ADAPTIVE SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

MAIN PROJECT REPORT

Submitted in partial fulfillment of curriculum

by

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List of Publications

1. Rishbiya Abdul Gafoor, Riya Kuriakose, Sibila M, Lakshmi C K, Reshmi S, Ashok S Kumar, "A Survey on Traditional and Advanced Spectrum Sensing in Cognitive Radio Networks", Communicated to *IEEE International Conference on Control, Power, Communication and Computing Technologies,* Kannur, Kerala, India, March 2018.

Abstract

Cognitive Radio (CR) is a capable technology, which has provided a different way to increase the efficiency of the electromagnetic spectrum utilization. CR allows unlicensed users or Secondary Users (SUs) to use the licensed spectrum through dynamic channel assignment strategies or spectrum access when the Primary Users (PUs) are in a dormant state to improve the spectrum utilization and hence avoid spectrum scarcity. For this we need intelligent spectrum sensing techniques which can detect the presence of spectrum holes and allocate them to the secondary users without interfering with the activities of the primary users. This project specifically investigates the performance of energy detector, matched filter, eigen value detection and wavelet based spectrum sensing. Using these techniques an adaptive spectrum sensing technique is proposed and their simulation is done in MATLAB.

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List of Abbreviations

AWGN	Additive White Guassian Noise
BPF	Band Pass Filter
CR	Cognitive Radio
CSD	Cyclic Spectral Density
CSS	Cooperative Spectrum Sensing
CWT	Continuous Wavelet Transform
DCAED	Double Constraints Adaptive Energy Detection
DWT	Discrete Wavelet Transform
EME	Energy with Minimum Eigen value
FCC	Federal Communications Commission
HPF	High Pass Filter
LPF	Low Pass Filter
MME	Maximum-Minimum-Eigen value
Pd	Probability of Detection
Pfa	Probability of False Alarm
Pm	Probability of Missed Detection
PU	Primary User
SCF	Spectral Correlation Function
SCN	Standard Condition Number
SCSD	Squares of magnitude of CSD
SNR	Signal to Noise Ratio
SU	Secondary User
WPT	Wavelet Packet Transform

Chapter 1

Introduction

1.1 Future of Wireless Communication

Radio frequency spectrum is a limited natural resource and its proficient use is very important. Over the past two decades there is an enormous progression in wireless communication, and we are now living in a world where there are ever-increasing number of wireless communication devices in operation. The rapid growth in wireless communications has contributed to a huge demand on the deployment of new wireless services in both the licensed and unlicensed frequency spectrum. However, recent studies show that the fixed spectrum assignment policy enforced today results in poor spectrum utilization.

Next generation communication systems are expected to provide higher data rate, good performance and simple data processing. In order to provide these requirements, higher bandwidth and large amount of power transmission are required. Inefficient use of spectrum made it a scarce commodity in many countries. Thus, efficient use of radio spectrum is a key feature of next generation systems. Energy efficient or environment friendly design is another feature that should be incorporated in the next generation networks. Consequently future wireless communication systems will rely on intelligent, less complex and power saving designs.

1.2 Cognitive Radio

The conventional method of electro-magnetic spectrum licensing and then utilizing it gave rise to static and inefficient use of available spectrum. The solution to this problem required the introduction of innovative licensing policies and proper coordination infrastructure which will enable dynamic use of radio spectrum and hence will increase the spectrum efficiency.

Cognitive Radio (CR) which was first proposed in late 1990s has been renowned as a suitable way to ameliorate spectrum efficiency of wireless communications by exploiting under-utilized licensed spectrum in frequency, spatial and temporal domains. Cognitive radio is a wireless communication system which is attentive of the environment and its changes and can adapt its transmission/receiver parameters accordingly with the objective of reliable communication whenever and wherever needed.

With the rapid growth of wireless applications, we are consuming more spectrum bands for wireless communications and the spectrum resources become critical. Cognitive Radio technology enables more efficient utilization of the spectrum. In cognitive radio networks, SU can opportunistically utilize the spectrum without interfering with PUs. To guarantee the SUs introduce no harm to PUs, SUs have to conduct spectrum sensing before accessing the spectrum. Spectrum sensing for CR has been a hot research topic for several years and a large number of sensing algorithms have been proposed. Depending on the prior knowledge available and the computational complexity involved, spectrum sensing techniques can be classified as matched filter detection, energy detection, cyclostationary detection etc.

Matched filter algorithm is originally designed for signal processing that can be used for spectrum sensing as well. It requires a huge amount of prior knowledge of the PUs such as the modulation schemes, data format, channel occupancy etc. As one of the simplest algorithms, energy detection has been widely advocated and studied. Given a spectrum being sensed, SUs measure the received signal strength at the spectrum and compare it with a given threshold. This threshold is assumed to be the energy level of the white noise at the location. And therefore when the measured signal strength exceeds this threshold, it implies that PUs are using the spectrum. Cyclostationarity can distinguish the signal and noise at low SNR. It use the autocorrelation function to compute the cyclic characteristics of a signal. When the cycle spectrum is high, it implies that there is a signal in the spectrum band and is being used by PUs.

1.3 Problem Definition

Each spectrum sensing techniques has its own pros and cons. Radio environment is changing constantly. Some sensing techniques work well under low SNR conditions while some other at high SNR. A single spectrum sensing technique cannot adapt according to the varying radio environment and hence it facilitates the need for a Adaptive Spectrum Sensing Technique.

1.4 Objective

To create an adaptive spectrum sensing technique using existing traditional spectrum sensing techniques like matched filter, energy detection and eigen value detection method. This scheme is proposed to adapt the sensing method according to frequently changing wireless environment and available information.

1.5 Motivation

The cognitive radio offers a very rewarding area of research field. Need of more spectrum due to the under utilization of the available spectrum is the main motivation behind cognitive radio and implementing it leads to lessening of spectrum scarcity and hence the optimal use of spectrum resources. Spectrum sensing which basically checks for the vacant or unused spectrum band forms the main part of the cognitive radio. There are different schemes based on which spectrum sensing is done like energy detector, matched filter detector, cyclostationary detector, eigen value based sensing, wavelet based sensing etc. Energy detector works very well in high SNR environments, matched filter detector needs much more information about the signal which is called priori information and the complexity of others is high. These constraints led to search for an optimal detector which performs well under low SNR conditions as well as high SNR conditions and with a complexity not so high.

1.6 Organization of the Report

Chapter 2 briefs literature review on traditional and advanced spectrum sensing techniques in Cognitive Radio networks. **Chapter 3** deals with the software used and the flowchart of adaptive spectrum sensing technique. **Chapter 4** shows the performance analysis of all sensing techniques independently as well as the analysis of Adaptive Spectrum Sensing Technique. **Chapter 5** gives the overall conclusion of the report and some of the future research areas which can be taken up in this field.

Chapter 2

Literature Review

2.1 Cognitive Radio Network

The Federal Communications Commission (FCC) is responsible for regulation of inter state telecommunication, management and licensing of electromagnetic spectrum within the United States and it enforces requirements on inter station interference in all radio frequency bands. They license segments to particular user's in particular geographic areas. A few, small, unlicensed bands were left open for anyone to use as long as they followed certain power regulations. With the recent boom in personal wireless technologies, these unlicensed bands have become crowded with everything from wireless networks to digital cordless phones.

To combat the overcrowding, the FCC has been investigating new ways to manage RF resources. The basic idea is to let people use licensed frequencies, provided they can guarantee interference perceived by the primary license holders will be minimal.Thus cognitive radio technology was proposed.

CR is defined as "A CR is a software defined radio that can interact with its neighbouring environment and respond based on its findings by changing its transmission parameters (e.g transmission power, modulation technique and transmission frequency) using an intelligent approach" [1].

Two types of users are defined for operation of cognitive radio. They are Primary Users (PUs) and Secondary Users (SUs). A PU is a user of primary network which has a license to operate in a certain spectrum band. A PU should not be affected by any unlicensed user or user of any other network. Therefore, primary users do not need any change for coexistence with Cognitive Radio base-stations and Cognitive Radio users. Cognitive Radio user or Secondary User (SU) has no spectrum license for its operation so some additional functionality is required to share the licensed spectrum band. CR technique is a new concept that allows the spectrum to be utilized by the SU without causing interference to PUs by detecting the unused spectrum, also known as spectrum holes or white spaces as shown in figure 2.1 [2].

CR has two main characteristics called cognitive characteristics as follows.

2.1.1 Cognitive Capability

It is the capability of the CR to sense the radio spectrum using refined techniques and to identify the appropriate parameters to adapt to varying environment. Figure 2.2 shows a cognitive cycle [3],[4],[5].

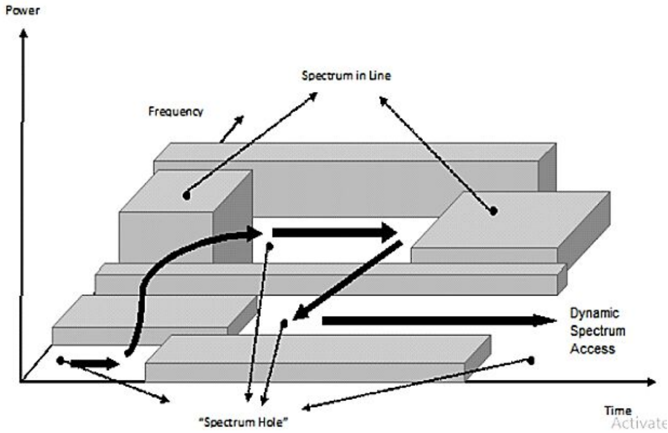

Figure 2.1: Spectrum hole concept

The main steps in cognitive cycle are

- **Spectrum sensing** : A CR senses the available radio spectrum, collects their information and detects the spectrum holes.
- **Spectrum analysis**: The characteristics of the detected spectrum hole is analysed through spectrum sensing.
- **Spectrum decision**: It is the ability to select the best available band for the communication of SU depending on the characteristics identified and requirement of the user.

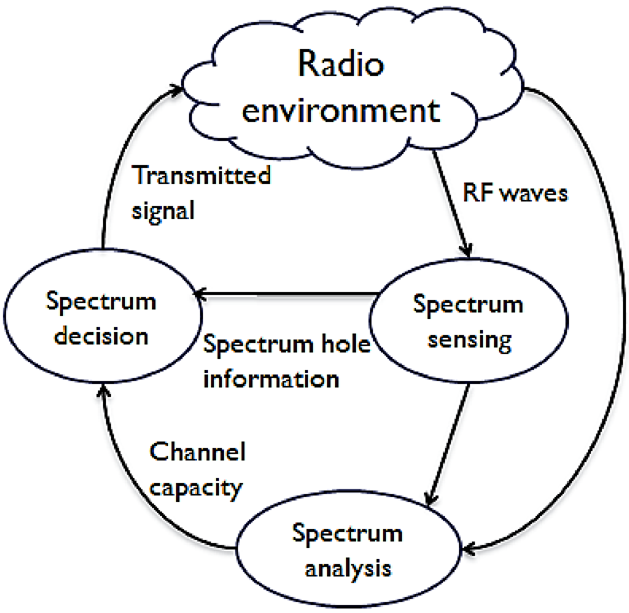

Figure 2.2: Cognitive Cycle

2.1.2 Reconfigurability

It is the ability of the CR to adapt to the changes in operating parameters without any change in hardware components while the CR is functioning . Its parameters are

- Modulation techniques
- Operting frequency
- Transmission power
- Communication technology

2.2 Spectrum Sensing Techniques

Spectrum sensing allows CR users to study about the radio environment by sensing the presence of an event using one or more sensors. It detects the PU's signal transmission in a given time to make a decision about transmitting in a particular frequency band [6]. The spectrum sensing model can be formulated as follows:

$$y(n) = w(n) \qquad H0 : \text{PU absent} \tag{2.1}$$

$$y(n) = s(n) + w(n) \qquad H1 : \text{PU present} \tag{2.2}$$

where n = 1.....N, N is the sample number, y(n) is the received SU signal, s(n) is the PU signal, w(n) is the additive white Gaussian noise with zero mean and variance σ^2.$H0$ denotes the PU signal is absent , and $H1$ denotes the PU signal is present. The output T of the detector is compared with a threshold value to make the accurate decision [7].

$$\text{if } T \geq \text{threshold, PU signal is present} \tag{2.3}$$

$$\text{if } T < \text{threshold, PU signal is absent} \tag{2.4}$$

If PU signal is absent, SU can start to transmit its streams; or else, SU stops its transmission. Fig 2.3 represents the general model of spectrum decision.

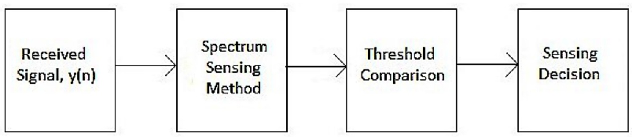

Figure 2.3: General model of spectrum sensing

Spectrum sensing techniques can be classified as shown in figure 2.4. Transmitter detection methods involves only one cognitive user who performs sensing and takes decision by itself. Transmitter detection method involves energy detection, matched filter detection, cyclostationary feature detection and eigen value based detection. Cooperative sensing mathods involve multiple CR users and shares their sensing information with each other for better performance and accuracy. Cooperative sensing methods can be of 3 types as given below.

- **Centralized Spectrum Sensing:** In centralized sensing, a central unit called cluster head or server collects sensing information from cognitive devices, identifies the unused spectrum, and transmits this information to other cognitive radios or directly controls the cognitive radio traffic.
- **Distributed Sensing:** In distributed sensing, cognitive nodes share intra cluster information among other cluster nodes, which make their own decisions as to which part of the spectrum they can use. Distributed sensing is more advantageous than centralized sensing in the sense that there is no need for an extra infrastructure and hence reduced cost.
- **Hybrid Sensing:** In hybrid technique, CR shares information in decentralized method. Each user will independently identify the channel. When the primary user arrives it vacates the channel immediately without informing other nodes. The detection time in this technique is less but it requires dedicated hardware for cooperation, which will increase the hardware cost.

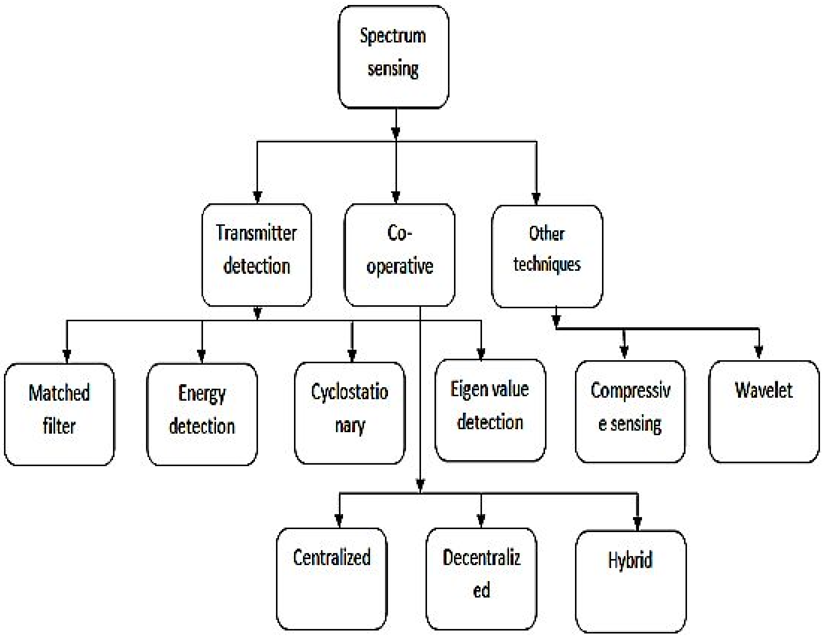

Figure 2.4: Classification of spectrum sensing techniques

2.3 Matched filter detection

Matched filter is an optimal detection method of an unknown signal. Detection of unknown signal is done by matching it with a known signal or its template. In the presence of the Additive White Gaussian Noise (AWGN), matched filter maximises the signal to noise ratio of the received signal [8]. The transmitted signal from the PU is passed through the matched filter in the presence of AWGN, to maximize the SNR. It is also known as non-coherent detection. To detect the presence or absence of PUs activity ,the matched filter correlates the unknown signal (from PU) with an already known signal. It is equivalent to convolving the PU's signal and its own delayed version. The whole process is clearly depicted on figure 2.5 where H1 indicates presence of PU's and H2 indicates absence of PU's.

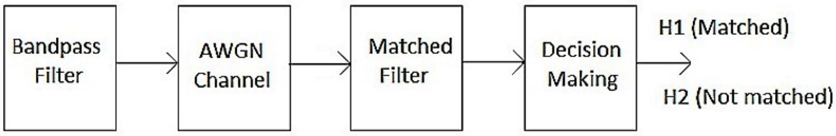

Figure 2.5: Block diagram of matched filter detection

A matched filter is a linear filter designed to maximize the output signal to noise ratio for a given input signal [9]. Matched filter detection is applied when secondary user has a prior knowledge of primary user signal. The prior knowledge include modulation type, order, the pulse shape and the packet form. The sensing is performed by correlating the observed signal with the known sample to detect the presence of PU.

In matched filter technique, the received signal y(t) is given by

$$y(t) = x(t) + n(t) \tag{2.5}$$

where x(t) is the transmitted signal or primary user signal and n(t) is the additive white noise with zero mean and variance σ^2. Then by applying the matched filter to the received signal i.e by convolving the known signal with the unknown signal as

$$z(t) = mf * y(t) \tag{2.6}$$

where mf is the matched filter gain.

Advantages: Matched filter detection needs less detection time because it requires a very few samples to meet a given probability of detection constraints. When the information of primary user is known to the CR user, matched filter detection is the optimal detection in stationary Gaussian noise.

Disadvantages: Matched filter detection requires a prior knowledge of every primary user, if this information is not accurate, the matched filter performs poorly.

Inorder to increase the efficiency of the sensing detection, a matched filter with an estimated and dynamic sensing threshold is proposed in [10].

A matched filter based spectrum sensing with a new cognitive radio in which the PU transmits with one of multiple power levels randomly is proposed in [11]. Such a consideration well matches the practical standards and the theoretical demands for power adaptation.

A matched filter based spectrum sensing with SU having multiple antennas where as PU is equipped with single antennas is proposed in [12]. Here the SU knows PU's training signals due to some prior cooperation. Later on deriving the optimum matched filter detector for identifying the presence of PU and the current transmit power level when it is detected. Apart from the conventional CR detector, which uses only one threshold to differentiate the presence and the absence of PU, here multiple thresholds are calculated to identify PU's power levels.

2.4 Energy detection

Energy detection is one of the most common method of spectrum sensing in cognitive radio networks. An energy detector involves a Band Pass Filter (BPF) followed by a square law device and an integrator. The received signal are filtered by BPF and helps in reducing the noise bandwidth which in turn makes the noise at the input of square law device to have a band limited and flat spectral density. The integrator integrates its input and gives an output which is equal to the energy of the signal present at the input of square law device for a time interval of T. Inorder to decide whether there is a PU present, the output from integrator is compared with a threshold. The block diagram of energy detection algorithm is shown in figure 2.6 [13].

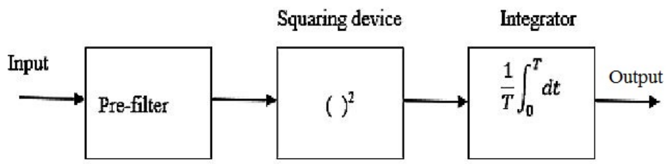

Figure 2.6: Block diagram of energy detection

The goal of energy detector is to identify the sample signal, find its energy and then compare it with a threshold to detect the presence or absence of the PU [14]. This is formulated as an hypothesis test as H0 and H1 as given by eqn(1) and eqn(2).

The performance of energy detector is specified by the following parameters.

1. *Probability of detection* P_d
   It is the probability of the energy detector to make a correct decision. It indicates the level of protection provided to PUs from SUs interference. It should be high.

2. *Probability of false alarms* P_{fa}
   It is the probability of the occurrence of the event such that the detector makes a decision of H1 when the right decision was exactly H0 (refer eqn(1)and eqn(2)). Because of the false alarm event, the SU would miss a chance to make use of the free channel. Therefore this should be kept small inorder to avoid the underutilization of the spectrum. $\mathrm{P_{fa}} <$ 0.1 as per IEEE standard.

3. *Probability of missed detection* P_m
   It is the probability of the occurrence of an event such that the detector makes the decision H0 when the right decision was exactly H1. If this event occurs there is a chance of causing interference to PUs by SUs. Hence $\mathrm{P_m}$ should also be kept small [15].

Advantages: Requires no prior information of PU signal. It is less complex and easy to implement.

Disadvantages: Since there is no prior information of PU signal, it does not differentiate between PU signals and noise properly. Its performance degrades in fading environments and does not work well in low SNR regions.

In basic energy detection, the sensing duration is fixed to an optimum quantity based on interference caused to PU in the worst case.If the sensing duration is fixed , then there is a chance that the SNR may become high after the sensing interval. This may lead to a false alarm event and inefficient spectrum utilization. Inorder to tackle this problem, the spectrum sensing can be made adaptive based on the instantaneous received SNR. This method is proposed in [16]. In fading environments, this method can enhance the performance of energy detection.

In order to overcome the problem of fixing threshold many methods have been proposed. Hyon-Ho Choi proposed a method of adaptive threshold based on the power of SU transmission in [17]. To enhance the spectrum sensing in low SNR regions, a novel adaptive threshold based energy detection is proposed in [18].

Spectrum sensing based on Double Constraints Adaptive Energy Detection (DCAED) is proposed in [19]. DCAED makes the threshold adaptive by exploiting the interrelationship between probability of detection $\mathrm{P_d}$ and probability of false alarm $\mathrm{P_{fa}}$. It is better than basic energy detection and adaptive energy detection but the value of $\mathrm{P_{fa}}$ is slightly higher than the value specified according to IEEE standard. In order to increase $\mathrm{P_d}$ and reduce $\mathrm{P_{fa}}$, multi slot DCAED is propose in [20]. It splits each spectrum sensing slot into multiple mini slots. Spectrum sensing is performed in each mini slot by using DCAED. Finally, a decision fusing process combines decisions from each mini slot and determines if PU is present or not [21].

2.5 Cyclostationary feature detection

It make use of the cyclostationary features of PU signal to determine the presence of PU signal. A signal is said to be cyclostationary if its mean and auto correlation are periodic w.r.t a time period. These cyclostationary features are due to the periodicity from carrier waves, hopping sequences or pulse trains that are associated with modulation of PU signal. These cyclostationary features cannot be found in any interference signal or stationary noise. Hence these features can be exploited to identify the PUs. This method has higher noise immunity than energy detection especially in low SNR regions. Here, Cyclic Spectral Density CSD or cyclic Spectral Correlation Function (SCF) is used for detecting the PU signals. By plotting SCF, we can find out if spectrum is occupied by PU or not. A peak in the centre of SCF indicates the presence of PU and vice versa [22].

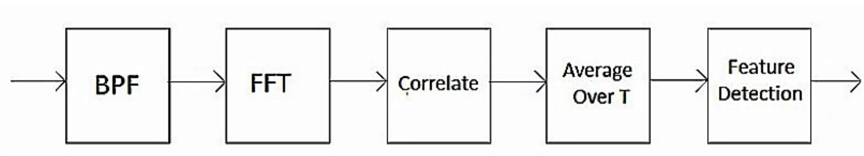

Figure 2.7: Block diagram of cyclostationary feature detection

The block diagram of cyclostationary feature detector is shown in the figure 2.7.

Advantages:It performs better than any other detection method in the low SNR regions. Also, cyclostationary spectrum sensing method can be used to find out the type of modulation scheme used by the PU signal.

Disadvantages:It requires long sensing duration and has highly complex circuitry. Because of the high complexity involved , it also costs high.

Inorder to reduce the circuit complexity of this method, a blind cyclostationary spectrum sensing is proposed in [23]. Here, instead of finding CSD , sum of Squares of magnitude of

CSD (SCSD) is found out and used for the detection. This method has relatively low power consumption.

Inorder to enhance the CR throughput and reduce the sensing duration, wide band spectrum sensing can be used [24]. To enable fast sensing in wideband spectrum, a cooperative cyclostationary compressed algorithm is proposed in [25]. This algorithm has two stages. The first includes the cooperation between SUs and recovery of signal spectrum using compressive sensing whereas the second stage contains the cyclic feature detection.

2.6 Eigen value based spectrum sensing

To overcome the problems of the above mentioned sensing techniques, Eigen value based detection method, which uses the eigen values of the covariance matrix of the received signal, is proposed [26]. The major part of a CR is its detector. The detection method is usually based on eigen value analysis, when the device has multiple antennas [27].

In eigen based detection method, there is no correlation among the received signals and the non diagonal element of the covariance matrix is zero and diagonal elements contain noise variance, when there is no primary signal [28].
The detection methods are classified based on the Eigen values of the sample covariance matrix as below:

1. Maximum-Minimum-Eigen value (MME)
2. Energy with Minimum Eigen value (EME)

MME detection: In this, the ratio of maximum and minimum eigen value is compared with a threshold value. The decision is given by comparing the calculated value with threshold value , and the threshold value doesn't depends on the noise variance.

EME detection: In this, the ratio of average energy and the minimum eigen value is compared with a threshold . The decision is made if the ratio of average power of the received signal with minimum eigen value is greater than the set of threshold value.

Most of the eigen value based techniques identifies the presence of white noise at the CR receiver. Even then, noise may be correlated due to the imperfections in interference, filtering and oversampling.

The effect of noise correlation on eigen value based spectrum sensing technique is analyzed by using a Standard Condition Number (SCN) of the noise covariance matrix [29]. The SCN of a matrix is defined as ratio of the maximum eigen value to the minimum eigen value. An SNR estimation technique based on maximum eigen value of the received signal's covariance matrix have also been proposed.

Another method for sensing under noise correlation is proposed in [30]. A sensing threshold proposed for the uncorrelated scenario may not be suitable for sensing threshold in presence of noise since the value of noise correlation deviates from its value in uncorrelated scenes. In order to derive sensing threshold, Random Matrix Theory (RMT) is used. This threshold is used for sensing the presence of noise. The performance is evaluated in terms of false alarm deviation and probability of correct decision.

$$\text{False alaram deviation} = \text{observed P}_{fa} - \text{target P}_{fa} \tag{2.7}$$

where P_{fa} is the probability value of false alarm.

Advantages: The most important advantage of eigen value based spectrum sensing is that it does not require any prior information of the PU's signal and especially in presence of noise covariance uncertainty, it outperforms energy detection techniques.

Disadvantages: Its complexity is high.

2.7 Cooperative spectrum sensing

It refers to those spectrum sensing methods where the information from more than one CR user is incorporated for primary user detection.

The hidden terminal problem, which occurs when the CR is shadowed is one of the greatest challenges of implementing spectrum sensing. A CR may fail to notice the presence of PU, due to hidden terminal problem, and then will access the licensed channel and cause interference to the licensed channel. Inorder to deal with this problem in CR network, multiple cognitive users can cooperate together for spectrum sensing [31].

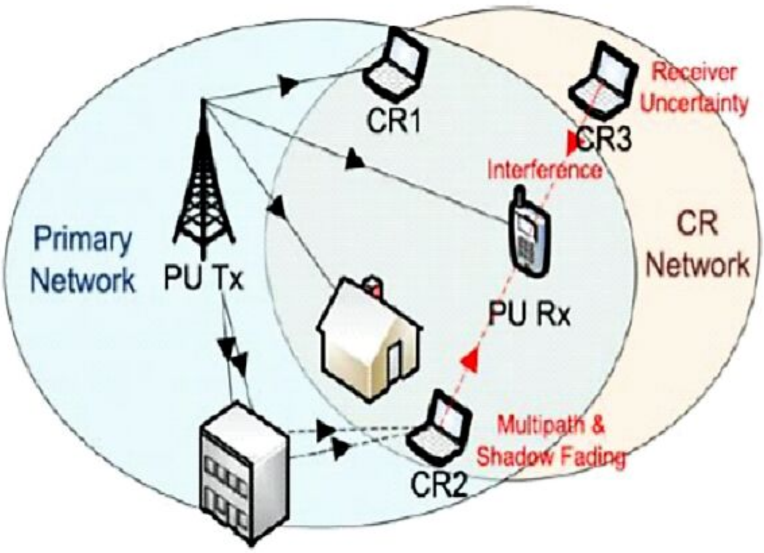

Figure 2.8: Receiver uncertainty and multipath/shadow fading

In figure 2.8, multiple path fading, shadowing etc are illustrated. As shown CR1 and CR2 are inside the transmission range of primary transmitter (PU TX) and CR3 is outside the range. CR2 experiences multiple path and shadow fading, due to multiple attenuated copies of PU signal and blocking of a house and finally PU's signal may not be correctly detected.

The sensing performances are enhanced by cooperative spectrum sensing by exploiting the spatial diversity of spatially located CR users. By cooperation, the sensing information can be shared by multiple CR users for making a combined decision which are more accurate than individual decisions.

In general, cooperative spectrum sensing is performed as follows:

Step 1: Every CR j will perform local spectrum measurements and then makes a binary decision $B_j \epsilon [0\ 1]$ for all $j = 1........K$

Step 2: These binary decisions from all the CR users are then passed to a common receiver.

Step 3: The common receiver will then combine all the binary decisions and make a final decision D0 and D1 to categorize the absence or presence of the PU in the observed frequency band. Here, each cooperative partner will make a binary decision based on its local observation and then pass one bit to the receiver. All one bit decisions are clubbed together at the receiver according to the given rule:

$$R = \sum_{j=1}^{K} B_j = \begin{cases} D1, \geq n \\ D0, < n \end{cases} \tag{2.8}$$

where $D1$ and $D0$ represent the inferences that the PU signal is transmitted or not transmitted.

As stated above, Cooperative Spectrum Sensing (CSS) and its related problems have been studied in many ways. How ever it has been rarely studied how to collect the spectrum sensing data of secondary users for cooperative sensing even though this is a critical problem. One of the possible methods for solving this issue is to use Random Access approach [32]. In this, special slots are not allocated to secondary users for the report of sensing data. As an alternative SU report their sensing data in a random manner.

In order to minimize the sensing delay of the SU, a CSS scheme, under the structure of PCA [33] with sequential detection mechanism, is proposed which is based on machine learning technique.

The cost of sensing data can agreeably be defined as a means to signify the resource spent (such as energy) or opportunities sacrificed for sensing (such as sensing duration). Various cooperative methods that will minimize the cost of sensing data are explored in [34].

Even if, CSS offers significant advantages it may have some disadvantages including energy consumption. Hence a new energy based sensor selection cooperative algorithm is proposed in [35]. Here, the SUs that consume less amount of energy for CSS and not encounter energy constraints help those with energy constraints in order to keep them alive longer. That is SUs which are sensing properly are dynamically selected with respect to their energy constraints. In this way, this algorithm provides all SUs with almost same life time. Various energy efficient techniques in CSS including local sensing, reporting diffusion fusion etc. are proposed in [36].

2.8 Wavelet transform spectrum sensing

This transform decomposes the signal into mutually orthogonal set of wavelets. This is different from the Continuous Wavelet Transform (CWT). Wavelets provide a better way to tackle spectrum sensing. This method is easier and more reliable compared to conventional energy detector.

Discrete Wavelet Transform (DWT) is a transform technique to analyze the signals [37], [38], [39]. Here the signal are represented in terms of coefficients of scaling and wavelet functions ϕ(t) and ψ(t) respectively. Decomposing a signal by means of wavelet transform is same as passing the signal through a high pass filter and low pass filter [40].

The algorithm can be summarized as:

- Perform DWT for the required number of levels of decomposition.
- Calculate the power in each bands.
- Power to bandwidth ratio for each bands are calculated.
- In case the estimated R is relatively high, bands with minimum power can be directly categorized as unoccupied since the contribution of the power is mostly due to noise.
- In case the estimated R is relatively low, arrange the bands in ascending order and the bands with minimum power are again scanned using some other better spectrum sensing techniques.

Another method includes a novel based wavelet transform spectrum sensing algorithm known as WATRAB [41]. The very basic idea is, the signals of PU only carry a limited amount of information, while the noise can be considered as having many. By carefully selecting a wavelet transform method, such a difference can be exploited to generate very different transform results.

Wavelet transformation algorithm is to be applied in determining whether the original received wave from antenna holds signals or not i.e $H1$ or $H0$ (refer eqn(1) and (2)), as shown in figure 2.9.

Here, we use a mixture and a combination of LPF and HPF in case of a bandpass filter and then apply the daubechies db4 wavelet transform. We can see that the signals will remain nearly unaffected after the transform, whereas noises will be intensely affected. Wavelet transform is sufficient for identification of information for low frequency but not in high frequency band.

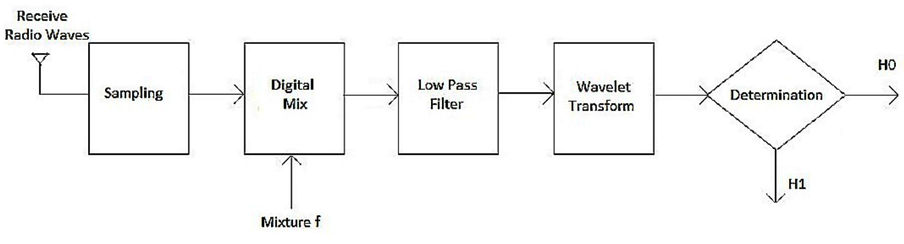

Figure 2.9: General architecture of WATRAB

The Wavelet Packet Transform (WPT) has the capability to identify information in high frequency band also in comparison to WT. WPT is an ideal tool for handling non stationary

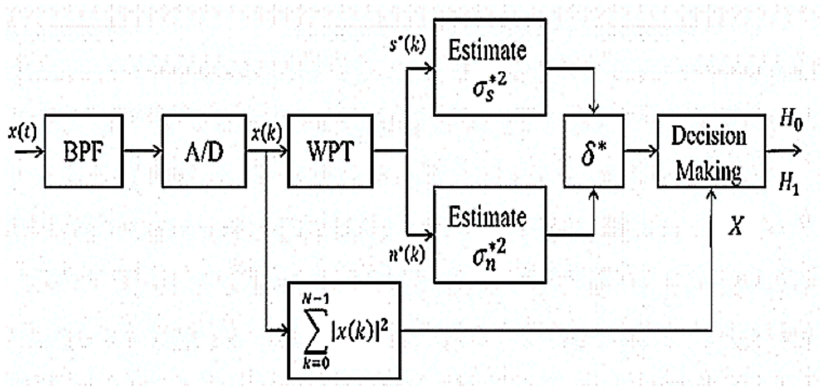

Figure 2.10: Energy Detection based on WT

time variable signal. Energy detection algorithm based on WT for spectrum sensing is shown in figure 2.10 [42].

Its operation can be summarized as:

Case 1: If X> δ^*, the PU are currently using the channel and so the channel shall not be allotted to the SU.

Case 2: If X< δ^*, the channel is not occupied by PU. So that channel can be allotted to SU to be used at this instant.

The major advantage of wavelet transform includes low computational cost and reduced SNR.

2.9 Compressive sensing

Compressive spectrum sensing technique which is based on compressive signal processing provides good accuracy at lower complexity[[43],[44]. According to Nyquist-Shannon theorem, every band limited energy signal can be recovered from its discrietization if its sampling rate is atleast two times its highest frequency component. If the sampling rate is less than Nyquist rate then it leads to loss of information commonly termed as aliasing. Compressive sensing goes against this common wisdom of data acquisition and allows for signal recovery at rates much lesser than Nyquist rate. This reduces sampling rate and computational complexities.The application of compressed sensing technique and the resulting improvement of energy efficiency is proposed on [45]. This algorithm is also applicable to multi antenna cognitive radios [46].

However, there are two significant challenges:

1. Choosing an appropriate number of sub-Nyquist measurements.
2. Deciding when to terminate the greedy recovery algorithm that reconstructs wideband spectrum.

An Autonomous Compressive Spectrum Sensing (ACSS) framework is presented in [47]. This enables a CR to choose the number of measurements automatically. At the same time it guarantees the wideband spectrum recovery with a predictable small recovery error. A method of dynamic compressive sensing measures the channel powers continuously and recovers the occupied channels in a dynamic environment [48].

2.10 Overview of spectrum sensing techniques

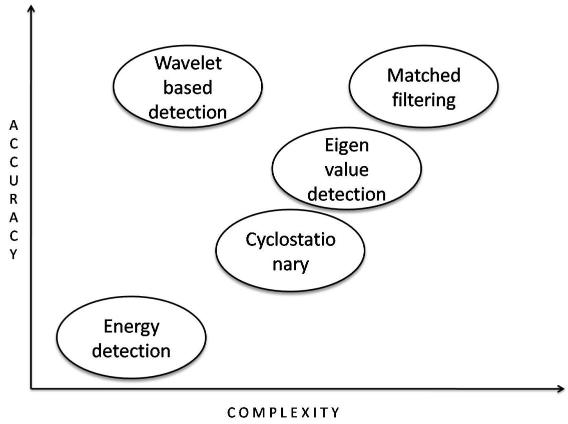

Figure 2.11: Accuracy vs complexity for spectrum sensing techniques

Figure 2.11 shows that accuracy is highest for wavelet based detection and has lowest complexity. Matched filtering also has high accuracy but its complexity is also high. Energy detection is the most simplest method but has the lowest accuracy. Eigen value detection has moderate accuracy as well as complexity.

Chapter 3

Methodology

3.1 Software Introduction

MATLAB is an interactive, matrix-based system for scientific and engineering numeric computation and visualization. MATLAB,short for MATrix LABoratory is a programming package specifically designed for quick and easy scientific calculations.Its strength lies in the fact that complex numerical problems can be solved easily and in a fraction of the time required with a programming language such as Fortran or C. It has literally hundreds of building functions for a wide variety of computations and many tool boxes for specific research disciplines, including statistics, optimization. It is also powerful in the sense that by using its relatively simple programming capability, MATLAB can be easily extended to create new commands and functions.

3.2 Flowchart

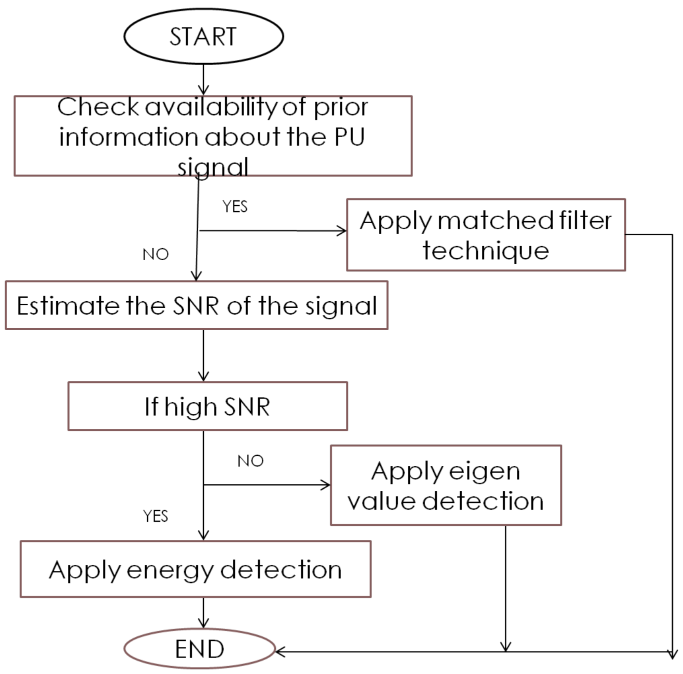

Figure 3.1: Adaptive Spectrum Sensing

At the secondary user: If primary user signal knowledge is known matched filter detection is used. Else estimate the SNR of the primary user signal. If SNR is greater than the threshold set, energy detection is applied else go for eigen value detection.

From the survey conducted, it has been found that accuracy and complexity of eigen value detection is more whereas wavelet based spectrum sensing can provide better accuracy in low SNR regions with low complexity. Hence in low SNR region eigen value detection can be replaced by wavelet based detection. Therefore flowchart can be modified as shown in figure 3.2

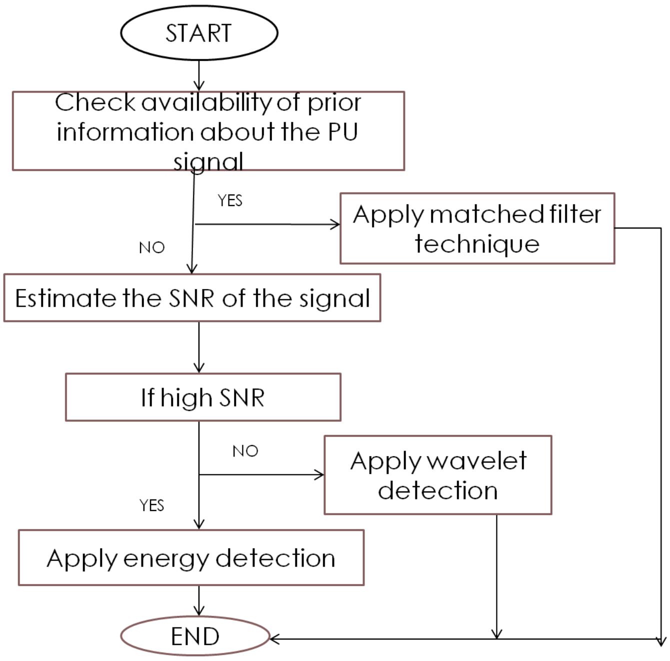

Figure 3.2: Modified flow chart

Chapter 4

Results

Here we present the simulation results and evaluate the performance of the three different spectrum sensing algorithm considering the parameters such as probability of detection, probability of false alarm and signal to noise ratio. Then we have showed the adaptive spectrum sensing scheme to adapt the method according to the frequently changing wireless environment and the available information.

4.1 Simulation of Energy Detection

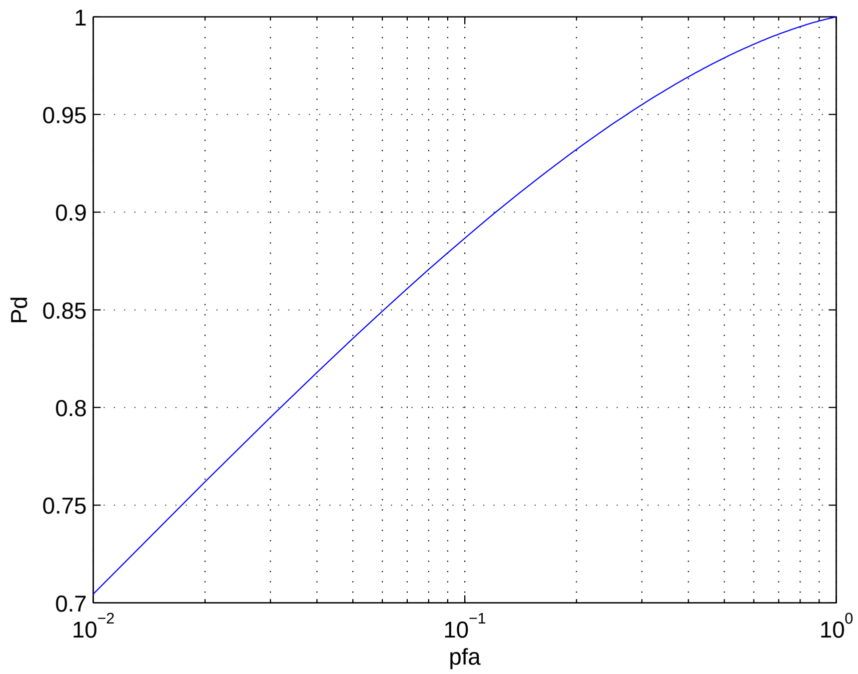

Figure 4.1: Plot of Pd vs Pfa for energy detection

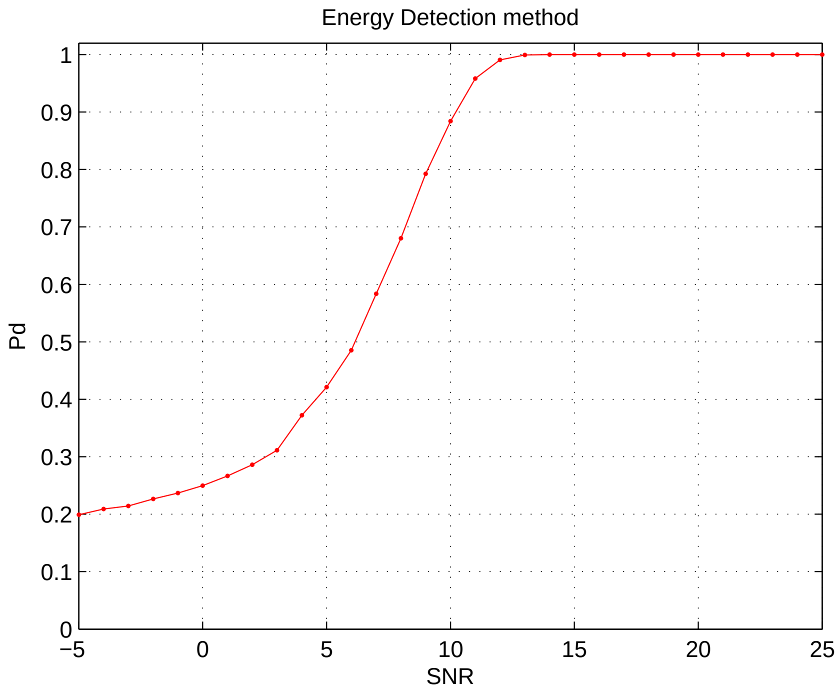

Figure 4.2: Plot of Pd vs SNR for energy detection

Figure 4.1 shows a plot of Pd vs Pfa for SNR = 10db for energy detection. It is observed that there is a trade off between Pd and Pfa values. For Pfa values from 0.09 to 0.8 the detection probability is optimum. After that the detection probability approaches 1 for SNR=10db. Figure 4.2 shows the plot of Pd vs SNR for Pfa=0.1. From the graph it is observed that for increasing SNR values there is a linear increase in the probability of detection. For low values of SNR the detection probability is almost 0. Above 10db the detection probability approaches one.

4.2 Simulation of Matched filter detection

Matched filter detection is used when prior information about user is known. Therefore it has the highest accuracy among all other methods.

Figure 4.3 shows plot of Pd vs Pfa for matched filter detection. It shows that as probability of detection increases, the probability of false alarm also increases.

Figure 4.9 shows the plot of Pd vs SNR for Pfa=0.1 for matched filter detection. The detection probability is high even for low values of SNR. Above 5db the detection probability reaches 1.

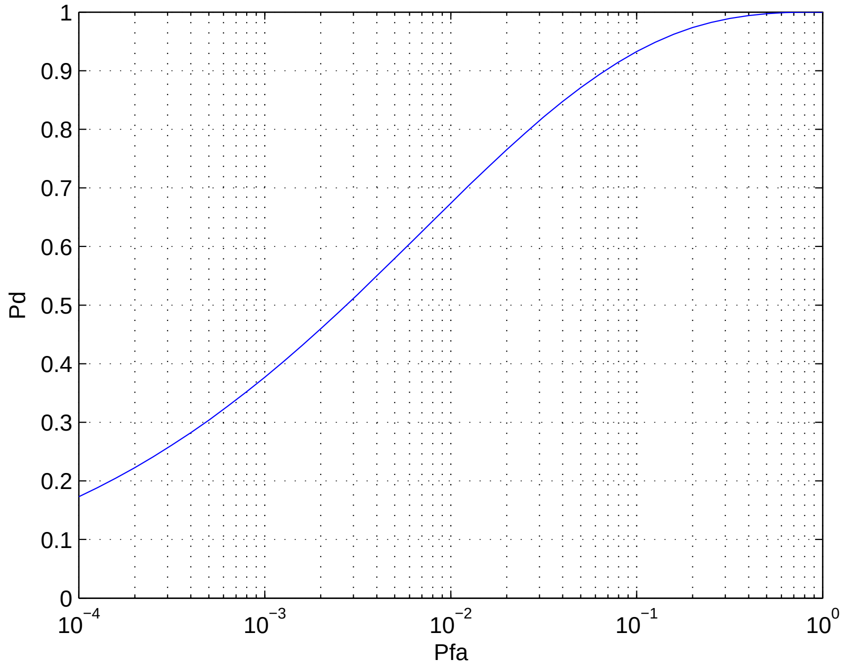

Figure 4.3: Plot of Pd vs Pfa for matched filter detection

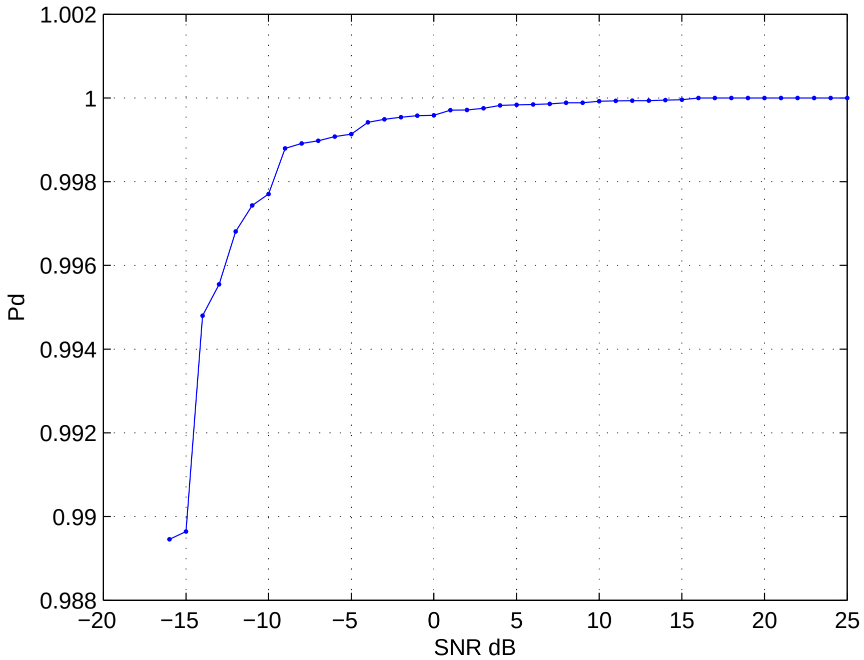

Figure 4.4: Plot of Pd vs SNR for matched filter detection

4.3 Simulation of Eigen value detection

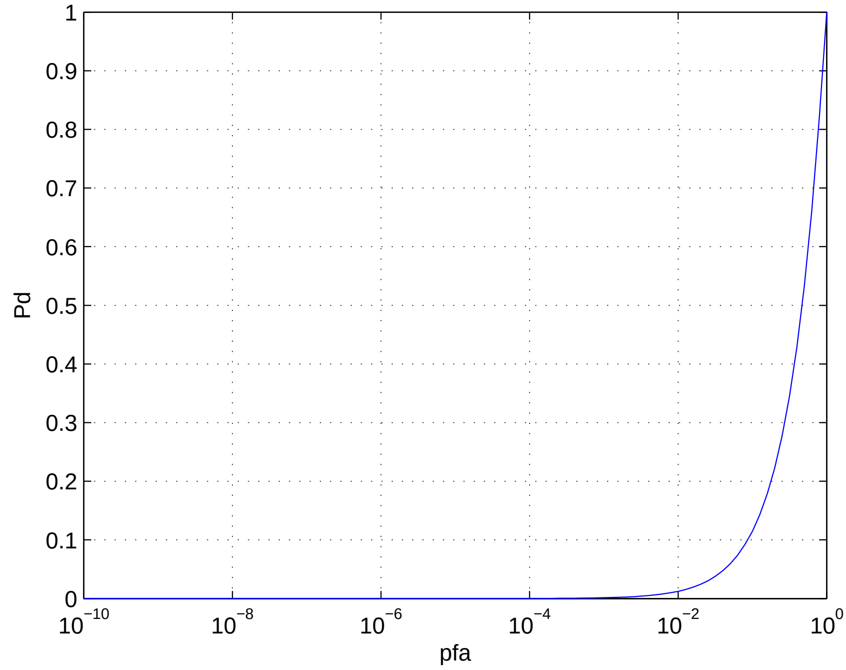

Figure 4.5: Plot of Pd vs Pfa for eigen value detection

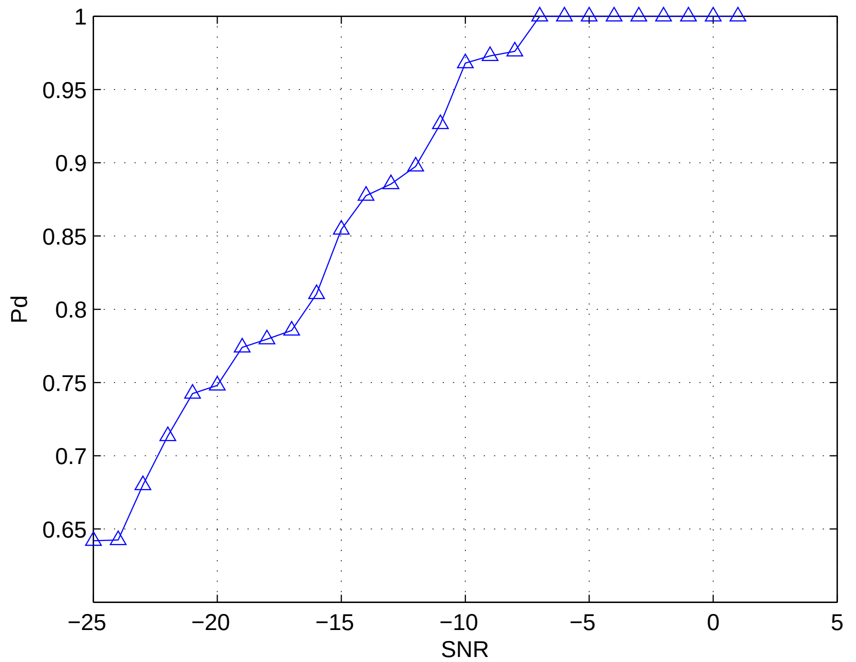

Figure 4.6: Plot of Pd vs SNR for eigen value detection

Figure 4.5 shows a plot of Pd vs Pfa for eigen value detection. It is observed that the detection probability is optimum for eigen value detection. The detection probability approaches 1 for Pfa values greater than 0.01. Figure 4.6 shows the plot of Pd vs SNR for Pfa=0.1. It is observed that for increasing SNR values there is a linear increase in the probability of detection. The Probability of detection is high even for low values of SNR. Above -6db the detection probability reaches 1.

4.4 Simulation of Wavelet based Spectrum Sensing

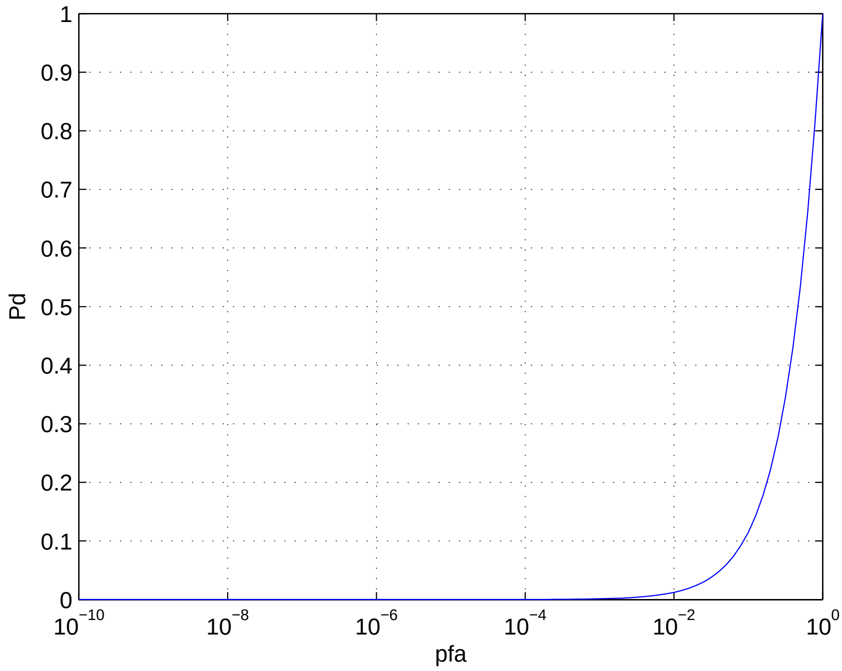

Figure 4.7: Plot of Pd vs Pfa for wavelet based detection

Figure 4.7 shows plot of Pd vs Pfa for wavelet based detection. The detection probability approaches 1 for Pfa values greater than 0.01. Figure 4.8 shows the plot of Pd vs SNR for wavelet based detection.

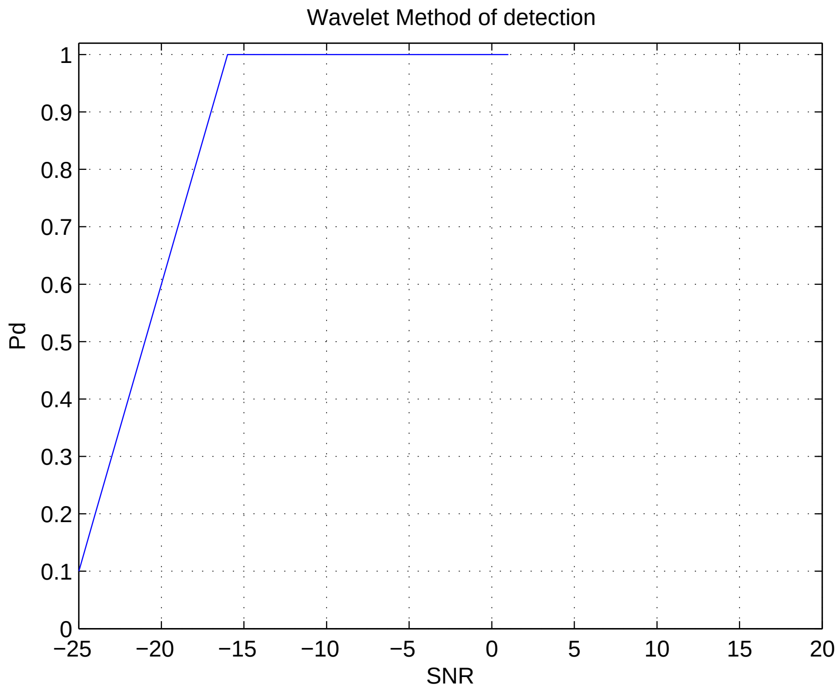

Figure 4.8: Plot of Pd vs SNR for wavelet based detection

4.5 Simulation of Adaptive Spectrum Sensing

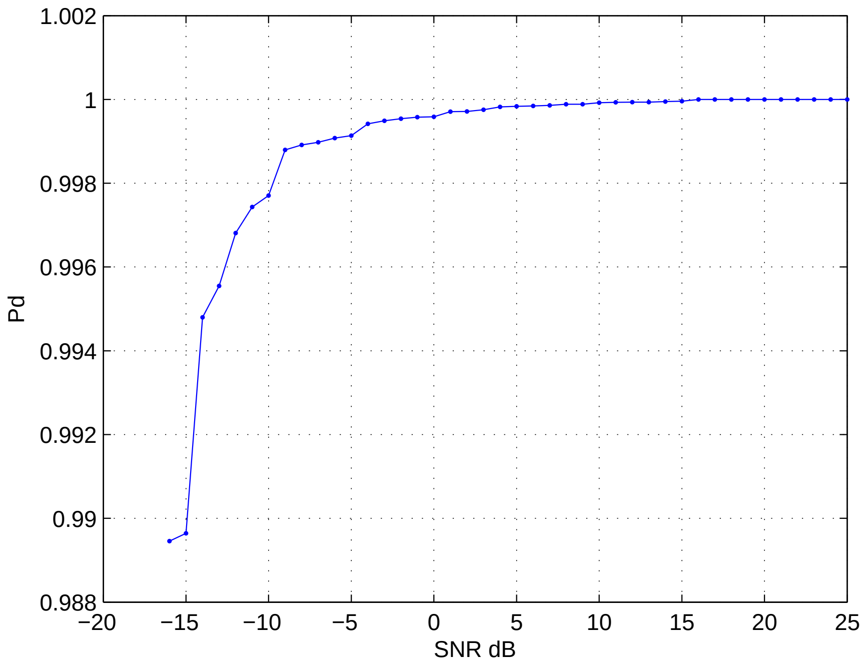

Figure 4.9: Plot of Adaptive Spectrum Sensing with prior knowledge about primary user (matched filter)

Figure 4.9 shows the plot of adaptive spectrum sensing with prior knowledge about primary user available. It is the same as the plot of matched filter detection.

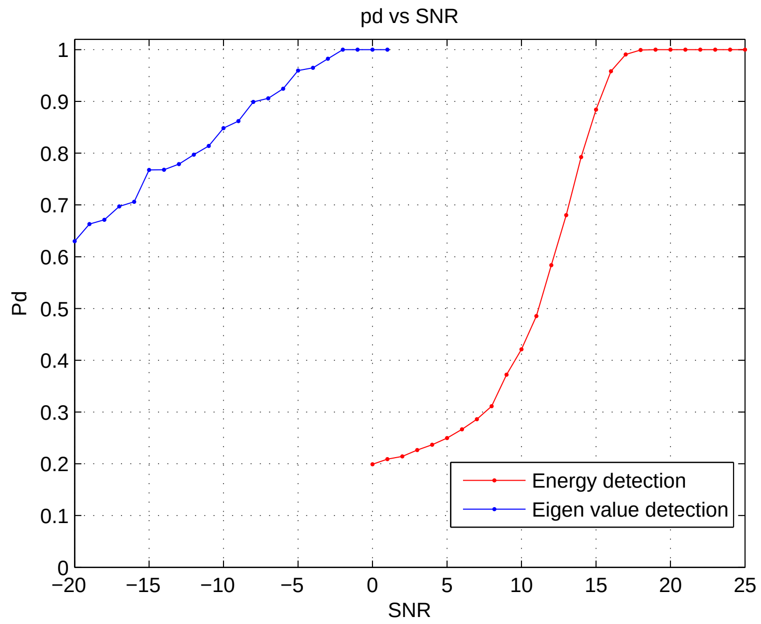

Figure 4.10: Plot of Adaptive spectrum sensing without prior knowledge about primary user

In figure 4.10, for low SNR regions, it uses eigen value detection and switches to energy detection when the SNR becomes high. Here switching take place at around 0-5 dB.

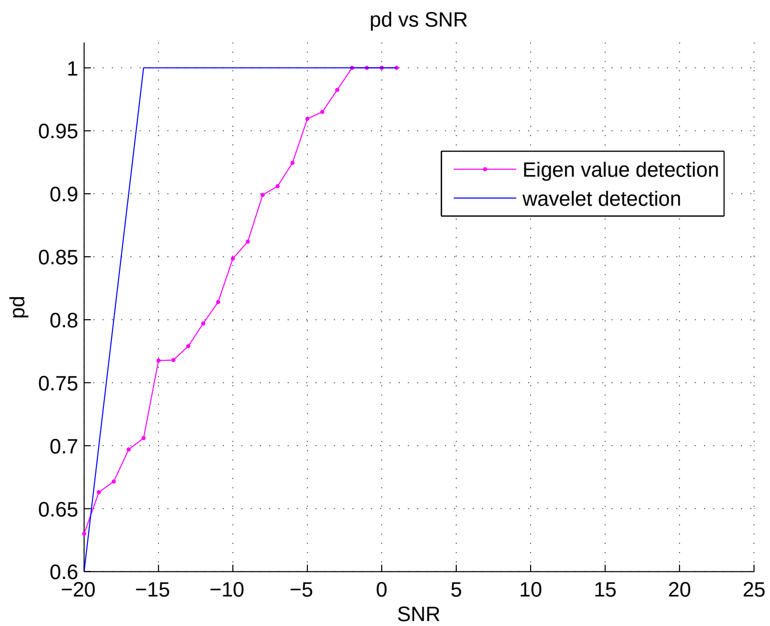

Figure 4.11: Comparison of eigen value and wavelet based detection

From figure 4.11 it can be found that wavelet based spectrum sensing has a high probability of detection for -20 to -5 dB where as eigen value detection has a lower probability of detection over the same range. Also effect of noise is less in wavelet based detection. Therefore wavelet based spectrum sensing is much better than eigen value based detection.

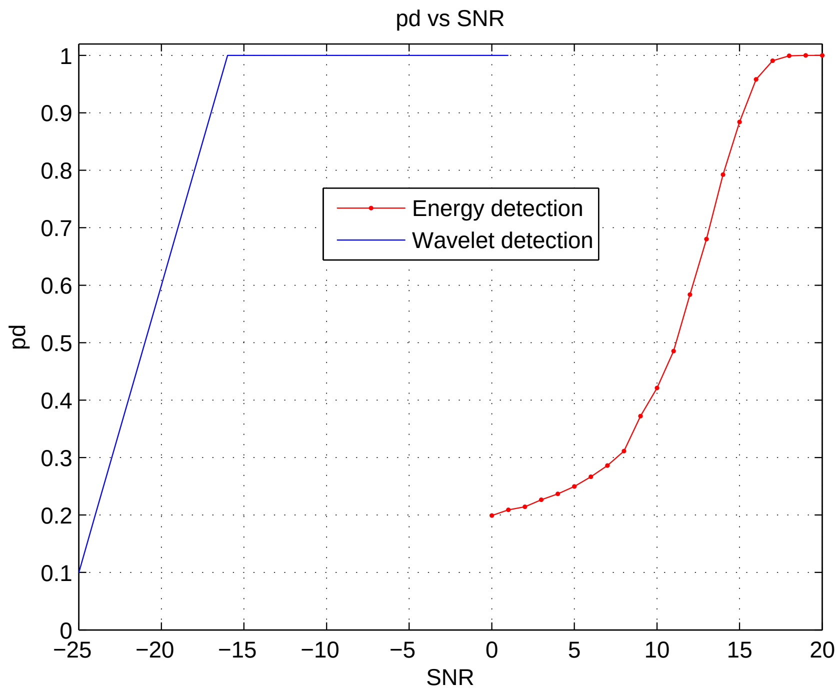

Figure 4.12: Introducing wavelet spectrum sensing to adaptive spectrum sensing

Figure 4.12 shows modified adaptive spectrum sensing by adding wavelet based spectrum sensing instead of eigen value detection. From figure 4.10, it can be seen that probability of detection is low in the region -20 to -5 dB. But by the addition of wavelet based spectrum sensing a high probability of detection can be obtained in this range as shown in figure 4.12. Hence much better accuracy can be provided by the addition of wavelet based spectrum sensing together with energy detection instead of eigen value based detection.

Chapter 5

Conclusion

An adaptive spectrum sensing technique has been implemented and all the three transmitter detection techniques Energy detection, Matched filter detection and Eigen value detection have been simulated using MATLAB and the results of all the three techniques have been compared. When prior information about the primary user signal is available matched filter technique is applied .Energy detection and Eigen value detection technique doesnot require prior information about the Primary user signal. It is observed that Energy detection is the simplest technique but it suffers from SNR wall problem i.e the detection performance is high only after a certain value of SNR(4db). Eigen value detection implementation is slight complex compared to energy detection but it shows good detection performance even under low SNR conditions where energy detector doesnot work well. Therefore energy detection is applied when the SNR value is greater than 4db and Eigen value detection is applied when SNR is less than 4db. This adaptive spectrum sensing technique reduces complexity of the spectrum sensing process.

From the survey we conducted, it is found that Wavlet based detection technique outperforms Eigen value based method. On applying the daubechies db4 wavelet transform for spectrum sensing replacing Eigen Value method, we found that signals will keep nearly unchanged after the transform, while noises will be dramatically affected. Experimental results showed that, compared with eigen value detection, wavelet detection provides improved accuracy under low SNR regions.

5.1 Future Scope

Apart from using traditional methods, much more advanced methods like machine learning techniques, cooperative detection etc can be used for adaptive spectrum sensing.

Also in our report, we have discussed the software implementation of spectrum detectors. We can extend it to implement these detectors in hardware and use in real time systems.

Security issue is another area in cognitive radio which needs attention. Security can be enhanced by detecting the malicious user in cognitive radio network and minimizing their effect.

References

[1] F. K. Jondral, "Software-defined radio: basics and evolution to cognitive radio," *EURASIP journal on wireless communications and networking*, vol. 2005, no. 3, pp. 275–283, 2005.

[2] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey," *Computer networks*, vol. 50, no. 13, pp. 2127–2159, 2006.

[3] H. Shahzad and J. Botchu, "Applying ostbc in cooperative cognitive radio networks," 2010.

[4] J. Mitola, "An integrated agent architecture for software defined radio," Ph.D. dissertation, The Royal Institute of Technology, KTH, 2000.

[5] R. W. Thomas, D. H. Friend, L. A. DaSilva, and A. B. MacKenzie, "Cognitive networks," in *Cognitive radio, software defined radio, and adaptive wireless systems.* Springer, 2007, pp. 17–41.

[6] A. A. El-Saleh, M. Ismail, M. Akbari, M. R. Manesh, and S. A. R. T. Zavareh, "Minimizing the detection error of cognitive radio networks using particle swarm optimization," in *Computer and Communication Engineering (ICCCE), 2012 International Conference on.* IEEE, 2012, pp. 877–881.

[7] A. Goldsmith, S. A. Jafar, I. Mric, and S. Srinivasa, "Breaking spectrum gridlock with cognitive radios: An information theoretic perspective," *Proceedings of the IEEE*, vol. 97, no. 5, pp. 894–914, 2009.

[8] A. Sahai, "Spectrum sensing: fundamental limits and practical challenges," *Tutorial Document on DySPAN 2005, Nov.*, 2005.

[9] W. Wang, "Spectrum sensing for cognitive radio," in *Intelligent Information Technology Application Workshops, 2009. IITAW'09. Third International Symposium on.* IEEE, 2009, pp. 410–412.

[10] F. Salahdine, H. El Ghazi, N. Kaabouch, and W. F. Fihri, "Matched filter detection with dynamic threshold for cognitive radio networks," in *Wireless Networks and Mobile Communications (WINCOM), 2015 International Conference on.* IEEE, 2015, pp. 1–6.

[11] X. Zhang, R. Chai, and F. Gao, "Matched filter based spectrum sensing and power level detection for cognitive radio network," in *Signal and Information Processing (GlobalSIP), 2014 IEEE Global Conference on.* IEEE, 2014, pp. 1267–1270.

[12] Q. Lv and F. Gao, "Matched filter based spectrum sensing and power level recognition with multiple antennas," in *Signal and Information Processing (ChinaSIP), 2015 IEEE China Summit and International Conference on.* IEEE, 2015, pp. 305–309.

[13] P. Pandya, A. Durvesh, and N. Parekh, "Energy detection based spectrum sensing for cognitive radio network," in *Communication Systems and Network Technologies (CSNT), 2015 Fifth International Conference on*. IEEE, 2015, pp. 201–206.

[14] A. Bagwari and B. Singh, "Comparative performance evaluation of spectrum sensing techniques for cognitive radio networks," in *Computational Intelligence and Communication Networks (CICN), 2012 Fourth International Conference on*. IEEE, 2012, pp. 98–105.

[15] N. Sonawane and S. Borse, "Performance evaluation comparison of primary user signal detection methods for cognitive radio system," *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 3, no. 6, 2014.

[16] Y. H. Chye, E. Dutkiewicz, R. Vesilo, and R. P. Liu, "Adaptive spectrum sensing for cognitive radio systems in a fading environment," in *Wireless Personal Multimedia Communications (WPMC), 2014 International Symposium on*. IEEE, 2014, pp. 451–456.

[17] H.-H. Choi, K. Jang, and Y. Cheong, "Adaptive sensing threshold control based on transmission power in cognitive radio systems," in *Cognitive Radio Oriented Wireless Networks and Communications, 2008. CrownCom 2008. 3rd International Conference on*. IEEE, 2008, pp. 1–6.

[18] M. Z. Alom, T. K. Godder, M. N. Morshed, and A. Maali, "Enhanced spectrum sensing based on energy detection in cognitive radio network using adaptive threshold," in *Networking, Systems and Security (NSysS), 2017 International Conference on*. IEEE, 2017, pp. 138–143.

[19] K. Srisomboon, A. Prayote, and W. Lee, "Double constraints adaptive energy detection for spectrum sensing in cognitive radio networks," in *Mobile Computing and Ubiquitous Networking (ICMU), 2015 Eighth International Conference on*. IEEE, 2015, pp. 76–77.

[20] ——, "Multi-slot double constraints adaptive energy detection for spectrum sensing in cognitive radio networks," in *Communications and Information Technologies (ISCIT), 2015 15th International Symposium on*. IEEE, 2015, pp. 169–172.

[21] Y.-C. Liang, Y. Zeng, E. C. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE transactions on Wireless Communications*, vol. 7, no. 4, pp. 1326–1337, 2008.

[22] P. Aparna and M. Jayasheela, "Cyclostationary feature detection in cognitive radio using different modulation schemes," *International Journal of Computer Applications*, vol. 47, no. 21, 2012.

[23] W. M. Jang, "Blind cyclostationary spectrum sensing in cognitive radios," *ieee communications letters*, vol. 18, no. 3, pp. 393–396, 2014.

[24] O. Elnahas and M. Elsabrouty, "Wideband spectrum sensing technique based on multitask compressive sensing," in *Computers and Communication (ISCC), 2016 IEEE Symposium on*. IEEE, 2016, pp. 849–854.

[25] ——, "Cyclostationary-based cooperative compressed wideband spectrum sensing in cognitive radio networks," in *Wireless Days, 2017*. IEEE, 2017, pp. 77–82.

[26] Y. Zeng and Y.-C. Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio," *IEEE transactions on communications*, vol. 57, no. 6, 2009.

[27] R. Heimann, A. Leshem, E. Zehavi, and A. J. Weiss, "Non-asymptotic performance bounds of eigenvalue based detection of signals in non-gaussian noise," in *Acoustics, Speech and Signal Processing (ICASSP), 2016 IEEE International Conference on*. IEEE, 2016, pp. 2936–2940.

[28] V. M. Patil and S. R. Patil, "A survey on spectrum sensing algorithms for cognitive radio," in *Advances in Human Machine Interaction (HMI), 2016 International Conference on*. IEEE, 2016, pp. 1–5.

[29] S. K. Sharma, S. Chatzinotas, and B. Ottersten, "Eigenvalue-based sensing and snr estimation for cognitive radio in presence of noise correlation," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 8, pp. 3671–3684, 2013.

[30] ——, "Maximum eigenvalue detection for spectrum sensing under correlated noise," in *Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on*. IEEE, 2014, pp. 7268–7272.

[31] W. Zhang, R. K. Mallik, and K. B. Letaief, "Cooperative spectrum sensing optimization in cognitive radio networks," in *Communications, 2008. ICC'08. IEEE International conference on*. IEEE, 2008, pp. 3411–3415.

[32] D.-J. Lee, "Adaptive random access for cooperative spectrum sensing in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 2, pp. 831–840, 2015.

[33] X. Chen, F. Hou, H. Huang, and X. Jing, "Principle component analysis based cooperative spectrum sensing in cognitive radio," in *Communications and Information Technologies (ISCIT), 2016 16th International Symposium on*. IEEE, 2016, pp. 602–605.

[34] D. Xue, E. Ekici, and M. C. Vuran, "Cooperative spectrum sensing in cognitive radio networks using multidimensional correlations," *IEEE Transactions on Wireless Communications*, vol. 13, no. 4, pp. 1832–1843, 2014.

[35] M. Monemian and M. Mahdavi, "Analysis of a new energy-based sensor selection method for cooperative spectrum sensing in cognitive radio networks," *IEEE sensors journal*, vol. 14, no. 9, pp. 3021–3032, 2014.

[36] M. Awasthi, V. Kumar, and M. Nigam, "Energy—efficiency techniques in cooperative spectrum sensing: A survey," in *Computational Intelligence & Communication Technology (CICT), 2017 3rd International Conference on*. IEEE, 2017, pp. 1–6.

[37] N. Singh and M. Ansari, "Extraction of feature based on wavelet packet transform," in *Information Processing (IICIP), 2016 1st India International Conference on*. IEEE, 2016, pp. 1–5.

[38] S. M. Joseph, "Spoken digit compression using wavelet packet," in *Signal and Image Processing (ICSIP), 2010 International Conference on*. IEEE, 2010, pp. 255–259.

[39] F. Arab, S. M. Daud, and S. Z. Hashim, "Discrete wavelet transform domain techniques," in *Informatics and Creative Multimedia (ICICM), 2013 International Conference on*. IEEE, 2013, pp. 340–345.

[40] A. Chandran, R. A. Karthik, A. Kumar, M. S. Siva, U. S. Iyer, R. Ramanathan, and R. C. Naidu, “Discrete wavelet transform based spectrum sensing in futuristic cognitive radios,” in *Devices and Communications (ICDeCom), 2011 International Conference on*. IEEE, 2011, pp. 1–4.

[41] Y. Zhao, Y. Wu, J. Wang, X. Zhong, and L. Mei, “Wavelet transform for spectrum sensing in cognitive radio networks,” in *Audio, Language and Image Processing (ICALIP), 2014 International Conference on*. IEEE, 2014, pp. 565–569.

[42] R. Verma and A. Mahapatro, “Cognitive radio: Energy detection using wavelet packet transform for spectrum sensing,” in *Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB), 2017 Third International Conference on*. IEEE, 2017, pp. 168–172.

[43] H. Chen and C. H. Vun, “An efficient compressive spectrum sensing technique for cognitive radio system,” in *Region 10 Conference (TENCON), 2016 IEEE*. IEEE, 2016, pp. 1105–1110.

[44] A. Appaiah, A. Perincherry, A. S. Keskar, and V. Krishna, “Spectrum sensing in cognitive radio based on compressive measurements,” in *Emerging Trends in Communication, Control, Signal Processing & Computing Applications (C2SPCA), 2013 International Conference on*. IEEE, 2013, pp. 1–6.

[45] V. Ramachandran and A. Cheeran, “Improvement of energy efficiency of spectrum sensing algorithms for cognitive radio networks using compressive sensing technique,” in *Computer Communication and Informatics (ICCCI), 2014 International Conference on*. IEEE, 2014, pp. 1–6.

[46] E. Astaiza, P. Jojoa, and H. Bermúdez, “Compressive local wideband spectrum sensing algorithm for multiantenna cognitive radios,” in *Communications (LATINCOM), 2016 8th IEEE Latin-American Conference on*. IEEE, 2016, pp. 1–6.

[47] J. Jiang, H. Sun, D. Baglee, and H. V. Poor, “Achieving autonomous compressive spectrum sensing for cognitive radios,” *IEEE Transactions on Vehicular Technology*, vol. 65, no. 3, pp. 1281–1291, 2016.

[48] W. Yin, Z. Wen, S. Li, J. Meng, and Z. Han, “Dynamic compressive spectrum sensing for cognitive radio networks,” in *Information Sciences and Systems (CISS), 2011 45th Annual Conference on*. IEEE, 2011, pp. 1–6.

Appendix

Matched filter detection

```
clc
clear
close all
SNR=-16:25;
pdd=[];
for i=1:length(SNR)
antenna = phased.IsotropicAntennaElement('FrequencyRange',[5
   e9 15e9]);
transmitter = phased.Transmitter('Gain',4,'InUseOutputPort',
   true);
fc = 10e9;
target = phased.RadarTarget('Model','Nonfluctuating',...
    'MeanRCS',1,'OperatingFrequency',fc);
txloc = [0;0;0];
tgtloc = [5000;5000;10];
transmitterplatform = phased.Platform('InitialPosition',txloc
   );
targetplatform = phased.Platform('InitialPosition',tgtloc);
[tgtrng,tgtang] = rangeangle(targetplatform.InitialPosition,
   ...
    transmitterplatform.InitialPosition);

waveform = phased.RectangularWaveform('PulseWidth',25e-6,...
    'OutputFormat','Pulses','PRF',10e3,'NumPulses',1);
c = physconst('LightSpeed');
maxrange = c/(2*waveform.PRF);

Pt = radareqpow(c/fc,maxrange,SNR(i),...
    waveform.PulseWidth,'RCS',target.MeanRCS,'Gain',
       transmitter.Gain);

transmitter.PeakPower = Pt;
```

```
radiator = phased.Radiator('PropagationSpeed',c,...
   'OperatingFrequency',fc,'Sensor',antenna);
channel = phased.FreeSpace('PropagationSpeed',c,...
   'OperatingFrequency',fc,'TwoWayPropagation',false);
collector = phased.Collector('PropagationSpeed',c,...
   'OperatingFrequency',fc,'Sensor',antenna);
receiver = phased.ReceiverPreamp('NoiseFigure',0,...
   'EnableInputPort',true,'SeedSource','Property','Seed',2e3)
      ;
filter = phased.MatchedFilter(...
   'Coefficients',getMatchedFilter(waveform),...
   'GainOutputPort',true);

wf = step(waveform);

[wf,txstatus] = step(transmitter,wf);

wf = step(radiator,wf,tgtang);

wf = step(channel,wf,txloc,tgtloc,[0;0;0],[0;0;0]);

wf = step(target,wf);

wf = step(channel,wf,tgtloc,txloc,[0;0;0],[0;0;0]);

wf = step(collector,wf,tgtang);

rx_puls = step(receiver,wf,~txstatus);
[mf_puls,mfgain] = step(filter,rx_puls);

Gd = length(filter.Coefficients)-1;

mf_puls=[mf_puls(Gd+1:end); mf_puls(1:Gd)];

s=snr(abs(mf_puls));
[pd,pfa]=rocsnr(abs(s));

pd=sort(pd);
pdd(i)=pd(end-1);
end
pdd=sort(pdd);
figure,
plot(SNR,pdd,'-b.')
xlabel('SNR')
ylabel('Pd')
title('Matched filter detection')
```

```
grid on

save pd_2_out pdd SNR
```

Program 5.1: pd_2.m

Energy detection

```
clc
close all
clear all
L = 1000;
snr_dB = -25:16; % SNR in decibels
snr = 10.^(snr_dB./10); % Linear Value of SNR
Pf = 0.1;
for m = 1:length(snr)
    m
    i = 0;
for kk=1:10000 % Number of Monte Carlo Simulations
 n = randn(1,L); %AWGN noise with mean 0 and variance 1
 s = sqrt(snr(m)).*randn(1,L); % Real valued Gaussina Primary
     User Signal
 y = s + n; % Received signal at SU
 energy = abs(y).^2; % Energy of received signal over N
    samples
 energy_fin =(1/L).*sum(energy);
 thresh(m) = (qfuncinv(Pf)./sqrt(L))+ 1;
 if(energy_fin >= thresh(m))
     i = i+1;
 end
end
Pd(m) = i/kk;
end
plot(snr_dB+20, Pd,'-r.')
axis([-5 25 0 1.02])
xlabel('SNR')
ylabel('Pd')
title('Energy Detection method')
grid on
save pd_6_out snr Pd
```

Program 5.2: pd_6.m

Eigen value detection

```
clc;
clear;
close all;

%% SNR vs pd using maximum eigenvalue detection
Ns=10000;
SNR=-20:1;
snr=10.^(SNR./10);
L=8;
pf=0.1;
F1_inv=0.45;
num_iter=2000;
a=((sqrt(Ns)+sqrt(L))^2)/(Ns);
b=1+((sqrt(Ns)+sqrt(L))^(-2/3)*F1_inv)/((Ns*L)^(1/6));
threshold=a*b*12;
weight=0.02;

w=waitbar(0,'calculating probability of false alarm');
l=1;
for i=1:length(SNR)
count=0;
for h=1:num_iter
signal=randn(1,Ns);
noise=randn(1,Ns);
noise_power=norm(noise)^2;
signal_power=norm(signal)^2;
mult=sqrt(snr(i)*noise_power/signal_power);
signal=mult*signal;
signal=signal+noise;
%noise=noise/std(noise);
k=0;
Cx=zeros(1,L);
for n=0:L-1
for j=1:1:Ns-L-1
Cx(n+1)=Cx(n+1)+signal(j)*signal(j+k);
end
k=k+1;
end
Cx=Cx/Ns;
Cx_mtx=toeplitz(Cx);
eig_value=eig(Cx_mtx);
max_eig=max(max(eig_value));
min_eig=min(min(eig_value));
ratio=max_eig/(max_eig-min_eig);
```

```
if ratio>threshold
count=count+1;
end
end

pd(i)=count/2000+(weight*i);
if(pd(i)>1)
    pd(i)=1;
end
waitbar(i/length(SNR));
end
close(w);

plot(SNR,sort(pd));
xlabel('SNR');
ylabel('Pd');
title('Eigen Value Detection');
axis([-20 5 0 1.02]);
grid on

figure,
[pd1,pfa]=rocsnr(SNR);
semilogx(pfa,pd1(:,1))
xlabel('pfa');
ylabel('Pd');
axis([10^-4 1 0 1.02]);
title('Eigen Value Detection');
grid on

save pd_4_out pfa pd1 SNR pd
```

Program 5.3: pd_4.m

Adaptive spectrum sensing

```
clc
close all
clear all
figure,
load pd_2_out pdd SNR
plot(SNR, pdd)
xlabel('SNR')
ylabel('Pd')
```

```
title('Matched filter detection')
grid on

figure,
load pd_6_out
snr=0:41;
plot(snr, Pd,'-r.')
axis([-20 25 0 1.02])
hold on
load pd_4_out
plot(SNR,sort(pd),'-b.');
grid on
xlabel('SNR')
ylabel('Pd')
title('pd vs SNR')
legend('Energy detection','Eigen value detection')
```

Program 5.4: combined_1.m

Wavelet based detection

```
clc;
clear;
close all;

Ns=10000;
SNR=-25:1;
snr=10.^(SNR./10);
L=8;
pf=0.1;
F1_inv=0.45;
num_iter=2000;
a=((sqrt(Ns)+sqrt(L))^2)/(Ns);
b=1+((sqrt(Ns)+sqrt(L))^(-2/3)*F1_inv)/((Ns*L)^(1/6));
threshold=a*b*12;
weight=0.1;

l=1;
for i=1:length(SNR)
count=0;
for h=1:num_iter
signal=randn(1,Ns);
noise=randn(1,Ns);
```

```
noise_power=norm(noise)^2;
signal_power=norm(signal)^2;
mult=sqrt(snr(i)*noise_power/signal_power);
signal=mult*signal;
signal=signal+noise;
k=0;
Cx=zeros(1,L);
for n=0:L-1
for j=1:1:Ns-L-1
Cx(n+1)=Cx(n+1)+signal(j)*signal(j+k);
end
k=k+1;
end
Cx=Cx/Ns;
Cx_mtx=toeplitz(Cx);


wv=dwt2(Cx_mtx,'db4');
Cx_mtx=wv;

max_wv=max(max(wv));
min_wv=min(min(wv));
ratio=max_wv/(max_wv-min_wv);
if ratio>threshold
count=count+1;
end
end

pd(i)=count/2000+(weight*i);
if(pd(i)>1)
    pd(i)=1;
end
waitbar(i/length(SNR));
end
%close(w);

plot(SNR,sort(pd),'b');
axis([-25 20 0 1.02]);
title('Wavelet Method of detection')
xlabel('SNR');
ylabel('Pd');
grid on

figure,
[pd1,pfa]=rocsnr(SNR);
semilogx(pfa,pd1(:,1))
```

```
xlabel('pfa');
ylabel('Pd');
title('Wavelet method of detection')
grid on

save pd_7_out pfa pd1 SNR pd
```

Program 5.5: pd_7.m

Comparison between Eigen value & Wavelet detection

```
figure,
hold on
load pd_4_out
plot(SNR,sort(pd),'-m.');
grid on


load pd_7_out
plot(SNR,sort(pd),'-b');
axis([-20 25 0.6 1.02])
grid on
xlabel('SNR')
ylabel('pd')
title('pd vs SNR')
legend('Eigen value detection','wavelet detection')
```

Program 5.6: comparison.m

Modified adaptive spectrum sensing

```
clc
close all
clear all
figure,
load pd_2_out pdd SNR
plot(SNR, pdd)
xlabel('SNR')
ylabel('Pd')
```

```
title('Matched filter detection')
grid on

figure,
load pd_6_out
snr=0:41;
plot(snr, Pd,'-r.')
hold on
load pd_7_out
plot(SNR,sort(pd),'-b');
axis([-25 20 0 1.02])
grid on
xlabel('SNR')
ylabel('pd')
title('pd vs SNR')
legend('Energy detection','Wavelet detection')
```

Program 5.7: combined_2.m