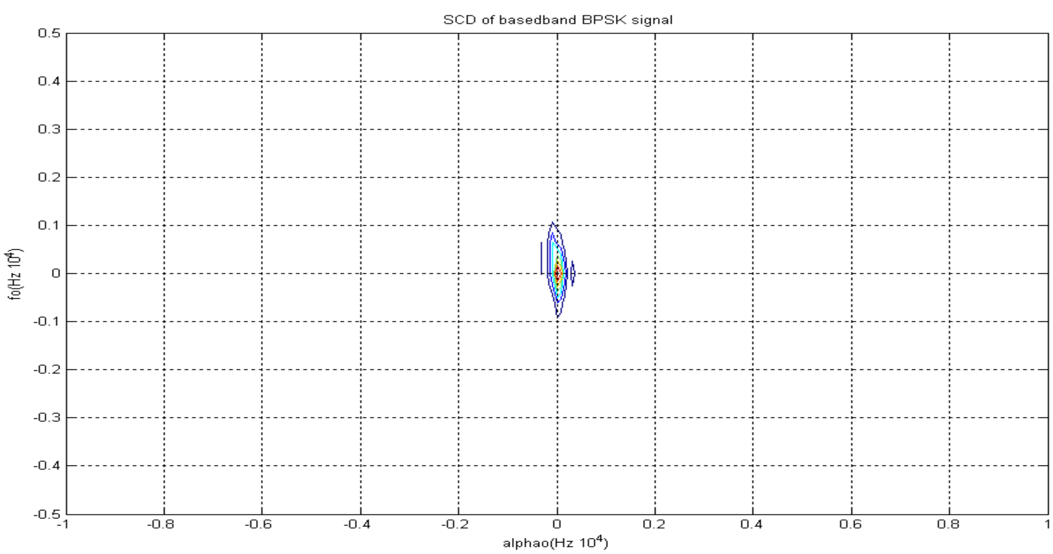


Figure 51. Contour plot of the SCD estimate magnitude for the baseband BPSK.

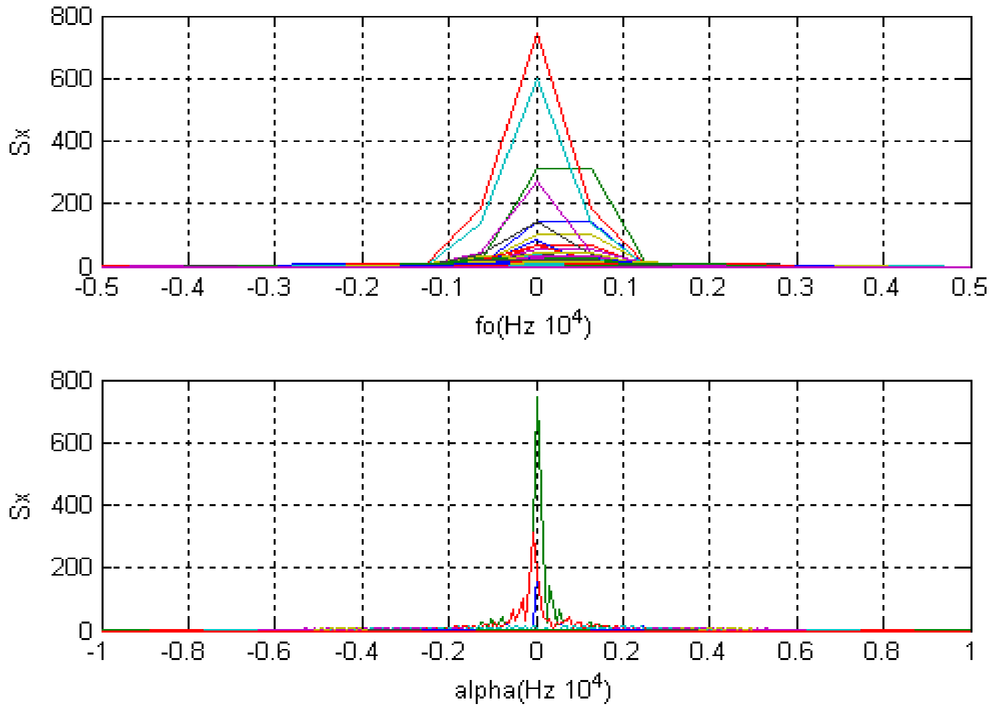


Figure 52. Plots of the SCD estimate magnitude for the baseband BPSK

Hence the cyclic spectra for the BPSK signal of x(t) is similar to ASK signal for M=2 and given in Equation 4.42 (Wenjie 2004).

$$S_x^{\alpha} = \begin{cases} \dfrac{1}{4T_o} Q(f + \alpha/2 \pm f_o) Q^*(f - \alpha/2 \pm f_o) e^{-i[2\pi(\alpha + 2f_o)t_o \pm 2\phi_o]}, & \alpha = \pm 2f_o + k/T_o \\ \dfrac{1}{4T_o} [Q(f + \alpha/2 \pm f_o) Q^*(f - \alpha/2 + f_o) + Q(f + \alpha/2 - f_o) Q^*(f - \alpha/2 - f_o) e^{-i2\pi t_o}] & \alpha = k/T_o \\ 0 & others \end{cases} \tag{4.47}$$

Thus the results are the same for fc=1012 and fs=8192 which are illustrates in Figures 53-55.

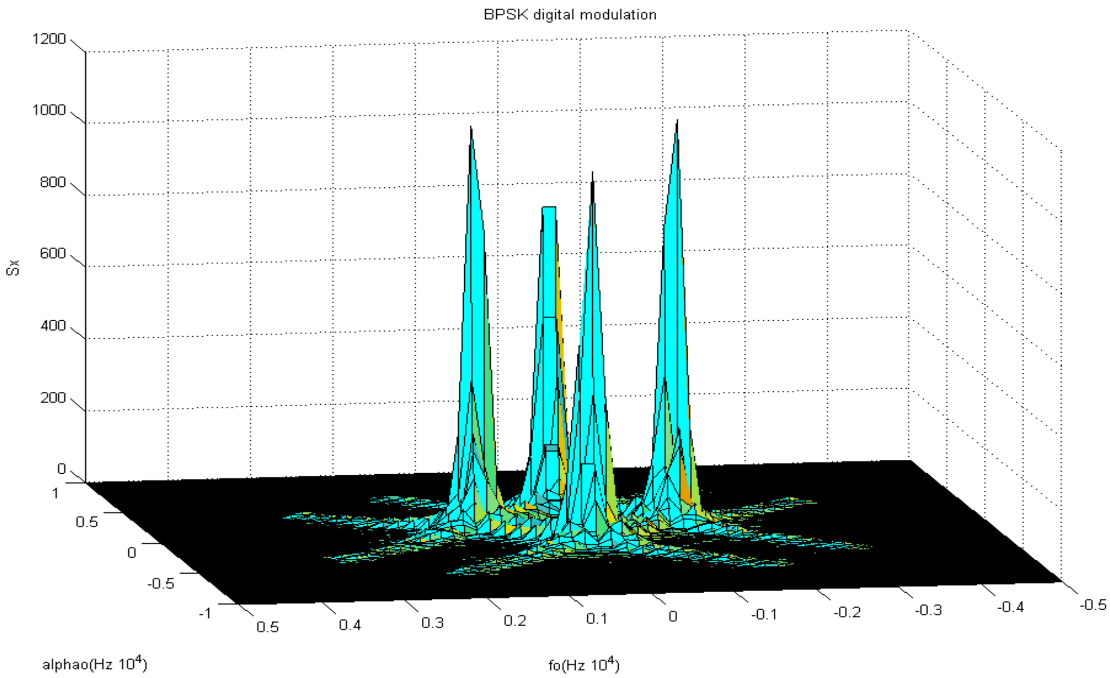


Figure 53. Surface plot of the SCD estimate magnitude for BPSK with the parameter Δf=128Hz, $\Delta\alpha$=64Hz, fc=1012Hz and fs=8192Hz.

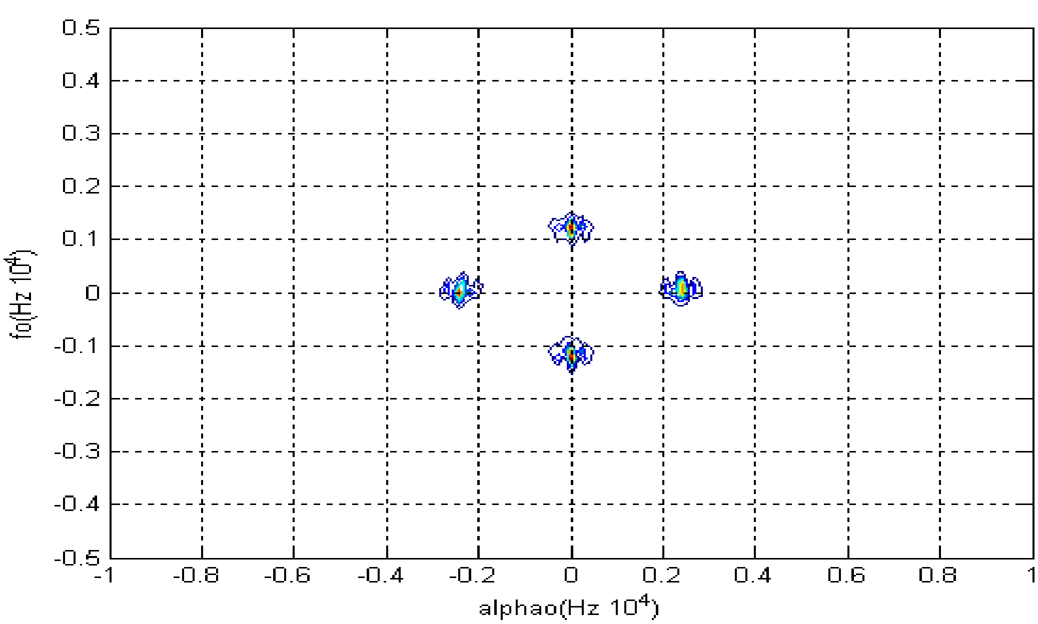


Figure 54. Contour plot of the SCD estimate for BPSK.

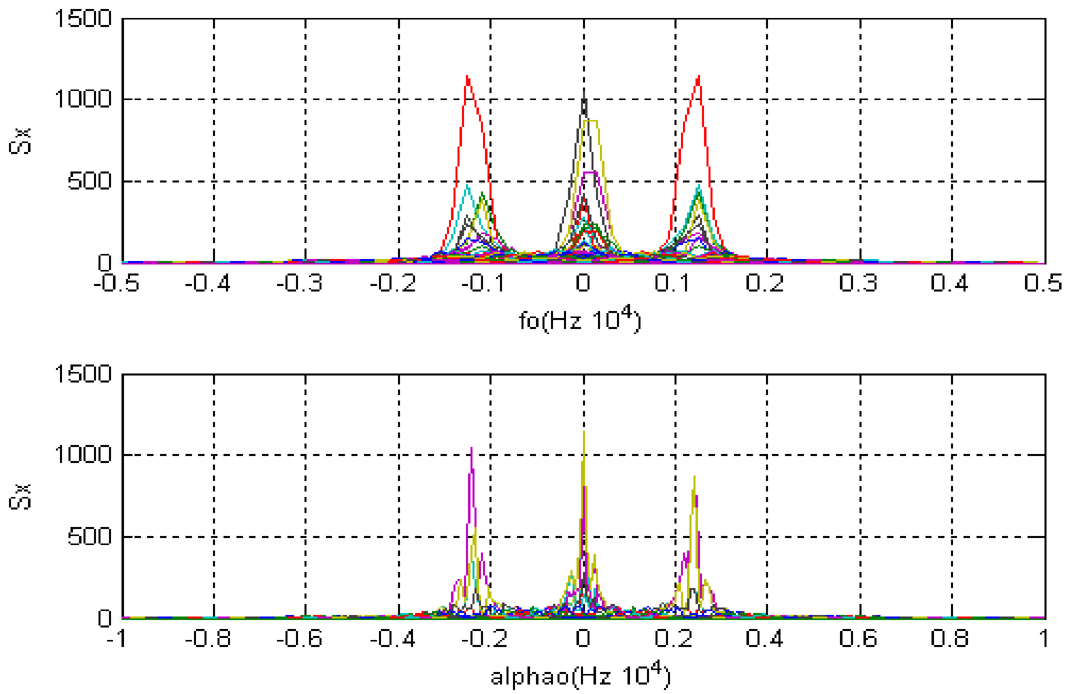


Figure 55. Plots of the SCD estimate magnitude for BPSK.

From Equation 4.47 we expect to obtain four terms of the SCD function forms. Four peaks at the points at f= ±fo = ±1012Hz, for α=0 and at the points α= ±2fo = ±2024Hz in which the experimental result in Figures from 50-52 agree with the expectation.

5. CONCLUSIONS AND FUTURE WORK

Cognitive radio systems introduce an innovative way to better utilization of the available spectrum. One critical challenge is to construct an efficient spectrum sensing method. For this reason several sensing methods (e.g. Cyclostationary, Matched Filter etc) are utilized to overcome this problem. In this thesis the work mainly concentrates on the sensing processes algorithms which are one of the main technical challenges that allow cognitive radio functionality to implement.

The main concepts of cognitive radio and the spectrum scarcity, also the artificial cognition and the main tasks which plays the significant role in cognitive radio system implementations were over viewed in Chapter one. Several fundamental issues are discussed based on cognitive radio system design, physical layer and cognitive radio receiver architecture. Also the new standard IEEE 802.22 was explored and has been reviewed in Chapter two. Different concepts of noise uncertainty, comparison between sensing methods and several important concepts on improving sensing process have been introduced in Chapter three.

Cyclostationary spectral analysis is a technique exploits the periodicities associated with modulated signals. It is one of the most promising methods that can be utilized to sense the spectrum. It enables signals with overlapping temporal spectra to be identified at their cycle frequency based on treating the signal under cyclostationary rather than stationary process. We consider in this thesis the time-smoothing approach that gives the basic equation for cyclostationary spectral analysis (the cyclic autocorrelation and cyclic spectral density) are reviewed in both deterministic and probabilistic approaches. The FAM and SSCA algorithms are simulated in MATLAB. In the simulation large amount of data are generated to get good resolution. Moreover different types of modulated signals such as AMDSB, ASK and BPSK has been evaluated. Decimation and data taper windowing are considered to reduce the number of computation. The results evaluated by these two algorithms can be displayed in different ways, such as surface plots, contour plots and cross-section plots. The main drawback of this method is the computational complexity in which that can be solved by improving the speed of existing algorithms and reducing the supported frequency area or completely new fast algorithms.

Obviously, our experimental study was to evaluate the theoretical result. A step which not evaluated in this thesis was an analysis and experimentation of the spectral correlation density function in the presence of white-noise and interferences.

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