A fast sensing algorithm for spectrum detection in cognitive radios

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Chapter 1

Introduction

1.1 Overview

The radio spectrum is a highly prized commodity and its scarcity has been felt for quite some time. More and more wireless devices to satisfy the ever increasing demand of consumers are coming into the market which has invariably lead to the clogging of the wireless spectrum. A study conducted by the Federal Communications Commission (FCC) revealed the glaring fact that hardly 25% of the allocated spectrum gets utilized [1]. Similar studies conducted by various other countries, for instance Singapore, also resulted in identical conclusion [2]. This fact motivated the research on how to optimally use the idle spectrum so that the devices are not left out due to want of bandwidth for communication. The concept of cognitive radio tries to precisely address this problem of spectrum scarcity.

Dr. Joseph Mitola III proposed that these vacancies created in the spectrum due to inactive licensed users can be used by unlicensed secondary users provided they give up the spectrum back to the licensed user when it becomes active again [3]. He termed this concept as Cognitive Radio (CR). A CR device is therefore defined as one which is aware of its surroundings, intelligently scans the electromagnetic spectrum to look for vacant frequency bands and adapts its transmission parameters accordingly. There are many aspects that a CR device must handle before it can achieve the task of intelligently using the idle spectrum and extensive research is being done on each of these aspects. The areas of research which deal exclusively with the utilization of spectrum can be divided into four main categories as Spectrum Sensing, Spectrum Sharing, Spectrum Management and Spectrum Mobility.

Although all these fields offer exciting scope for further research, an accurate sensing of the spectrum forms the core part of any CR device. Without an efficient spectrum sensing algorithm to detect the present and absence of the primary user in the licensed band, the concept of CR cannot proceed to the next step of utilizing it. Thus this thesis focuses on the various spectrum sensing algorithms and their performance with respect to accuracy and time to arrive at the result.

Additionally, to see how the real world signals behave, a hardware setup based on an universal serial radio peripheral (USRP2) and GNU Radio framework was implemented. This setup was used to capture and analyze the GSM and other modulated signals.

1.2 Motivation

Spectrum sensing forms the core of any CR unit. Developing an algorithm which can detect the presence of a primary user (the owner of the licensed spectrum) without fail and at the same time never raise a false alarm is the main challenge here. This should be done with low complexity so that a fast real time analysis can be done. Also since a CR would most likely be a battery powered device, the hardware implementation of the algorithm should not lead to a high consumption of power. Mathematically this would mean that the number of computations to arrive at the right decision should be low.

Central to any algorithm which discriminates between the presence and absence of a primary user is the threshold used for making the decision. Consequently setting of the threshold holds the key to the robustness in the performance of an algorithm. Hence an extensive analysis on how the setting of threshold affects the performance parameters of a CR has been done in this thesis. The energy detector (ED) algorithm, which computes the energy of the data samples obtained by filtering the desired frequency band, has been used for this study. This is because the ED algorithm is the simplest and computationally least complex of all the known algorithms [4].

It has been observed that the threshold used to make the decision in a conventional ED based CR is static and that the threshold value is not changed even though additional information about the channel is available for the CR unit to take a more informed decision. Also it has been found that when the time to sense the channel is short, the performance of a conventional ED with respect to its probability of detection deteriorates drastically. This observation motivated investigation into mechanisms to improve the detection probability under short sensing time conditions. Continuing on this work, it was also observed that for a given sensing time, the conventional ED exhibits the same degradation in performance when the SNR of the primary user falls below a certain value. This motivated the need to explore the reason behind the fall in the probability of detection at low SNRs.

Since the threshold of an ED is a function of the noise variance, the performance of the ED depends on the accuracy of the noise variance estimate. Any uncertainty in the noise variance estimate can lead to a drastic reduction in the performance of ED. The effects due to uncertainties

in the estimation of the noise variance have been explained in [5, 6]. The motivation for the work in this thesis arose from the need to accurately identify the operating regime for an ED based CR in an uncertain noise environment where a minimum performance can be guaranteed. If the operating limitations of the ED are known before hand, then it can help in switching over to other spectrum sensing algorithms when the environment becomes less favorable for using energy based sensing algorithm.

When the SNR at which the CR is operating falls below a certain value, using the principles of energy detection for sensing the spectrum is not possible. Hence other algorithms like cyclostationary feature detection (CFD) which are robust to noise and are independent of noise variance estimates have been considered. But the CFD algorithm is known to be computationally complex. Thus techniques to improve the speed of detection for identifying cyclic frequencies of the primary user present in the licensed spectrum were also one of the motivating factors behind this thesis.

All the data that is used for simulating and analyzing the various spectrum sensing algorithms are themselves simulated in the software. To get an accurate picture of how the signals in the real world operate, a laboratory setup was required which can capture the data, digitize the data using a Analog to Digital Converter (ADC), and bring the spectrum signal to the base band. This motivated the need to setup a GNU Radio framework to interface with a USRP2 board since the GNU Radio provided built in functionalities for many signal processing tasks.

1.3 Objectives and Contributions

The thesis seeks to develop an algorithm for spectrum sensing such that it mitigates the disadvantages of the algorithms found in the literature, yet at the same time, improves the performance parameters like probability of detection, probability of false alarm, time to arrive at the result, etc. To this end, this thesis goes in depth into the merits and demerits of the algorithms presented in the literature. It is intended to study the causes that lead to the disadvantages of the various methods and find techniques to reduce the impact of the demerits without leading to any loss of benefits accruing from them.

In the case of the energy detection algorithm, the various aspects of setting the threshold of an ED and investigating its impact on the performance of an ED based CR under different signal to noise

ratio (SNR) conditions needs to be thoroughly studied. Also the objective is to realize the effect of uncertainty in the estimation of noise variance on the performance of the ED.

A CFD method, though is robust to noise, requires a huge computational time since it tries to seek out the cyclic frequency patterns present in the input spectrum. These patterns are caused due to the presence of preamble codes, modulating signal, etc. However, since the cyclic frequencies are usually not known, a CFD based CR takes a large time in obtaining the cyclic frequencies present in the captured spectrum, if any. For a CR device, the time to sense the spectrum is a crucial parameter, since if the time taken to acquire data and take a decision is high, then it could lead to a potential loss of throughput for the CR device. Also it could happen that the PU could require the licensed spectrum even before the CR had an opportunity to sense and arrive at a result. Hence quick detection and analysis of the spectrum is a parameter which determines the throughput of the CR device. In [7], the authors present a detailed analysis of the tradeoff between sensing time and the throughput of a CR device. Thus reducing the time taken for cyclic frequency identification is also an objective of this thesis.

The data used for simulation and analysis of the various algorithms were simulated using Matlab. Though the data represents the near real world scenarios, it cannot reflect the vagaries of a real world signal. With this objective in mind, this thesis attempts to use a GNU Radio framework to communicate with a USRP2 board to capture and sense the real world spectrum. This enables an appreciation of the difficulties in doing a reliable estimation of the signal at low SNR conditions.

In order to realize the stated objectives, the contribution in this thesis is elaborated as follows.

1. Analysis of impact of reduced sensing time and low SNR on the detection performance of a conventional energy detector based cognitive radio

As stated previously, the selection of the threshold is the most crucial parameter for any binary hypothesis detector. In this thesis, the dependency of the threshold of an ED on the number of samples, the operating SNR and the noise variance have been investigated. The minimum number of samples and the minimum SNR required guaranteeing the target performance characteristics have also been validated. The thesis helps in establishing that a constant false alarm rate (CFAR) based threshold for an ED employed conventionally is not the most appropriate one at low SNR conditions. It shows that the probability to detect the primary user falls substantially when the SNR is low. The thesis proposes that by using an estimate of the channel SNR, the threshold can be adaptively switched to a constant detection rate (CDR) based threshold thereby

arresting the fall in the detection probability. However, the trade-off between probability of detection and probability of false alarm cannot be avoided. It is shown that the increase in detection probability at low SNR comes with an increase in the false alarm probability as well. Therefore, the strategy to choose the threshold adaptively depends on the operating scenario intended for the CR. The operating scenarios and the adaptations required in the thresholds to suit them have also been described.

The thesis also analyzes the impact of uncertainties in the estimation of noise variance on the performance of an ED based CR. It validates through mathematical analysis and simulation that the ED hits an SNR wall beyond which detection is not possible for an ED. This study is then used to determine the minimum SNR required in uncertain noise environment below which the ED cannot achieve a target probability of detection and target probability of false alarm for a given number of samples.

2. Development of a fast two-stage algorithm to operate in uncertain noise environment

The thesis develops a two-stage algorithm employing ED in its first stage and CFD in its second stage to enable satisfactory performance in uncertain and low SNR environments. To reduce the computational complexity of a CFD analysis, pilot assisted cyclostationary feature detection (PACD) has been proposed so that the cyclic frequencies are known before hand. The thesis then dwells on optimizing the usage of the second stage of a two-stage detector and shows that it is not prudent or necessary to use the second stage detection always as done conventionally. It is shown that if the SNR of the CR is more than the minimum SNR required for guaranteed performance in uncertain noise, then the results of the ED should be trusted and a redundant analysis using CFD can be avoided. The algorithm proposed leads to substantial savings in time, and consequently power, at high SNR regimes without any loss of detection performance.

3. Integration of USRP2 with GNU Radio framework to capture and obtain I & Q values of real world signals

In order to not restrict the analysis to simulated data alone, an USRP2 board was used to sense the environment and obtain I & Q data to get a better sense of real world signals. This was achieved by integrating the GNU Radio framework with the USRP2 board and using the inbuilt signal processing blocks of GNU Radio to demodulate and obtain the I & Q data. Also the inbuilt

signal processing blocks were used to look at the real time Fast Fourier Transform (FFT) plot of the spectrum. The thesis describes the steps to be taken to integrate the GNU Radio framework with the USRP2 board and also shows the FFT plot and I & Q data of the captured spectrum.

1.4 Outline

The rest of the thesis is organized as follows. Chapter 2 presents the literature review of the various spectrum sensing algorithms and highlights the merits and demerits of the algorithms. The chapter also briefly delves into the field of cooperative communication. Chapter 3 presents the first contribution of this work. It includes mathematical derivations to compute the sensing time and the SNR required to maintain the desired performance characteristics. It also shows the impact of uncertainties in the estimation of noise variance on the performance of an ED. The simulation results obtained are presented to validate the quantitative results obtained. In chapter 4, a PACD algorithm is presented to detect Orthogonal Frequency Division Multiplexing (OFDM) symbols. This algorithm represents the second stage of the two-stage algorithm proposed in this thesis. The chapter presents an optimized algorithm to reduce the mean detection time of a two-stage algorithm without compromising the detection performance of the CR unit. Chapter 5 describes the USRP2 board and the GNU radio framework in brief and explains the steps needed to be taken to build the GNU Radio framework and communicate with the USRP2 board. Finally Chapter 6 concludes the results in the thesis and suggests the direction of work for the future.

Chapter 2

Literature Review

This chapter details the literature survey on the state of the art in spectrum sensing and identifies the strength and weakness of the different algorithms available for spectrum sensing. It also briefly covers the hardware implementation scheme and practical applications of cognitive radio.

2.1 Spectrum Allocation and Utilization

As mentioned in the Chapter 1, the real motivation for research into dynamic spectrum access was the apparent lack of spectrum availability due to the fact that all the bands had been licensed out. Figure 2.1 shows the frequency allocation chart of the USA obtained from the National Telecommunication and Information Administration (NTIA) [8].

The scenario shown is not restricted to the USA alone. Since spectrum is a very scarce and finite national resource, the regulatory authorities in every country either license them to various stakeholders like TV operators, mobile operators, space agencies for satellite based communications, etc or they are retained by the government for military purposes. Hence the possibility of getting new spectrum for wireless communication looks limited unless some of the existing agencies vacate the air waves.

However, the actual situation on the ground is not as expected. Figure 2.2 shows the actual utilization of the allocated spectrum averaged over 6 locations in the USA [9]. The results in Fig. 2.2 is in conformity with the study report by the Federal Communications Commission (FCC) task force which observed that 70% of the spectrum remains underutilized on average [1]. Thus it is quite evident from the measurements that there is lot of scope to improve the efficiency of the spectrum being utilized.

The motivation behind Cognitive Radio (CR) is that the spectrum allocated to the licensed users (referred to as Primary Users) can be given to unlicensed users (referred to as Secondary Users) when the Primary User (PU) is not using it. Thus by allowing the Secondary Users (SU) to locally

[illegible]

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Figure 2.2. Actual utilization of spectrum captured over 6 locations [6].

2.2 Origin of Cognitive Radio Concept

The term Cognitive Radio (CR) has been defined by FCC as "a radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets." [10].

Prior to accepting this definition, FCC had tried to define a CR based on a concept known as the Interference Temperature [11] [12]. Interference Temperature is used to quantify and manage the source of interference. It is used to characterize the worst case scenario of a Radio Frequency (RF) band. It gives an accurate representation of the amount of interference that can be accepted in a frequency band without going over board (increase the noise floor). So if there is a frequency band in which the interference temperature has not been exceeded, then RF energy can be introduced in it till the interference temperature limit is reached. Thus the interference temperature serves as the upper limit. But there were many practical difficulties encountered to measure the interference temperature [11] and hence it was decided by FCC that interference temperature based CR cannot be continued and hence was recommended by FCC to be terminated.

The current definition adopted by FCC is in agreement with Dr. Joseph Mitola III's concept of a CR [3]. Dr. Mitola had conceptualized a CR to be a intelligent entity that can take every parameter into account and make an intelligent decision by using those parameters in the most intelligent way. The sensing of the spectrum to look for vacant holes is just one of the parameters in the definition of CR by Dr. Mitola. A CR should be able to sense, measure and analyze the various attributes of the spectrum. It should also be aware of the operating environment of the radio, the requirements of the user, the policy based decisions to be taken and the availability of the network infrastructure.

Thus broadly speaking, a CR is not just limited to sensing a vacancy in the spectrum. It involves a host of parameters to be considered ranging from the geo location of the CR, the operating frequency, the time of analysis, etc. However, in this report the focus has been on the spectrum sensing aspect of the CR.

2.3 Spectrum Sensing in Cognitive Radios

Spectrum sensing is a form of signal detection which can be defined as a method for identifying the presence of a signal in a noisy environment. Signal detection has been thoroughly studied in the field of military communications. In order to utilize the vacant frequency bands in the licensed spectrum, various spectrum sensing algorithms have been developed and their merits and demerits have been extensively researched. The basic aim of spectrum sensing is to distinguish the presence or absence of the PU. PU is the licensed user who has full authority over the spectrum allotted to it. At no cost shall a CR interfere with a PU. Hence it is imperative that the CR detects the presence of PU with a high degree of accuracy and does not transmit or receive using the spectrum utilized by the PU. It should use the spectrum for communication only when it is sure that PU is not using it. This constraint gives rise to the performance metrics of a CR. The probability of detection (P_d) and probability of false alarm (P_{fa}) defines the performance parameters of a CR. P_d defines the ability of the system to identify the PU of the licensed spectrum correctly. P_{fa} defines the error in the detection algorithm where in the CR system incorrectly estimates the PU to present while in reality the PU is not actually using the spectrum at that particular instant. Ideally a CR should have a very high P_d and very low P_{fa} , but practically there exists a tradeoff between these two parameters. A high P_d leads to an undesirably high P_{fa} and a low P_{fa} consequently leads to a low P_d as well. These tradeoffs have been discussed in great detail in [13]. Thus, the motivation of any spectrum sensing algorithm is to maximize the P_d and minimize the P_{fa} .

A signal sampled at the input of a spectrum sensor can be represented mathematically as

$$Y(k) = \begin{cases} w(k) & : H_0 \\ s(k) + w(k) & : H_1 \end{cases} \quad (2.1)$$

Figure 2.3 represents the equation in a diagrammatic form.

Figure 2.3. Binary hypothesis testing.

Here $Y(k)$ is the sample to be analyzed at each instant ' k ', $w(k)$ is the ambient noise and $s(k)$ is the signal to be detected. H_0 and H_1 are the noise-only and signal plus noise hypotheses, respectively. Thus, four possible cases can be defined for the above hypothesis testing [14]:

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

Here cases 1 & 2 form the right decisions, whereas cases 3 and 4 are a missed detection and a false alarm, respectively. Clearly, the aim of the signal detector is to achieve correct detection all of the time, but this can never be perfectly achieved in practice because of the statistical nature of the problem. Therefore, signal detectors are designed to operate within prescribed minimum error levels. Missed detection is the biggest issue for spectrum sensing, as it means possibly interfering with the primary system. Nevertheless, it is desirable to keep the false alarm rate as low as possible for spectrum sensing, so that the throughput of the system can be maximized.

The performance of the spectrum sensing technique is usually influenced by the probability of false alarm $P_f = P(H_1 | H_0)$, since this is the most influential metric. Usually, the performance is presented by receiver operation characteristics (ROC) curves, which plot the probability of detection $P_d = P(H_1 | H_1)$ as a function of the probability of false alarm P_f .

Figure. 2.4. Various spectrum sensing techniques.

Figure 2.4 [4] gives a snapshot of the various spectrum sensing techniques available in the literature. Broadly the techniques to sense the spectrum can be divided into two schemes. Non cooperation based sensing and cooperation based sensing. A comprehensive analysis of the state of the art for the non cooperative based sensing is presented in this thesis.

In cooperative sensing, the sensing information obtained from different CR nodes, each employing its own spectrum sensing technique, is pooled and a decision is taken based on the inputs received from the various CR nodes. Since cooperative sensing based CR is not a technique in itself, this thesis does not include the details of the cooperative sensing scheme.

2.4 Spectrum Sensing for Non Cooperative Sensing Scheme

In a non cooperative sensing scheme, each CR acts independently of any other CR in its vicinity. The CR takes a decision about the presence or absence of the PU based on the input samples it receives. The main techniques in the literature to sense the spectrum are presented in this thesis.

2.4.1 Energy Detector

An energy detector (ED) computes the energy present in the captured samples to detect the presence of a signal. It is the most common method because of its simplicity and ease of design. This approach is also called as the periodogram method or the radiometry method. In an ED, the input samples are squared and averaged over a period of time. This averaged result is then

compared with a pre computed value of threshold to establish the presence or absence of signal. The block diagram of an ED is shown in Fig. 2.5.

Figure 2.5. Conventional energy detector.

The test statistic $Z(y)$ can be computed as

$$Z(y) = \frac{1}{N_s} \sum_{n=1}^{N_s} |y[n]|^2 \quad (2.2)$$

Here $y[n]$ is the received signal sample, N_s is the number of samples used for calculating the test statistic. The computed value of the test statistic $Z(y)$ is then compared with a pre computed threshold, λ . The result can be used to distinguish between two hypotheses H_1 and H_0 as expressed in (2.1). H_0 indicate the presence of noise, $w[n]$, alone, while H_1 indicate the presence of both signal, $s[n]$, and noise. The hypothesis H_0 follows a chi squared distribution since it represents noise which is a random variable. H_1 on the other hand represents the presence of a deterministic signal and therefore follows a non central chi squared distribution [7].

It is evident that the fundamental element in deciding the presence or absence of a signal is by comparing the computed test statistic with a threshold. The threshold selected to discriminate between the two hypotheses is the critical factor determining the performance of the ED. Hence the selection of the threshold for making the decision has a significant impact on the performance of the CR. Choosing the threshold decides the probability of detection and the probability of false alarm of the CR. Figure 2.6 shows the distribution of the hypothesis H_0 and H_1 when the number of samples taken are large enough such that the central limit theorem is satisfied. Thus the distribution of H_0 and H_1 follow a Gaussian model.

The role of selecting the right threshold can be seen from Fig. 2.6.

Figure 2.6. Distribution pattern of H_0 and H_1 [15].

It can be seen that the performance metrics of the energy detector, namely the probability of detection (P_d) and the probability of false alarm (P_{fa}) are dependent on the threshold chosen. Also it can be inferred that there exists a tradeoff between the two metrics. Thus if the threshold is moved one way or the other, it would always lead to improvement in one parameter while at the same time degrading the other parameter.

Mathematically P_{fa} and P_d can be related to the threshold as [6]

$$P_f = P(Z(y) > \lambda | H_0) \quad (2.3)$$

For a sufficiently large number of samples, N_s , P_{fa} can be expressed as

$$P_f = Q\left(\frac{\lambda - \mu_0}{\sigma_0}\right) \quad (2.4)$$

Similarly the probability of detection, P_d , of such a system is given by

$$P_d = P(Z(y) > \lambda | H_1) \quad (2.5)$$

where P_d can be expressed as

$$P_d = Q\left(\frac{\lambda - \mu_1}{\sigma_1}\right) \quad (2.6)$$

Here μ_i , σ_i are the mean and variance under hypothesis H_i ($i = 0, 1$) respectively. $Q(x)$ is defined by the complementary distribution function of the standard Gaussian.

2.4.1.1 Setting of threshold

There are various ways to select the threshold (λ). The available literature on setting a threshold suggest fixing a target P_{fa} , which is called the Constant False Alarm Rate (CFAR) principle or by setting a target P_d , which is called a Constant Detection Rate (CDR) principle [16] and then calculating the threshold required to achieve the same. Since setting the threshold based on P_d requires information about the SNR of the channel, conventional practice is to set the threshold based on a target P_{fa} [4]. Once the threshold is set, it is no longer changed even though the channel conditions might have changed and more information about the channel might be known.

The λ to be set as the threshold can be derived from (2.4)

$$\lambda = Q^{-1}(P_{fa})\sigma_0 + \mu_0 \quad (2.7)$$

No information on the SNR of the channel is required to estimate any parameter in (2.4) and so a conventional ED sets the threshold as calculated from (2.4). There are many other techniques discussed in the literature which deal with the question of setting the right threshold with the intension to maximize the performance metrics (P_d and P_{fa}) of the ED based CR.

In [16], a fixed threshold which is neither CFAR based nor CDR based has been proposed. The threshold is derived from an analytical model so as to meet the target performance metrics. The noise variance is assumed to be uncertain and hence an estimated value for the noise variance is used. However, the proposed model is shown to work only when there are more than one CR nodes to share the results. Thus the model proposes an adaptive setting of threshold for CR nodes in a cooperative sensing scheme.

In [17], a technique similar to the one used in image processing is used. The technique proposed is to set the threshold as a linear function of the received signal's mean and standard deviation. Thus the threshold gets progressively updated with each received signal sample. Though the technique has the obvious advantage that it does not need an estimate of the SNR or the noise variance, it has a severe limitation that it needs high amount of computations to arrive at the threshold which needs to be repeated at every sampling instant. To avoid these frequent computations, a one-time setting of the threshold is also proposed but no mathematical basis is given about the effect of setting the threshold based on the mean and variance of the received signal on the performance metrics of the CR. Another limitation of the method in [17] is that it assumes a uniform SNR throughout the operating life cycle of the CR which is hardly the case practically. Also the operating SNR considered is in relative high SNR regions.

Algorithms for setting the threshold for mobile channels has been considered in [18, 19]. The operating channel has been modeled as a Suzuki channel which takes into account the Doppler spread due to the mobility of the receiver. The proposed method combines fixed setting of threshold with adaptive setting of threshold and tries to get the best of both. The adaptive algorithm sets the threshold as the average of the current threshold and the received signal energy. If the received energy is less than the current threshold, then the threshold is not changed and set to a fixed level. However it is not clearly specified as to how the algorithm has been arrived at. Moreover the operating SNR considered is in the positive and hence the performance of the algorithm at low SNR has not been given.

A patent has been filed recently proposing an algorithm for adaptive setting of threshold for energy detection [20]. In this method, initially the threshold is set arbitrarily and then with each sensing cycle, the threshold is updated. A new detection threshold, which is a function of the current detection threshold and the estimated energy of the received signal, is set if the received energy is below the current detection threshold. On the other hand, if the received signal energy is above the threshold, then the threshold is not changed. The advantage of the proposed method is that there is no need to estimate the noise variance and also there is no need for any apriori information about the signal to be detected. But the method requires the calculation of the threshold with each sensing cycle which could lead to lot of computations in practical scenario.

Changing the threshold based on transmit power control is discussed in [21]. Here the threshold is calculated based on physical parameters like the transmission power of the PU and the transmission power of secondary user (SU), the distance between the PU and the SU, minimum decodable signal to interference noise ratio. The threshold is changed adaptively by changing the transmission power of the SU. The whole issue of setting the threshold is seen from the perspective of power control with the main intension being the co existence of the SU device with the PU. At the same time it should also be ensured that the interference caused due to the SU at the PU should not in any case exceed the maximum signal to interference noise ratio expected by the PU.

An adaptive setting of threshold which takes into account the interference due to signals in the adjacent bands have been discussed in [22]. The authors provide an insight on how the interference due to the presence of other channels can impact the performance of an ED based CR. However there is no distinction made between noise power and adjacent channel signal power for

calculating the threshold. The adjacent channel signal power has been added on to the noise power for all calculation purposes.

Adaptive setting of threshold in the context of cooperative sensing has also been dealt with in the literature [23, 24]. Here a two level threshold has been proposed wherein the decision as well as the data is sent by the CR nodes to the fusion centre. In [23], if the energy received by the individual CR node is below or above the two pre fixed threshold, then the final result alone is sent to the fusion centre. Otherwise, if the test statistic calculated based on the received energy is in between the two selected thresholds, then the test statistic itself is sent to the fusion centre. The CR node does not take any decision in that case. The improvement over the conventional technique has not been found to be major in this algorithm. A similar algorithm is used in [24] with the difference that only the test statistic is sent to the fusion centre.

2.4.1.2 Merits and Demerits of ED

The primary disadvantage of using ED for spectrum sensing is the high dependence on accurate estimation of noise power [5]. It has been shown that under the presence of noise uncertainties, the ED based CR hits an SNR wall below which it cannot detect the signals reliably [6]. Quantization of the signals makes detection more difficult and also makes the uncertainties in noise the ultimate barrier to accurate detection. There are some ways to get over these limitations, for instance as proposed in [25], a pilot signal can be transmitted by the primary user. But this would require fundamental change in the transmission scheme of the primary users.

Another significant disadvantage is that the performance of the ED is poor under low SNR values. This can hamper its practicality since real world TV signals have receiver sensitivity as low as -116 dBm which translates to a working SNR region of -21 dB [26]. As the SNR worsens, the uncertainties in estimating the noise power increases further and hence compounds to the degradation in performance of the ED. It should also be noted that it is not enough for the CR to work satisfactorily at SNR of -21 dB. The CR should take care of hidden node problems because there is a possibility that the CR might be in a region where it is facing a natural obstruction and hence does not feel the presence of a PU. Hence to take care of the possibility of a hidden node, the CR receiver sensitivity should be much higher than the sensitivity quoted for a TV receiver. Another problems associated with ED is its inability to distinguish between presence of other secondary user signals from the PU signal. Moreover ED based CR cannot detect the presence of spread spectrum signals and hence an ED based CR is rendered ineffective under such use cases

[27]. Also the number of samples required by an ED to meet a target P_d and P_{fa} is inversely proportional to the square of the SNR [25].

However there are many advantages of employing the ED in a CR. The main reason for using ED based CR for real time signal detection is that it is very simple to implement and the design is easy to understand. Thus an ED does not consume much power and so is suitable for low power applications. Also no knowledge of the signal characteristics of the PU is required in the ED method. For this reason, an ED is also called a blind detector because it does not require any information about the structure of the signal.

2.4.2 Cyclostationary Feature Detector

Cyclostationary analysis of signals is a powerful technique and has been extensively studied. The applications of exploiting the cyclostationarity of wireless communication signals range from signal detection, classification, synchronization and equalization [28].

Cyclostationary feature detectors use the inherent features present in a communication signal. These features arise due to the addition of cyclic prefixes, modulation, preambles or spreading codes. Cyclostationarity can be also be intentionally induced so as to aid in spectrum sensing. Since noise is assumed to be wide sense stationary, it does not exhibit any cyclostationarity.

A continuous time random process $x(t)$ is said to be second order cyclostationary if its mean and autocorrelation show periodicity in time. From this it can be inferred that if the autocorrelation function of a received set of samples of spectrum show periodicity in them, then it indicates the presence of a communication signal.

Mathematically this means that for a cyclic period 'T', mean can be represented as

$$E[x(t)x(t + \tau)] = E[x(t + T)] \quad (2.8)$$

And autocorrelation as

$$R(x, \tau) = E[x(t)x(t + \tau)] = E[x(t + T)x(t + T + \tau)] \quad (2.9)$$

for all t and τ .

From (2.9), it can be seen that if the autocorrelation function is periodic then it will have a Fourier representation given by

$$R(x, \tau) = \sum_{\alpha} R_x^{\alpha}(\tau) e^{j\alpha\tau} \quad (2.10)$$

The Fourier coefficients of (2.10) can be expressed as

$$R_x^{\alpha}(\tau) = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{\tau=0}^{N-1} R(x, \tau) e^{-j2\pi\alpha\tau} \quad (2.11)$$

Here α is the cyclic frequency of the autocorrelation function and $R_x^{\alpha}(\tau)$ is called the cyclic autocorrelation function (CAF). Thus, a process is called cyclostationary if there exists an $\alpha \neq 0$, such that $R_x^{\alpha}(\tau) \neq 0$ for some values of τ . In other words, the cycles of $R(x, \tau)$ are to be detected for testing the presence of cyclostationarity.

Further, from (2.11), it can be inferred that the cycles of $R(x, \tau)$ are to be detected for testing the presence of cyclostationarity. To this end, the Cyclic Spectral Density (CSD) can be obtained by taking the Fourier transform of the CAF as shown in [29].

$$S_x^{\alpha}(f) = \sum_{\tau=-\infty}^{+\infty} R_x^{\alpha}(\tau) e^{-j2\pi f\tau} \quad (2.12)$$

In other words, (2.12) represents the cross spectral density of the frequency shifted signals $x(t)e^{-j\pi\alpha t}$ and $x(t)e^{+j\pi\alpha t}$. When $\alpha=0$, (2.12) reduces to the power spectral density (PSD) of the signal.

It is difficult to do a blind search for the cyclic frequency α and this adds to the computational complexity of the CFD. Also if there is no knowledge about the possible cyclic frequencies of the signal to be detected, it leads to a very high detection time. But extensive studies have been done to document the cyclic frequencies of signals of practical interests [14, 30]. These cyclic frequency values can be used to reduce the computation time significantly.

2.4.2.1 FFT Accumulation Method for computing CSD

The computational complexity of computing the CSD of a spectrum and consequently the time taken to arrive at a conclusive result has been well documented in the literature [31] and is one of the major disadvantages of the CFD. To address this concern, various algorithms were developed to enable a faster computation of the CSD of a given spectrum. The techniques are broadly classified as frequency smoothing algorithm and time smoothing algorithm. It has been reported that the time smoothing algorithm is computationally faster than the frequency smoothing algorithm [32]. In [33], the authors developed two seminal algorithms to estimate the CSD. They

are classified as Fast Fourier Transform (FFT) based Accumulation Method (FAM) and Strip Spectral Correlation Method (SSCA). In this thesis the FAM algorithm is used to estimate the CSD as done in [34]. To obtain the CSD, first the complex demodulates of the input signals are generated. This is done by using a sliding N-point FFT followed by downshifting the frequency to baseband. The generated complex demodulates are as follows.

$$X_T(n, f) = \sum_{k=-\frac{N}{2}}^{\frac{N}{2}} \psi(k)x(n-k)e^{-j2\pi f(n-k)T_s} \quad (2.13)$$

$$Y_T(n, f) = \sum_{k=-\frac{N}{2}}^{\frac{N}{2}} \psi(k)y(n-k)e^{-j2\pi f(n-k)T_s} \quad (2.14)$$

Here T_s is the sample duration and $\psi(k)$ is the data tapering window of length $T = N \cdot T_s$. Generally, the N-point FFT is hopped over the received data in blocks of L samples. Typically, the value of L is chosen to be N/4 so as to obtain a reasonable tradeoff between maintaining computational efficiency and minimizing the cycle leakage and cycle aliasing [33]. After the computation of the complex demodulates, an element wise product of the $X_T(n, f)$ is done with the conjugate of $Y_T(n, f)$. Time smoothing of the resulting data is ensured by means of a second P-point FFT. The values of N and P depend on the frequency and cyclic frequency resolution desired. Thus for a sampling frequency f_s , desired frequency resolution of Δf and cyclic frequency resolution of $\Delta \alpha$, the chosen value of N and P are

$$N = \frac{f_s}{\Delta f} ; P = \frac{f_s}{L \Delta \alpha} \quad (2.15)$$

Both N and P are chosen to be power of 2 so that zero padding can be avoided before using the FFT algorithm. From [33], the CSD using the FAM estimator can be obtained as

$$S_{XY_T}^{\alpha_i + q \Delta \alpha}(nL, f_j)_{\Delta t} = \sum_r X_T(rL, f_k) Y_T^*(rL, f_l) g_c(n-r) e^{\frac{-j2\pi r q}{P}} \quad (2.16)$$

$g_c(n-r)$ is the window operation, q is the index in the range

$$-\frac{PL}{2N} \leq q \leq \frac{PL}{2N} - 1 \quad (2.17)$$

k and l range from 1 to N .

Figure 2.7. FAM estimator to calculate the CSD of input signal.

Figure 2.7 summarizes the steps explained in this section to compute the cyclic spectral density values of a given input signal using the FAM based method. Figure 2.8 shows the region of support of the CSD values obtained. It is interesting to note the region of support of the result obtained is populated in a $N+1$ by $2N'+1$ array where $N' = P*L$. Only the data falling within the Region of support contains useful information. The FAM approach to compute the CSD is a fast technique to arrive at the result. But the speed of detection can be further increased if the cyclic frequencies to look for are also known apriori. In Chapter 4, the advantages of intentionally embedding cyclostationary features in the transmitted waveform are looked at. Particularly with respect to helping in improve not only the detection and analysis of the spectrum but also enabling to be robust at low SNRs.

Figure 2.8. Region of support within the bifrequency plane. Source: [33]

2.4.2.2 Merits and Demerits of CFD

The advantages of using CFD for CR is that CFD based techniques are much more robust to noise. So the problems associated with the uncertainties in the estimation of noise power in energy detector based CR do not affect a CFD based CR. Also cyclostationary analysis does not require phase or frequency synchronization.

On the flip side, CFD techniques are computationally very complex and hence require more time to arrive at the result. This not only consumes precious sensing time, but also increases the power consumption of the device due to higher number of computations. Also CFD operates at high sampling rates and any sampling time error can affect the cyclic frequencies [14]. Moreover, CFD techniques require long observation times for accurate signal analysis [28].

2.4.3 Matched Filtering

A matched filtering based spectrum sensing can be employed only if the signal to be sensed is completely known. In the presence of Gaussian noise, it has been shown that a matched filter maximizes the SNR of the signal [15]. However, a matched filter is effectively a demodulator of the primary user signal. This means that cognitive radio should have prior knowledge of various parameters of the primary user signal such as its modulation type and order, the pulse shaping applied to the input signal, the frame and packet format, etc. Also the CR should be able to achieve a high degree of synchronization in terms of timing and carrier frequency.

Mathematically, the operation can be represented as

$$\hat{S} = \sum_1^N y(k)x(k)^* \quad (2.18)$$

Here $y(k)$ is the received signal samples and $x(k)^*$ is the transpose of the conjugate of the pilot sequence.

Thus a matched filtering can be used to sense the spectrum only if the targeted primary user is known. For a specific application of CR targeting a known PU's license band, this is possible since most PUs use pilots, preambles, synchronization words or spreading codes which can be used for coherent detection [35]. For instance, TV signal has narrowband pilot for audio and video carriers, CDMA systems have dedicated spreading codes for pilot and synchronization channels, WiFi and WiMax signals use OFDM which have standardized preambles for packet acquisition.

2.4.3.1 Merits and Demerits of Matched Filtering

The advantage of matched filter is that it requires fewer number of samples to achieve the same performance metrics as other sensing techniques. The required number of samples are of the order of $\frac{1}{\text{SNR}}$ samples [25].

The main disadvantage of a matched filter based CR is that it needs a demodulator specific to the PU it intends to identify. This would make the CR impractical in terms of the cost of hardware required to have the demodulators for all the different PU signals to be detected.

2.4.4 Eigen Value Detection

Recently some new spectrum sensing algorithms based on the eigenvalues of the sampled signals have been proposed [36, 37]. These methods can be classified as blind sensing techniques since they do not require any prior knowledge about the signal structure or characteristics. The technique builds on some of the latest random matrix theories (RMT) to quantify the distribution of the eigenvalues and to calculate the probability of detection and probability of false alarm of the system.

To calculate the eigenvalues, first the statistical covariance matrix of the received input vector $y[n]$ needs to be computed. Considering 'L' consecutive samples of the received vector,

$$Y[n] = [y(n) \ y(n-1) \ \cdots \cdots \cdots y(n-L+1)]^T \quad (2.19)$$

the statistical covariance is given by

$$R_x = E[Y(n)Y^T(n)] \quad (2.20)$$

Practically, the statistical covariance matrix can only be calculated by using a limited number of samples [38]. Thus, a sample covariance matrix is estimated by calculating the sample auto correlation of the received signals. This is given as

$$\psi(l) = \frac{1}{N} \sum_{n=1}^N y(n)y(n-l), \quad l = 0, 1, \dots, L-1 \quad (2.21)$$

From the autocorrelation values obtained, the sample covariance matrix can be obtained. From the sample covariance matrix, the statistical covariance matrix can be approximated.

$$\widehat{R}_x(N) = \begin{bmatrix} \psi(0) & \cdots & \psi(L-1) \\ \vdots & \ddots & \vdots \\ \psi(L-1) & \cdots & \psi(0) \end{bmatrix} \quad (2.22)$$

It should be noted that the sample covariance matrix given by (2.22) is symmetric.

To detect the presence or absence of the signal, the maximum and minimum eigenvalues, $\psi_{\max}$ and $\psi_{\min}$ respectively, of the sample covariance matrix are calculated. Two algorithms proposed in [36] to detect are Maximum - minimum eigenvalue (MME) and Energy with minimum eigenvalue (EME) ratio tests. In the MME technique, if $\psi_{\max} / \psi_{\min}$ exceed a threshold then the presence of the signal is hypothesized. Else it is assumed that the spectrum is vacant. In the EME technique, the average power of the received signal is computed (using 2.3) and a ratio of the computed power to $\psi_{\min}$ is taken. If this ratio exceeds the set threshold then the spectrum is assumed to be occupied. The threshold for the MME and EME technique depends only on the number of samples N , the smoothing factor L and the probability of false alarm (P_{fa}). Unlike the energy detector, the threshold can thus be pre computed since it is independent of the signal and noise power.

2.4.4.1 Merits and Demerits of Eigenvalue Detection

The major advantage of eigenvalue detection is that it does not require any knowledge about the signal, channel or the noise power. It is blind detection technique and yet it is more robust to fluctuations to noise than the conventional energy detector. The technique works best when the input signals are highly correlated, like wireless microphone signals, Digital TV signals, etc.

The disadvantage of the technique comes from the fact that a high number of computations are required to arrive at the final decision. For a smoothing factor of L and an oversampling factor of M , the total time required to arrive at the result is approximately $M*L$ times that required for an energy detection.

2.4.5 Multi Resolution Spectrum Sensing

Multi resolution technique is based on the premise that detecting the presence or absence of signal in one parse of the spectrum need not give an accurate result. Sometimes it is prudent to have a closer look at the spectrum again to verify the result once again. The multi resolution technique available in literature is generally based on energy detection principle. In [39] a simple wavelet based approach is adopted to get the spectrum information. The technique uses FFT operation to get the required spectral information about each signal. During the coarse sensing stage, the

frequency is incremented in big blocks while for fine sensing stage the increment in frequency is lesser. The processing is done in analog domain and hence the power required is low. Thus this method can be realized in real time. This technique has shown excellent results even when signal power is as low as -120 dBm.

In [40], a similar strategy is adopted. The technique proposes a coarse sensing in the first stage and if it finds that the energy is 0 or more than a limit, (say $p\%$), then the decision to use or not use the spectrum respectively, is taken in the first stage itself. But if the number of bands having some energy is somewhere between 0 and p , then another round of fine sensing is done for those subbands which showed some energy above the threshold (noise floor). This technique has the advantage that if the spectrum is sparsely populated, then the number of computations is greatly reduced.

Other similar works on multi resolution sensing can be found in the literature [41-43]. It should be noted that both the sensing stages of a multi resolution sensing need not be the same. For instance, in [42] the second stage uses a CFD for validating the results of the ED used in the first stage. Since the multi resolution technique internally uses one of the known algorithms for sensing, no analysis is being presented on the merits and demerits of this technique.

2.4.6 Other Known Techniques

In this section, a very brief overview of techniques on which active research is going on, is presented.

Compressive sensing is a relatively new technique to be used for spectrum sensing and detection. It is more useful when the signal to be detected is very sparse in nature. The fact that the wireless signals are typically sparse justifies the usage of compressed sensing techniques. Recently it has been demonstrated that for sufficiently sparse signals, sub nyquist rate sampling can be done and the signal recovered via computationally feasible algorithms [44]. The quality of the reconstruction depends on how compressive the signal is, the algorithm chosen for reconstruction and the incoherence of the sampling dictionary [45]. In [44], the authors use the compressed sensing technique to show that the system is more robust to noise and together with wavelet based edge detector can be used for recovery of the target signal.

The wavelet based edge detectors are also the latest entrants to the domain of spectrum sensing. In this approach, the wideband signal spectrum is subdivided into smaller building blocks of non

overlapping sub bands. Then the wideband is modeled as a sequence of consecutive frequency sub bands in which the power spectral density is smooth and continuous within the sub band but discontinuous at the edges of the sub bands. These discontinuities of the spectral density plot gives an accurate picture about the presence of spectral holes in the wideband spectrum[46, 47]. The ability to dynamically tune the frequency and time resolution of the wavelets have been put to good use to locate the frequency boundaries of each band within the wideband of interest.

A technique based on distribution analysis has been presented in [48]. The distribution analysis detector (DAD) uses model selection tools like the Akaike information criterion (AIC) to detect the vacant holes in the spectrum bands. The basic assumption behind this technique is that if the captured signal samples contain only noise, then the distribution of the weights will be Gaussian in nature whereas a presence of deterministic signal in the samples will make the weights follow the Rician distribution. Thus by analyzing the distribution pattern and classifying them to be Rayleigh distributed or Rician distributed, the absence or presence of signal can be estimated, respectively.

2.5 Spectrum Sensing for Cooperative Sensing Scheme

2.5.1 General overview

Till now, in this thesis, only those sensing schemes which did not require any sort of communication between the various cognitive users have been presented. In this section, a brief description of a scheme based on cooperation among the various CRs is presented. In a cooperative sensing scheme, each CR communicates with other CRs or to a common entity so that a better overall perspective of the sensing environment can be established. This scheme has the advantage that the classical wireless communication problems like shadowing, fading and problems due to hidden node can be mitigated to a great extent.

Figure 2.9 shows a pictorial representation of the cooperative scheme that can be utilized in CR network to enhance the overall performance of the system. The cooperative, also called collaborative, scheme are broadly classified into two methods known as Centralized sensing and Distributed sensing.

Figure 2.9. Cooperative sensing scheme in Cognitive radio.

Centralized Sensing

In the centralized sensing technique, all the CR nodes in the network communicate to a central unit called the Fusion centre. The fusion centre collects the information from the various CR nodes and then takes a decision based on all the obtained data. The decision is then broadcasted to all the CR nodes in the network.

Distributed Sensing

In distributed sensing, each node communicates with the other node and themselves take a final decision. The decision to use which part of the spectrum is taken individually by each node [4]. The advantage of such a system is that it does not require a central unit to collect, analyze and disseminate the information to all the CR nodes.

Data Processing

The sensed data by each CR node can be processed in two ways [7], **data fusion** and **decision fusion**. In **data fusion** (also called **Soft Decision**), the measurements from all the CR nodes are sent to the fusion centre where the received data from all the sources are jointly processed to arrive at the final result.

In other words, if $Z(y)$, is the received test statistic for an energy detector based cluster of CR users, then the fusion centre computes a final test statistic, $T = \sum w_i * Z(y)$. The individual weight of each result depends on the amount of information the fusion centre has about the SNR

of each CR node. If no information is available, then all the weights are assigned equally. There are many techniques in the literature which describe the optimal way to set the parameters when the signal power at the sensing CR node is known [7, 49]. This method is not viable where there are large numbers of nodes. A lot of bandwidth will be required to send the measurement data and hence it runs counterproductive to the whole idea behind CR.

In **decision fusion** (also called **Hard Decision**), each CR node takes a hard decision based on its local observation and sends this final result to the fusion centre. At the fusion centre, depending on the reliability of the CR node which sent the result, the decisions are weighted and a final decision is arrived at. There are many ways to fuse the decision. Most fusion methods in literature assume no knowledge of the local SNR at each CR node [50]. However, some recent works [51] have emerged which take into account the difference in the SNR at the individual CR node and assign a weight depending on the SNR at each CR node. The most commonly used fusion techniques are Logical OR rule, Logical AND rule and K-out of N - fusion rule.

Logical OR Rule

If one of the CR nodes decision is “H₁,” then the final decision is “H₁”. If it is assumed that all decisions are independent, then the probability of detection and probability of false alarm of the final decision are given by,

$$P_d = 1 - \prod_{i=1}^N (1 - P_{d,i}) \quad (2.23)$$

$$P_{fa} = 1 - \prod_{i=1}^N (1 - P_{fa,i}) \quad (2.24)$$

where N is the total number of CR nodes, $P_{d,i}$ and $P_{fa,i}$ are the probability of detection and probability of false alarm for user i , respectively.

Logical AND Rule

If and only if all the CR node decisions is “H₁,” only then the final decision is “H₁”. If it is assumed that all decisions are independent, then the probability of detection and probability of false alarm of the final decision are given by,

$$P_d = \prod_{i=1}^N P_{d,i} \quad (2.25)$$

$$P_{fa} = \prod_{i=1}^N P_{fa,i} \quad (2.26)$$

where N is the total number of CR nodes, P_{di} and $P_{fa,i}$ are the probability of detection and probability of false alarm for user i , respectively.

K- out -of- N fusion rule

This rule is a general rule encompassing the rules earlier mentioned. This rule states that for a decision to be accepted, at least K out of the N CR nodes should arrive at the same decision. The above mentioned OR and AND rule are special cases of this rule, i.e, when $K = 1$, this rule becomes the OR rule. When $K = N$, this rule becomes the AND rule and when $K = \frac{N}{2} + 1$, this rule becomes the Majority rule. The probability of detection and probability of false alarm for this rule is given by [16]

$$P_d = \sum_{i=K}^N \binom{N}{i} P_d^i (1 - P_{di})^{N-i} \quad (2.27)$$

$$P_{fa} = \sum_{i=K}^N \binom{N}{i} P_{fa}^i (1 - P_{fai})^{N-i} \quad (2.28)$$

Some studies have been carried out to investigate the benefits of soft decoding with respect to hard decoding. In [52], the authors simulate a group of users at a distance of 60km apart from a TV transmitter. A probability of detection of 95% was kept as the target performance metric. The study showed that there are no significant benefits by using the soft decoding approach. Thus conventional cooperative schemes use hard fusion of data rather than a soft fusion.

A control channel needs to be established for the collaborating among the various CR devices and to the central unit if present. This can be done by using a dedicated band or an unlicensed band such as the Industrial Scientific and Medical (ISM) or by having an underlay system such as an ultra wide band (UWB). [53] These control channels can be used for sharing spectrum sensing results among CR users as well as for sharing channel allocation information.

2.5.2 Merits and Demerits of Cooperative Sensing

Cooperative sensing negates the effects of fading or shadowing to a large extent. Also shadowing and fading can be reduced by using beam forming and directional antennas. Similarly the effects of multipath can also be mitigated through cooperative sensing [52]. Moreover by using

information like the SNR of the PU at each CR node, a better and more reliable estimate about the presence or absence of signal can be established and thus the overall detection probability of the network can be enhanced.

On the other hand, there are many challenges in cooperative sensing. They include developing efficient and guaranteed information sharing algorithms, robustness to data errors due to channel impairments, interference and noise. Also the impact of malicious nodes in the network should also be considered when formulating an overall strategy for cooperation. These malicious users place an upper bound on the achievable sensitivity.

2.6 Hardware Implementation of Cognitive Radio

The literature survey on practical implementation of CR and the applications of CR in real world scenarios is presented in this section.

The most intended use case for deployment of CR, which is also the main motivating factor, is the inefficient usage of the TV bands. These bands fall in the most ideal range suited for wireless communication, i.e., 300MHz to 1 GHz. Thus exploiting the vacancy created in TV bands is a primary interest to all players in the field of CR. In [54], the authors present a design of a system which can detect the presence of TV signals and perform high speed data communication in a vacant TV band without interfering with the adjacent TV bands. The implementation uses a Matched filter to identify the presence of Digital TV signal or analog NTSC signal. The detector is reported to sense signals as low as -114dBm which is much lower than the reception threshold of -85dBm normally expected from a TV receiver. Hence if the input signal characteristics are known, then using a matched filter is the best and most effective way of detecting the presence of signal.

In [55], the authors implement an eigenvalue based algorithm on a real time prototype to detect the vacancy in TV bands. The implementation uses a commercial RF transceiver to down convert the TV bands to a 44MHz IF. The analog IF is then further digitized and down converted to a digital IF. The numbers of sensing samples used were around 400K which corresponded to a signal acquisition time of 200msec with a 2 MHz ADC. The implementation could detect ATSC signals as low as -118.5dBm with 90% accuracy which can be considered to be a good performance.

Some other prototype implementations for detecting TV signals have been discussed in [56, 57]. For instance in [57], the authors exploit the cyclostationary features present in a Digital TV signals

to detect its presence. The novelty of the approach used in this work is the use of decimation of the spectrum. This decimation factor acts as the lever which controls the tradeoff between the sensing time and the probability of detection. The input is sampled at 20MHz and decimated by a factor ranging from 2^0 to 2^4 . The decimated output is sent to a FFT unit. The output of the FFT is used to calculate the covariance matrix from which cyclic features of the input signal can be extracted. The algorithm was implemented on a FPGA which was accompanied by a WLAN RF receiver for measurement purposes. The input signal chosen used OFDM with 52 subcarriers and each subcarrier employing 16 QAM modulation. A similar implementation to detect the presence of IEEE 802.11g primary system using cyclostationary detection of the OFDM induced features has been done in [58].

An experimental study of the performance of the various sensing algorithms mentioned earlier in the report has been presented in [59]. The algorithms compared by the authors were the ED, CFD and Model selection based algorithm discussed in [48]. The platform consisted of a PC data acquisition card. The input signal was a signal in the frequency range of 1.900GHz to 1.920GHz with 5MHz channels and 21dBm transmit power per OFDM antenna. The SNR was varied from -18dB to 0dB. It is shown that, of the three detectors under investigation, the ED performed the worst while CFD gave the best performance. However this is due to the fact that the cycle frequency parameters were known and hence the computation time required to arrive at the result was sufficiently long. The advantage of the model based selection technique in doing a blind detection based on the distribution pattern of the received samples is reinforced by this work.

2.7 Applications of Cognitive Radio

Cognitive radio has immense applications in the fields of public safety, military communication and other similar domains where an ad hoc network becomes the most apt form of communication. Several applications have been described in the literature. A brief review of these applications is covered in this section.

In [60] the author proposes a deployment of CR network to support vital communication among troops and vehicles in a foreign territory where the radio environment might be both unfamiliar and dynamically changing. In these circumstances, a CR network can look for available white spaces and the use it to communicate. Other applications of CR in military communication has been presented in [61]. Some of the most promising ones include a jammer which will look for military communication signals and activate a high powered RF signal at the same frequency to

cause enough interference to the signal so as to render it meaningless. But since most military communication employ Direct Sequence Spread Spectrum (DSSS), conventional energy detector techniques cannot be used for detection purposes. They need development of more sophisticated techniques for tracking the CDMA communication signals. The spectrum sensing algorithm can also be used to compare the spectral envelopes of the spikes and record the frequency hopping sequence of the source.

Apart from military communication, the uses of CR for civilian applications have also been explored. In [62] the author proposes to use CR to replace the current analog VHF based communication for aeronautical air to ground communication. It is reported that the utilization of spectrum in the air traffic control band is less than 5% and thus provides a good opportunity to use CR to optimize the usage of available spectrum so that the spectrum is not wasted away and instead be freed for use for other communication purposes. The CR discussed by the author is an extension of the Software Defined Radio (SDR) and uses the concept of SDR to dynamically reconfigure the communication system after analyzing the information it receives from sources like sensors and its policy engine. Such a CR can dynamically use the available channels based on its location, environmental conditions and using these inputs optimize the usage of limited spectrum.

Other civilian application of CR have been presented in great detail in [63]. The authors describe the use of CR for public safety purposes by providing uninterrupted communication link during disaster relief operations. A CR device can utilize the licensed/unlicensed spectrum holes and create and manage a temporary emergency communication link. CR concepts can also be employed for scenarios like Traffic control, Medical applications, Biomedical engineering, etc. The cognitive concepts can also be employed for assisting in environmental protection by relaying information about air pollution, global warming, weather forecast and research on behaviors of endangered species. CR can also be used for personal level applications like tracking a school going child or in a office environment where the CR can prioritize a radio network connection according to pre set priority status. For instance, a conference among the CXO's can receive the highest priority in getting access to spectrum. CR concepts can also be used in Man Machine Interfacing (MMI). Some of the prominent use cases of CR in MMI can be User authentication, Noise cancellation, detecting user emotions, etc. Thus, it can be seen that the concept of CR can have wide ranging applications and is currently limited only by the human imagination.

2.8 Summary

In this chapter, a comprehensive review of the state of the art in spectrum sensing algorithms has been presented. Spectrum sensing algorithms employing various design philosophies and exploiting different characteristics of a signal has been presented in detail. It has been observed that the best spectrum sensing algorithm to choose for a CR depends on the operating needs of the CR. If a fast but less accurate detection is required, then ED based CR can be chosen. But if the information about the primary user is available, then a matched filter can also be designed for detection purposes. CFD can be used if there is some information, like the cyclic frequency, about the signal. CFD is robust to noise but complex to implement and hence takes lot of power and time. Cooperation among the various CR nodes in a network could be the only method by which a reliable estimate of the primary user can be done if the operating environment is such that each of the CR nodes has reached its SNR wall. By having a meaningful and trustworthy cooperation, the overall performance of the network can be improved and the vacancy in the spectrum due to the absence of the licensed user can be exploited more effectively. Brief surveys of the state of the art in cooperative sensing schemes have been presented in this chapter.

Literature survey pertaining to implementation of CR in hardware was also undertaken to understand the hardware and software requirements needed. A survey of the various hardware implementations of the CR by universities and industrial groups have been presented in this chapter. Also brief mentions of the practical applications of CR to solve real world problems have also been discussed.

Chapter 3

Threshold Selection at Low SNR for Energy Detectors

This chapter presents the impact of threshold on the performance of an energy detector (ED) based cognitive radio (CR) and analyzes the parameters which determine the performance of the CR. As mentioned in Chapter 2, setting of threshold for an energy detector based CR holds the key in determining its performance metrics i.e. probability of detection (P_d) and probability of false alarm (P_{fa}). In this chapter, a theoretical analysis of the impact of threshold on the performance of ED is done. The analysis is further validated by simulation results which are also presented in this chapter.

The two parameters considered for analyzing the selection of threshold for ED based CR are the time to sense the channel to acquire required number of samples (N_s) and the signal-to-noise ratio (SNR) denoted as γ , of the channel under consideration. Though both these parameters impact the performance in similar ways, they present a different perspective to the role each parameter plays in determining the metrics of the CR.

3.1 Analytical Modeling of Threshold

As mentioned in Chapter 2, the performance metrics of a CR system is defined by its ability to detect a primary user (PU) correctly. The higher the probability of detection, the better is the chance that the presence of the PU will be correctly identified by the CR. This would allow the CR to stop transmission so that it does not cause any interference to the PU. Another important metric that defines the performance of a CR is its ability to minimize the false alarms raised. A low P_{fa} will ensure that the throughput of the CR system is not affected by false alarms raised about the presence of PU. Thus, P_d and P_{fa} determine the performance parameters of the CR. In practical scenarios, the operational requirement could be to cause no interference to the primary user (PU) (requires a high P_d throughout) or maximize the throughput of the cognitive radio (requires a low P_{fa} throughout).

The metric P_d of an energy detector depends on parameters such as the number of samples (N_s), the SNR (denoted as γ), the noise variance (σ_n) and the threshold selected for making the decision of presence or absence of signal (λ). On the other hand, P_{fa} does not need the information on γ of the system. The equations which deal with these parameters have been presented in Chapter 2. In this section, those equations will be further expanded to obtain an expression for calculating the number of samples required to meet the targeted performance metrics for the CR.

A brief review of the mathematical analysis presented in Chapter 2 is presented here. Let $s[k]$ represents the PU signal and $w[k]$ represents the noise introduced by the transmission channel. Then the signal sensed by the CR, $y[k]$, can be

$$Y[k] = \begin{cases} w[k] & : H_0 \\ s[k] + w[k] & : H_1 \end{cases}$$

H_0 is the hypothesis that the PU is not transmitting and hence $s[k]$ is 0, while H_1 is the hypothesis that the PU is using the channel for transmission.

Thus the aim of a CR system is to sense the spectrum and decide on one of the two hypotheses it estimates the channel is in. The CR system makes this decision based on the threshold (λ) it sets to discriminate between the presence and absence of signal. It is this threshold which, therefore, determines the performance metrics, P_d and P_{fa} of the system.

For the sake of simplicity, the primary signal and the noise are assumed to be an independent and identically distributed (iid) random process with zero mean and of variances, σ_s^2 and σ_n^2 respectively. The SNR (γ) is, therefore given as $\gamma = \frac{\sigma_s^2}{\sigma_n^2}$

The test statistic for the given model can be expressed as

$$Z(y) = \frac{1}{N_s} \sum_{n=1}^{N_s} |y[n]|^2 \quad (3.1)$$

For large N_s , the test statistic $Z(y)$ has a normal distribution with mean μ_i and variance σ_i under hypothesis H_i ($i = 0,1$) [13]. The mean and variance of the test statistic have been shown, using the results in [6, 7], as

$$\mu_0 = \sigma_n^2 \quad (3.2)$$

$$\sigma_0 = \frac{\sigma_n^2}{\sqrt{N_s}} \quad (3.3)$$

$$\mu_1 = \sigma_n^2 (1 + \gamma) \quad (3.4)$$

$$\sigma_1 = \sigma_0 (\sqrt{2\gamma + 1}) \quad (3.5)$$

The P_{fa} and P_d of such a system is given as

$$P_{fa} = Q\left(\frac{\lambda - \mu_0}{\sigma_0}\right) \quad (3.6)$$

$$P_d = Q\left(\frac{\lambda - \mu_1}{\sigma_1}\right) \quad (3.7)$$

where $Q(x)$ is defined by the complementary distribution function of the standard Gaussian and is given as

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-u^2/2} du \quad (3.8)$$

As seen from (3.6) and (3.7), the threshold, λ , can be set for a target P_{fa} or P_d . For the sake of notational simplicity, a threshold derived using (3.6) has been denoted as λ_f and the threshold derived using (3.7) as λ_d . It is clear from (3.4), (3.5) and (3.7) that setting a threshold based on target P_d require information about γ , i.e. SNR of the channel.

3.2 Conventional Energy Detector based CR

A conventional energy detector based CR sets the threshold based on the target P_{fa} . This avoids the need to estimate the SNR (γ) of the channel and also avoids the need to know about the signal characteristics. An energy detector based on threshold calculated for a target P_{fa} works well in high γ conditions. But when γ is less than -15 dB, the performance of the energy detector deteriorates significantly [4].

The simulation results to demonstrate this are shown in Fig. 3.1. Simulation results to obtain Fig. 3.1 were conducted at a SNR of -15dB and the numbers of samples were varied from 6000 to 20000. Since the knowledge of γ is not available, the conventional energy detectors calculate the threshold based on target P_{fa} by using (3.8) and then observe the P_d that can be managed for the system. This, as explained previously, has the disadvantage that if γ is less than the expected range, the performance is severely affected.

From Fig. 3.1 it is clearly seen that when the sensing time is short, which leads to reduced number of samples, a conventional λ_f threshold based detector will give a very poor probability of

detection metric. Thus, in practical scenarios where increasing the sensing time to get a comfortable number of samples is not feasible, the conventional approach will perform badly.

For the simulation analysis, a quadrature phase shift keying (QPSK) modulated signal has been considered as the PU and the probability of hypothesis H_1 has been fixed at 0.2. This implies that the channel is assumed to be vacant 80% of the times. The targeted P_d and P_{fa} are 0.9 and 0.01 respectively. 10000 Monte Carlo simulations were carried out to calculate the P_d and P_{fa} .

Figure 3.1 Performance of conventional detector for varying number of sensing samples at at -15dB and P_{fa} at 0.01.

Similar studies were conducted for a fixed number of samples and by varying the SNR of the channel to see the impact of the threshold selection at low to high SNR regimes. The results obtained for a sample size of 1000 are shown in Fig 3.2. It is evident from Fig. 3.2 that the performance of the conventional energy detector degrades drastically for short sensing times if the SNR of the channel is low. The probability of detection deteriorates significantly for a conventional energy detector (ED) based CR. In the next section, a mechanism to mitigate the degradation by switching to the P_d based threshold mechanism as per the operational need of the CR is proposed.

Figure 3.2. Performance of conventional detector for varying SNR with fixed sensing time and $P_{fa} = 0.01$.

3.3 Proposed System Model

It was observed that if the threshold is chosen as λ_d by computing it using (3.4), (3.5) & (3.7), then a high probability of detection can be established for a ED based CR. Hence if the CR can estimate the channel γ then λ_d can be set as the threshold level and thus a high P_d can be ensured. Since the threshold of λ_d can only be set if the γ is known, it is proposed that once the CR system is operational, it can estimate the channel γ and calculate λ_d . The block diagram in Fig.3.3 shows a CR system which estimates the SNR and passes on the information to the Threshold Setter module where an analysis is done based on the inputs received.

The analytical model developed can be used to compute the minimum sensing time required to meet the target performance metrics. Thus by using (3.6) and (3.7) and substituting the mean and variance values from (3.2) to 3.(5), it can be easily shown that the number of samples, N_s , is related to P_{fa} , P_d and γ , as

$$N_s = \frac{1}{\gamma^2} \left[Q^{-1}(P_{fa}) - Q^{-1}(P_d) \sqrt{2\gamma + 1} \right]^2 \quad (3.9)$$

The estimate of the SNR can be done by the various known techniques available in the literature such as [64-66]. For instance in [64], the authors argue that since IEEE 802.22 requires the base station to know the distances of the secondary users from the primary user, the power received at the secondary user can be calculated using the known propagation path loss model.

Figure 3.3. Block diagram of the proposed system model.

In [65], the authors suggest the use of principal component analysis decomposition of the noise covariance matrix to estimate the noise variance. Better techniques like matrix perturbation approach developed in [66] have also been suggested for estimating the noise variance. It should

be noted that the estimate of the SNR is an input to this algorithm. This thesis does not deliberate in detail on the techniques to estimate the SNR.

The equation (3.9) matches with the one in [6]. The significance of (3.9) is that it gives the minimum number of samples, N_s , required to achieve the target metrics (P_d & P_{fa}). In other words, if the CR can estimate the γ of the channel, then it can compute the minimum number of samples it requires to achieve the target performance metrics. The CR can then vary the sensing time of the signal and choose an appropriate threshold to perform as per its requirements. If the critical number of samples to achieve the target P_d & P_{fa} is known then it can be used to decide on how best to switch the threshold from one value to another. To do this, a control parameter, α , is introduced in this thesis which can be changed to vary the threshold from λ_f to λ_d . The threshold λ_{new} is given as

$$\lambda_{new} = \lambda_f + \alpha * (\lambda_d - \lambda_f), \quad 0 \leq \alpha \leq 1 \quad (3.10)$$

At a simple level, α can take a binary value of 0 or 1, thereby changing the threshold from λ_f to λ_d . But since any change in the threshold value is essentially a tradeoff between the P_d & P_{fa} of the CR, it is advisable to have finer control over the threshold to be set. Hence a careful study of the operational needs of the CR should be done before setting the value for α .

3.3.1 Extension to the proposed model - An SNR based perspective

The analysis of the performance of the ED based CR for a varying sensing time at a fixed SNR can be extended to observe the performance of the CR at varying SNR values at fixed sensing time. Equation (3.11) shows the critical γ required to meet the target P_d and P_{fa} .

$$\gamma_c = \left\lceil \frac{Q^{-1}(P_{fa}) - Q^{-1}(P_d)}{Q^{-1}(P_d) + \sqrt{N_s}} \right\rceil \quad (3.11)$$

This equation is similar to the equation derived in [6]. The importance of this equation is that it helps in identifying the SNR level below which the performance of a conventional ED based CR begins to fall drastically. Hence pre computing the critical SNR using (3.11) and comparing it with the SNR of the channel in which the CR is operating can give insights into how best to choose the threshold. The following section explains the proposed methodology in more detail.

3.4 Proposed Algorithm

Based on the findings outlined in Section 3.3, a possible strategy that a CR can adopt in a deployed state can be formulated. If the channel conditions are such that the SNR of the channel is more than γ_c and the mandate is to cause least interference to the PU, then the threshold can be maintained at λ_f . Otherwise if the mandate to increase the throughput of the CR then the threshold could be changed to λ_d by changing α to 1 and thereby capitalize on the very low P_{fa} beyond the γ_c region. If, instead, the γ of the channel is less than γ_c , then α can be set at a value which gives the most optimum P_{fa} and P_d for the given environment and operational need. By adopting this method, a compromise between P_{fa} and P_d can be achieved without being fixed on any one threshold value.

For this algorithm, it has been assumed that the sensing time available to the CR is short and that the CR is using its sensing slot to the maximum and acquiring as much samples as it can to compute the result. The algorithm can be easily modified to represent the scenario when the SNR of the channel is held constant while the sensing time to acquire the data samples is varied.

The algorithm that can be employed is as follows.

Step 1: Set the target P_{fa} and P_d and use (3.6) to compute λ_f .

Step 2: Set the number of samples, N_s , depending on the sensing time slot available and the sampling rate of the ADC. Use N_s , P_{fa} and P_d to calculate γ_c by using (3.11).

Step 3: Estimate the signal to noise ratio, γ , of the channel.

Step 4a: If γ is greater than γ_c then set α to be 0 since both the targeted parameters P_{fa} and P_d can be met.

Step 4b: If γ is less than γ_c , then calculate λ_{new} for a lower P_d using (3.7) and calculate a value for α by reworking (3.10). Set this value of α to change the threshold.

Step 5: Compute the test statistic $Z(y)$ using (3.1) and compare with the new threshold.

Thus, the threshold can be set as and when the sensing environment changes. The change in the environment could be due to the change in the γ of the channel or due to a change in the sensing time available for the CR to sense the channel. By carefully selecting the threshold, a guaranteed performance metric can be obtained.

The results for various values of α have also been simulated. Note that the value of α chosen here are for illustration purposes only. Any value of α within the range $[0,1]$ can be chosen.

Figure 3.4. Performance characteristics of energy detector for fixed sensing time at different values of α .

The simulation results when the γ is held constant while the number of samples acquired is varied also give similar response as shown in Fig 3.5.

An analysis of the response given in Fig. 3.4 and Fig 3.5 brings the following into light:

- (a). As the value of α changes from 0 to 1, the curve obtained moves away from the graph obtained for λ_f to the one obtained for λ_d .

(b). The best strategy to set the threshold to get the optimum response of the energy detector depends on the channel conditions, the sensing time available on hand and the operational requirements.

As observed from these results, a fixed threshold based on λ_f , as done conventionally, is not always the best way to set the threshold level. By estimating the γ of the channel and identifying the operational needs of the CR, a more suitable threshold can be set so that the CR performs as per the desired requirements.

Figure 3.5. Performance characteristics of energy detector for fixed γ at different values of α .

Let us now look at the reasons for the variations in the performance metrics as the channel γ changes from low SNR ($\gamma < \gamma_c$) to relatively higher SNR ($\gamma > \gamma_c$). To keep the analysis simple, the graph of Fig. 3.1 has been discussed here where the threshold values are λ_d and λ_f only. Figure 3.6 gives a comparison between the average noise power, ω , of the channel and the two threshold

values λ_d and λ_f as the γ of the channel changes for -18dB to -5dB for a target P_d of 90% and P_{fa} of 1%. When $\gamma < \gamma_c$, the thresholds and noise power are related by $\lambda_d \leq \omega \leq \lambda_f$. Since the average noise power ω is greater than λ_d , total power (sum of signal and noise power) exceeds λ_d almost always. Hence the P_d manages to stay at 90%.

Figure 3.6. Threshold levels computed for different SNR values.

This explains why the P_{fa} is also high correspondingly in this region for λ_d . But since λ_f is higher than ω , the total power and the noise power (when signal is absent) seldom manages to cross λ_f , which leads to a low P_d but favorably a low P_{fa} . When $\gamma > \gamma_c$, the threshold and noise power are related by $\omega \leq \lambda_f \leq \lambda_d$. A high γ here means that the noise power is significantly less. Hence it is the signal power which plays the dominant role in determining whether the total power will cross the set threshold or not. As seen from Fig. 3.6, the gap between λ_f and ω is narrow and so whenever signal is present, it manages to cross the set threshold most of the time. This explains a

high P_d when λ is set to λ_f . Since λ_d is larger than λ_f and ω , the number of times the signal power manages to take the total power beyond the threshold λ_d is not as high as it was for the case of λ_f based threshold. Hence P_d is lower for λ_d based threshold at high SNRs. For the same reasons, the P_{fa} at λ_d is much less than it is at λ_f .

3.5 Noise Uncertainty and SNR Wall

The ED described so far assumed an idealistic case wherein the estimate of the noise power is without any uncertainty. But practically this is hardly the case. The fundamental limitation of the ED is that any error in estimation of the noise power severely degrades its performance. In [5, 6], the authors show that there is a lower limit of the SNR beyond which it is impossible for the ED to detect the presence of the PU signal.

For an uncertainty in noise power estimation of δ , a noise power of σ_n^2 can vary from $[\delta\sigma_n^2, \sigma_n^2/\delta]$. Thus as shown in [5], in the worst case scenario, estimation is impossible beyond a certain SNR level. This SNR can be derived as

$$\sigma_s^2 + \frac{\sigma_n^2}{\delta} \geq \delta\sigma_n^2 \quad (3.12)$$

Solving the above equation leads to a minimum SNR of

$$\frac{\sigma_s^2}{\sigma_n^2} \geq \left(\delta - \frac{1}{\delta}\right) \quad (3.13)$$

To illustrate the point further, Fig. 3.7 shows the plot of an ED with an uncertainty of Δ ($=0.5$ dB).

Thus $\delta = 10^{\frac{\Delta}{10}}$.

The SNR Wall is

$$\gamma_{wall} = \left(\frac{\sigma_s^2}{\sigma_n^2}\right)_{wall} = 10\log_{10}\left(10^{\frac{\Delta}{10}} - \frac{1}{10^{\frac{\Delta}{10}}}\right)dB \quad (3.14)$$

For an uncertainty of $\Delta = 0.5$ dB, the theoretical value of γ_{wall} at -6.4dB has been validated with the simulation results.

Figure 3.7. SNR Wall for energy detector.

As seen from Fig. 3.7, once the SNR goes below -6dB, the performance deteriorates significantly and using an ED becomes impossible for spectrum sensing after the γ_{wall} is reached. This result can be expanded to obtain the SNR in an uncertain environment, denoted as γ_u , at which the target probability of detection and target probability of false alarm is maintained. With the help of results in [6], for an uncertainty of δ in estimation of noise power, the SNR required to reach the target performance (γ_u) can be obtained as explained.

As assumed in [5], the threshold, λ , can vary from $\delta\sigma_n^2$ to σ_n^2/δ . Hence the maximum uncertainty for λ can be

$$\lambda_{\max} = \frac{\delta\sigma_n^2}{\frac{\sigma_n^2}{\delta}} \lambda = \delta^2 \lambda \quad (3.15)$$

Substituting (3.15) in (3.7) and using (3.2) to (3.5), P_d can be expressed as

$$P_d = Q \left(\frac{\sqrt{N_s}(\delta^2 - 1) + \delta^2 Q^{-1}(P_f) - \gamma \sqrt{N_s}}{\sqrt{(2\gamma + 1)}} \right) \quad (3.16)$$

Squaring on both sides and solving for γ ,

$$\gamma_u \cong (\delta^2 - 1) + \frac{\delta^2 Q^{-1}(P_f) - Q^{-1}(P_d) \sqrt{2\delta^2 - 1}}{\sqrt{N_s}} \quad (3.17)$$

Thus it can be observed how a fundamental limitation of the ED restricts its operational deployment as a CR in a practical setup where perfect knowledge of the noise power cannot be guaranteed.

3.6 Summary

It has been shown that there is significant deterioration in detection performance at low SNR and hence keeping the threshold static at low SNR may not be ideal in a dynamically changing operating scenario of the CR. It has been also validated that though an ED should have a high P_d and a very low P_{fa} , practically there is always a tradeoff between the two parameters. Estimating the SNR to come up with a probability of detection based threshold is a good technique so that the tradeoff between a high P_d and low P_{fa} requirements can be managed in the best possible way by using an adaptive threshold in a time varying channel. It has been shown that the critical number of samples required should be calculated by the system by estimating the SNR so as to determine how best to vary the threshold to get the desired response for the given operating environment. The various reasons for the deterioration in the performance characteristics when the SNR goes below the critical value have also been discussed. This chapter shows the impact of uncertainties in the estimation of noise power on the detection performance of an ED. The minimum SNR required to maintain the targeted performance metrics of the cognitive radio device in an uncertain noise environment has also been discussed. In the next chapter, steps taken to overcome the problems due to uncertain noise power estimation are presented. This comprises of a two-stage sensing scheme where the second stage uses cyclostationary analysis for signal detection. The cyclostationary detection, being more immune to noise power fluctuations, helps in improving the detection performance at low SNRs.

Chapter 4

A Two-Stage Spectrum Detector for Uncertain Noisy Channels

4.1 Introduction

The merits and demerits of the various spectrum sensing algorithms have been discussed in great detail in Chapter 2. It is known that though the energy detector (ED) is a very simple detector to design, it suffers from a fundamental limitation due the errors in noise estimation which makes it unsuitable when the signal-to-noise ratio (SNR) falls below a certain threshold known as the SNR wall [5, 6]. This seriously hampers the deployment of a ED based cognitive radio (CR) in a practical scenario since it is not possible to estimate the noise accurately and there will always be an element of uncertainty in its estimation. Though the conventional cyclostationary feature detection (CFD) algorithm is excellent in its robustness to noise and can work well in low SNR regimes, it is highly computationally complex and takes more time in arriving at a result. In order to facilitate a faster detection of the cyclostationary features of a primary user (PU), a pilot assisted detection approach, which has come into prominence recently, has been investigated in this thesis. It has been established that a pilot assisted cyclostationary detection (PACD) can help in detecting the cyclic properties faster and more accurately [67]. Though the opponents of this scheme have the opinion that this leads to alteration in the basic waveform of the PU [31], it can be reasoned that in future it would be in the best interest of both PU and the secondary user (SU) to make the spectrum as efficient as possible. In fact it would be an incentive for the PU to make the SUs use as much of its spectrum possible with the condition that the SU pay a royalty fee for its usage and also that the spectrum be returned to the PU for use as and when the PU needs it. An alteration in the PU transmission characteristics should not be a major problem for a PU if it leads to more revenue by way of sharing the spectrum with the SU.

In this chapter, a two-stage sensing scheme is presented wherein the first stage is an ED followed by a PACD. A two-stage detector helps in optimizing the usage of the PACD yet at the same time

improves the performance of the CR node in low SNR regimes. Some studies have already been done on two-stage detectors for spectrum sensing in CR [42, 68]. The approach presented in this chapter differs from these techniques in that the proposed algorithm suggests an optimum utilization of the second stage detector. Unlike the scheme mentioned in [42] and [68] where the second stage is activated every time the ED is unable to detect the presence of a signal, this thesis proposes a SNR based decision unit which decides whether to trust the results of the ED or to do another round of sensing using the more robust PACD.

4.2 Performance Analysis of Conventional Spectrum Sensing Schemes

With the help of the algorithm in [42], the merits in using a two-stage sensing scheme over a single stage sensing scheme are discussed in this section. Fig. 4.1 shows a generic model of a two-stage detector employed conventionally [42, 43, 69].

Figure 4.1. Model of a conventional two-stage detector.

The ED is chosen as the first stage not only because of its simplicity but also due to the fact that the ED maintains a constant low probability of false alarm even at low SNR conditions. Thus the ED is the optimum choice for the first stage detection. Only if the ED fails to detect any signal does a need arise of activating the second stage of a two-stage detector. The second stage detection can be any of the known techniques like CFD, Eigen value based detection (EVD) [38], or fine resolution sensing of the same band by increasing the number of samples (N_s), for example, as in a multi-resolution detector [40]. As seen from Fig. 4.1, if the ED computes the total energy (T_1) to be greater than the first stage threshold (λ_1), then it is hypothesized that the band of spectrum under evaluation is in use. On the other hand, if T_1 is less than λ_1 , then a fine sensing of the spectrum band will be done using a second stage analysis which employs computationally complex techniques to do the analysis. The test statistic of the second stage (T_2) is

compared with a pre-computed threshold λ_2 and a final decision is taken accordingly. It is obvious that a second stage sensing to improve the accuracy of detection obtained by the first stage sensing comes at the high cost of sensing and analysis time. This is a huge penalty to be paid by the CR in a ever changing wireless environment.

As discussed in the Chapter 3, ED is beneficial when the SNR is high so that even though there could be some errors in estimation of the noise variance, the ED would work fine as long as the SNR is above the lower bound SNR Wall given by λ_u as in equation (3.17). CFD on the other hand is robust to noise and hence is useful when the SNR is low. But CFD leads to a high detection time owing to the computational complexity in calculating the cyclic frequencies. Thus an ED-CFD two-stage detector appears to be a good choice so that the benefits of both the detectors can be utilized while at the same time the disadvantages of one stage can be mitigated by the other.

In [42], the authors use an ED for the first stage and CFD for the second stage detection. The probability of detection and the time taken to arrive at the results in [42] have been shown in Fig. 4.2 and Fig. 4.3 respectively. Here 8192 samples have been used for the first stage detection. It can be observed that at low SNRs, a two-stage detection scheme leads to a high probability of detection as compared to a single stage detection scheme. Hence the use of a two-stage detector for spectrum sensing in a CR device can be justified on the grounds that it leads to an improvement in the detection accuracy of the system.

The penalty to be paid for this improvement in detection performance is the increase in time taken to arrive at the result. In Fig 4.3, the mean detection time plot of the two-stage detector as compared to the single stage detector for different SNRs has been reproduced. The plots clearly show that although the mean detection time of the two-stage detector is less than that of the CFD technique, it is very high when compared to the ED technique. To make the analysis more clear, a new term defined as the probability of activation (P_{act}) has been introduced in this thesis. The probability of activation (P_{act}) is defined as the number of times the spectrum analysis using the second stage is done over the total number of spectrum sensing events. The P_{act} of the second stage in a conventional two-stage detector is given as

$$P_{act} = P(H_0) (1 - P_{f1}) + P(H_1) (1 - P_{d1}) \quad (4.1)$$

$P(H_0)$ is the probability of the channel being vacant and $P(H_1)$ is the probability of the channel being occupied by the PU. P_{f1} and P_{d1} are the respective target probability of false alarm and probability of detection of the ED used in the first stage. It has been shown that in practice the $P(H_0)$ can be as high as 80% [9]. Thus for a P_{f1} and P_{d1} of 10% and 90% respectively for the first stage ED, (4.1) computes that the second stage will get activated for 74% of the times on average. Thus if τ_1 is the time taken by the ED in the first stage and τ_2 is the time taken by the stage used for secondary detection, then the total time taken (T) for arriving at the result can be calculated as

$$T = \tau_1 + P_{\text{act}} \times \tau_2 \quad (4.2)$$

Considering the time taken by the second stage detection (τ_2) process as observed from Fig. 4.3, it becomes evident that the cost of improving the detection performance is indeed high.

Figure 4.2. Comparison of probability of detection for a two-stage detector with conventional single stage detectors as given in [42].

Fig.

Figure 4.3. Comparison of mean detection time of a two-stage detector with conventional single stage detectors as given in [42].

A close look at Fig 4.2 reveals a hidden redundancy in the two-stage sensing scheme. It can be observed that at high SNRs, the improvement in the detection performance of the two-stage detector is negligible as compared to an ED stage. Hence at high SNRs, where the ED is not constrained by the SNR wall, sensing the spectrum a second time whenever the ED calculates the energy to be less than the threshold seems to be overkill. If the operating SNR of the CR is high, then the sensing accuracy of the ED stage can be assumed to be true. In other words, activating the second stage of the CR without considering the SNR of the channel the CR is in, will lead to an unnecessary evaluation by the time consuming second stage. The same inference can also be derived by observing the algorithm presented in [68]. The advantage in mean detection time proposed by [68] is due to the fact that at high SNRs, the decision is taken at the ED stage itself and the decision does not go to the Maximum Eigenvalue Detector (MED) stage. Since the two-stage method in [68] uses only 10^4 samples for energy detection while when ED alone is used, $1.1 * 10^5$ samples are used for analysis, the savings in time is due to the reduced number of samples in [68] and not due to the fact that ED - MED two-stage detector is being used. Thus, with these insights obtained, in the next section, a modification to the conventional two-stage spectrum sensing algorithms to optimize the usage of the second stage is proposed.

4.3 Proposed Two-Stage Spectrum Sensing Scheme

In this section a novel two-stage spectrum sensing scheme that addresses some of the problems discussed in Chapters 2 and 3 of this thesis is presented. With the help of existing literature, it is shown that intentionally embedding cyclostationary signatures in the PU waveform is beneficial for both the PU and the SU. This chapter also shows how estimating the SNR can help in reducing the mean detection time of a two-stage CR.

4.3.1 A Pilot Assisted Cyclostationary Detection (PACD)

The existence of a SNR wall for an ED due to uncertainties in estimation of noise power has been discussed in Section 3.5 of Chapter 3. The authors in [5] show that this limitation is not restricted to ED alone. Depending on the uncertainty, every detector has its own SNR Wall which should not be breached in order to have a non zero possibility of detection. Thus even though CFD is robust against co channel or adjacent channel interference and performs better than ED, in the face of uncertainties in frequency selective fading, even the conventional CFD has a limitation to its operating SNR regime [5]. Also in case of OFDM signals, due to the various interferences, the

features become close or identical and thus it becomes difficult to identify different systems [70, 71].

Thus to mitigate these problems faced by a CFD, it has been suggested that pilot tones be embedded into the transmission waveforms of the PU [5, 28, 67, 72]. Though this approach is also not devoid of its share of criticism [31], multitudes of benefits of embedding pilot tones have been discussed in literature like negating the effects of SNR wall [5], increasing the accuracy of detection even under doppler fading scenario [71], and also enabling faster detection [67]. Also in a cooperative communication framework, it would be in the best interest of the PU to send a known pilot tone so that SUs can accurately detect the presence of the PU and at the same time use the licensed spectrum whenever the PU is not using it. This will lead to increased revenue for the PU by way of royalty fees from the SU. Though such a financial model is in a very nascent at present, it looks like a definite possibility in the future.

In this thesis, the cyclostationary features arising due to embedding a known signature into the pilot subcarrier of a OFDM symbol have been exploited to enable faster detection. Also the performance of the boosted pilot subcarrier OFDM symbol under AWGN conditions has been analyzed. Table 4.1 briefly lists out some of the relevant parameters of the OFDM symbol used for analysis.

Table 4.1. Parameters of OFDM Symbol

No: of Subcarriers	64
No: of Pilot Subcarriers	4
No: of Data Subcarriers	48
No: of Guard Bands	12
Sampling frequency	20MHz
Pilot Subcarrier Gain	[0 - 14dB]
Cyclic Prefix Length	16
Sub Carrier Modulation	QPSK

Since the pilot tones are embedded at known locations, the cyclic frequencies can be pre calculated and the analysis can be restricted to looking for peaks only at the desired cyclic frequencies. This leads to enormous savings in detection time and thus forms one of the major

advantages of PACD. In the case presented in this thesis, the cyclic frequency of a pilot subcarrier at index 'k' of the 64 sub carrier OFDM symbol can be computed as

$$\alpha = \frac{f_s}{32} (k - 1) \quad (4.3)$$

For a FAM-based CSD analysis, having a sampling frequency f_s , desired frequency resolution of Δf and cyclic frequency resolution of $\Delta \alpha$, (4.3) can be rewritten as

$$\alpha = \Delta \alpha [j - (2PL + 1)] \quad (4.4)$$

where $N = \frac{f_s}{\Delta f}$, $P = \frac{f_s}{L\Delta \alpha}$.

Thus using (4.3) and (4.4), the exact location, j , of the pilot subcarriers can be determined within the region of support of a bifrequency plane. The peak values of the pilot subcarriers and the data subcarriers are averaged over ' M ' number of symbols so as to obtain clear peaks even in low SNR environments. In this thesis, the PACD detector has been analyzed by averaging 50 OFDM symbols which corresponds to approximately 4096 data values. Figure 4.4 shows the generated surface plot of the PACD scheme mentioned with the pilot subcarrier boosted by 6 dB at a SNR of 0 dB. The peaks of the pilot subcarriers can be easily made out. This figure has been plotted for 0 dB only for visual clarity. The pilot subcarriers with a boost of 6 dB work well even at SNRs as low as -15 dB.

Figure 4.4. The surface plot for 6 dB boosted pilot subcarrier at SNR of 0 dB.

The ratio of the pilot subcarrier and the data subcarrier at various SNRs for different boosts to the pilot subcarrier has also been analyzed. It can be seen from Fig. 4.5 that the Gaussian noise has a

ratio of ~ 1.1 for all SNRs whereas the ratio of the pilot to data subcarrier for the boosted subcarriers remain more than 1.2 even at a SNR of -15 dB. Since a SNR of -15 dB is a fairly low SNR for a CR to operate in, it can be reasoned that a boost of 6 dB to the pilot subcarrier is sufficient to allow normal operations even under low SNR conditions.

Figure 4.5. Ratio of pilot to data sub carrier cyclic frequencies at low SNRs.

It can be observed that when no boost is given to the pilot subcarriers, the ratio is similar to the ratio for noise signals (an overlap between the two plots can be seen). Hence boosting the pilot subcarriers is a pragmatic solution to aid signal detection. As seen from Fig. 4.5, a pilot to data subcarrier cyclic frequency ratio of 1.2 is sufficient to discriminate between the presence and absence of the PU.

4.3.2 Spectrum Sensing Using Two Stages

The benefits of using ED and also its disadvantages due to noise power uncertainties have been discussed in Chapter 2. In the previous section the advantages of CFD in low noise conditions as well as its disadvantages with respect to mean detection time was discussed. From literature, it has been found that the embedding a known pilot subcarrier is an efficient way to speed up the detection for a CFD system. The concept of two-stage detection to exploit the advantages offered by the different techniques was also studied. In particular, from Fig. 4.2 it can be observed that at low SNRs a two-stage detection leads to an increase in the detection performance. But when the

SNR is high, the performance of the ED and the two-stage detector is observed to be the same. Thus no apparent benefit is accrued by using a two-stage detector for high SNR operating regimes. Thus, the second stage detection can be deactivated in a two-stage detector if the operating SNR of the CR is high enough to trust the ED stage alone. The benefit of this approach is very apparent. Figure 4.6 shows the proposed modification to the algorithm that can be incorporated to reduce the mean detection time of a two-stage CR at high SNR values.

Figure 4.6. Proposed algorithm of a two-stage detector to reduce the mean detection time.

In this algorithm, the first stage ED computes the energy and compares it with the preset threshold (λ_1). If the energy is found to exceed the threshold, then the spectrum is assumed to be occupied by the PU and the CR looks for some other band to do the same analysis. However, if the energy is found to be less than the threshold, then the CR estimates the SNR of the channel the device is operating in. As explained in Chapter 3, the estimate of the SNR is an input to this algorithm. This thesis does not discuss in detail on the techniques to estimate the SNR. This input value of the estimate of the SNR, γ , can be compared to the computationally established value of SNR, γ_u , given by (3.17) to find out whether the operating SNR of the CR can meet the target P_d and P_f . If γ exceeds γ_u , then the result of the ED stage can be trusted and the channel can indeed be assumed to be vacant. On the other hand, if the γ is less than γ_u , then the analysis of ED stage need not be correct and could be a case of miss detection. Hence the second stage needs to be activated to have a better look at the samples and confirm or overturn the result obtained by the ED in the first stage.

The proposed two-stage detector was simulated for detecting the OFDM signal as structured in Table I. The target P_d and P_{fa} were kept at 90% and 10% respectively. Also the probability of the channel being vacant, i.e. $P(H_0)$, was kept at 80%. Figure 4.7 shows the comparison between the percentage of the times the second stage is activated in the two-stage detector discussed in [42] and the proposed algorithm. It can be clearly seen that by suitable modifications of the model described in [42] and incorporating an estimate of the SNR of the channel, the activation of the second stage can be avoided at high SNR regimes. For the set of parameters used in this simulation, the critical SNR is -10.5dB and hence once the SNR of the channel exceeds -10.5 dB, the algorithm switches to the ED stage alone. In other words, the algorithm uses both the stages of detection when the SNR is below the critical SNR γ_u , while it completely switches off the second stage and relies only on the ED in the first stage when the SNR is higher than γ_u .

Figure 4.7. Probability of activation of the second stage in the proposed method as compared to a conventional two-stage detector such as in [42].

It can be observed that, the second stage gets activated as much as 80% of the time in a conventional two-stage detector. This is consistent with the fact that the probability of the spectrum being vacant, $P(H_0)$, is 80%. Thus, in a conventional two-stage detector, at high SNRs, even though the ED correctly determines the spectrum to be vacant, a redundant analysis is done using the time and power consuming second stage. By avoiding the need for second stage analysis at high SNRs and trusting the results of ED, when it does not detect the signal, this redundant analysis by the second stage can be avoided. In other words, for instance, if this algorithm is implemented using the technique mentioned in [42], at sufficiently high SNRs ($\gamma > \gamma_u$), it would save the 150ms required for two-stage analysis and restrict the analysis to the ED stage alone. Thus the detection time can be brought down to 20ms thereby saving up-to 86% of the detection

time. It should be noted that the graph in Fig. 4.7 is dependent on both the sparseness of the spectrum and the uncertainty in the estimation of noise power. While the former decides the probability of activation of the first stage (the y axis), the later decides the switch over point (the x axis). It can be observed from Fig. 4.8 that this strategy does not have any adverse effect on the probability of detection of the proposed two-stage detector. This is because when γ is greater than γ_u , the ED stage is sufficient enough to meet the target P_d for a given P_{fa} and thus the need for a second stage evaluation is not necessary.

Figure 4.8. Probability of detection of the proposed two-stage detector as compared to a single stage detector.

Thus the CR manages to maintain the probability of detection while at the same time reducing the mean detection time. Also from Fig. 4.3 it is apparent that it is the second stage that consumes the most time for detection and analysis, any reduction in usage of the second stage would lead to a substantial savings in the mean detection time of the CR. It should be noted that the emphasis is not on the absolute time taken for detection but on the relative time taken by the two-stage detector discussed in [42] and the proposed technique. The absolute time would be specific to the CR system used and hence cannot be used for benchmarking purposes. Mathematically, the reduction in the detection time, T_{red} , over the conventional two-stage method at high SNR's ($\gamma > \gamma_u$) can be expressed as

$$T_{red} = \frac{P_{act} * \tau_2}{\tau_1 + P_{act} * \tau_2} \quad (4.5)$$

Here τ_1 and τ_2 are the time taken by the first and second stage respectively. Thus, as the spectral band under consideration becomes more and more sparse i.e. $P(H_0)$ increases, P_{act} also increases as given by (4.1). This leads to a reduction in the mean detection time obtained for the proposed

method over the method in [42]. The proposed algorithm was also analyzed by replacing the second stage PACD stage with a second stage employing ED with 5 times as many samples as the first stage. Here the noise has been assumed to be certain ($\Delta = 0$ dB). Note that this assumption does not have any impact on the idea the proposed algorithm conveys. The results are shown in Fig. 4.9. It can be seen that as soon as the probability of detection crosses the targeted value of 0.9, the second stage is turned off and the algorithm works in single stage mode.

Figure 4.9. Probability of detection of the proposed two-stage detector as compared to a single stage ED based detector.

Thus, the algorithm proposed is agnostic to the technique used in the second or subsequent stages. The emphasis is on the fact that the results of the ED need to be trusted when the SNR is greater than the SNR Wall. So when the ED does not detect the signal at high SNRs it could be very well due to the absence of the signal and not because of a fault of the ED technique. As shown, this approach leads to substantial savings in time over the technique mentioned in [42] when the operating SNRs are high.

4.4 Hardware Implementation of the ED - PACD Scheme

The proposed two-stage sensing of ED-PACD sensing scheme is implemented on Xilinx Virtex xc4vsx35-10ff668 FPGA. Figure 4.10 shows the hardware implementation of the ED-PACD based proposed two-stage sensing scheme. The threshold is calculated based on the parameters (N_s , $Q^{-1}(P_{fa})$, $Q^{-1}(P_d)$, γ and μ_0) as shown in Fig. 4.10. The hardware implementation of the ED

assumes that static parameters like the value of the error function (Q) and number of samples (N_s) will be supplied as input to the module. Also as mentioned in the Chapter 3 and in Section 4.3.2, the SNR (γ) and the noise variance (μ_0) is assumed as an input to the algorithm presented here. Thus, the ED estimates the threshold based on these parameters. The threshold is compared with the detected energy from the input to determine whether the channel is occupied or not. If the channel is not occupied, then the SNR of the input signal (γ) is compared with the SNR wall (γ_c) calculated using the 'SNR wall calculator' as shown in Fig. 4.10. If γ is greater than γ_c , then the decision of ED is taken as final as the SNR lies in the reliable limit within the SNR wall. If γ is less than γ_c , then the second stage is activated using 'second stage selector' as shown in Fig. 4.10. Figure 4.10 also shows the hardware realization of the second stage, PACD, which is used to compute the spectral correlation density. The spectral correlation density is used to obtain the cyclic frequencies present in the input spectrum. The figure shows two FFT units of 128 and 8 points. The accumulator is used to accumulate the spectral correlation values which are passed to the threshold module. Here the ratio of the pilot subcarrier cyclic frequency and the data subcarrier cyclic frequency is computed. If this ratio is found to be greater than 1.2, the rationale for which has been explained in Section 4.3.1, then it is assumed that the input signal is present and that the band is not free for use.

The bit stream of the proposed architecture is generated using Xilinx system generator. Table 4.2 summarizes the results of the implementation. It is clear from Table 4.2 that the implementation of the PACD comes at a huge cost of power required to be available on a platform. It can be observed that in cases where the second stage is not activated (due to the SNR wall comparison), the proposed scheme saves 0.915 W out of a total of 1.09 W, thus effectively saving 84% of the total dynamic power. Note that the dynamic power required to compute the value of the SNR wall is 0.05536W, which is just 5% of the total dynamic power consumed by the proposed two-stage sensing scheme. The dynamic and static power has been calculated using Xilinx XPower software tool. This software gives the flexibility in fixing the switching rate of the I/O ports, multipliers and the clock. It is obvious that using a second stage detection should be undertaken only if necessary. Thus as in the case of mean detection time, switching off the second stage as per the proposed two-stage sensing reduces the dynamic power by 84%. In a portable device such as a CR, the power consumption can be a very important design parameter as this has direct bearing on the capacity of the battery required. The algorithm proposed in this Chapter addresses this problem by switching off the time and power consuming second stage when the ED is sufficient for good

detection performance. This helps in saving time to arrive at a decision and equally importantly the power required by the CR device.

Table 4.2. Hardware resource utilization profile for two-stage algorithm

Technique	No. of Slices	DSP48's	Static power (W)	Dynamic power (W)
Energy Detector	2154	13	0.44443	0.17833
Cyclostationary Feature Detector	3970	38	0.47857	0.91499

Figure 4.10. Hardware Implementation Diagram of proposed scheme (ED-PACD).

4.5 Summary

The conventional two-stage detector uses an ED in the first stage and executes computationally complex and extensive analysis methods like the cyclostationary detection or Eigen value detection in the second stage. In this chapter, a two stage ED-PACD detector has been presented to improve the performance at low SNRs where the uncertainty in the estimation of noise power is high. FFT Accumulation Method has been used to estimate the cyclic frequencies since it is computationally faster than the other known techniques. Also the PACD technique has been used to reduce the time taken to detect the cyclic frequency of the PU signal.

In a conventional detector when the ED senses the spectrum to contain energy below a predetermined threshold, a second stage analysis is done to ascertain the veracity of the claim made by ED. Though the ED has its limitations, these impact the performance of the ED only at low SNRs. At high SNRs, the detection performance of the ED is good enough and comparable to any other detector. Thus in conventional detector, at high SNRs, even though the ED is able to detect the presence or absence of the primary user with high accuracy, the decision regarding the absence of the PU is not considered accurate. In this chapter it is shown that this strategy is not suitable for a CR unit since the fundamental premise of CR is that the spectrum is vacant most of the time and it is this inefficiency in the usage of the spectrum that is proposed to be exploited by the CR.

It is shown that by pre-computing the lower bound of the SNR at which the ED still works satisfactorily and by estimating the SNR of the channel the CR is in, the second stage of a two-stage detector can be switched off when the channel SNR is higher than the lower bound of the SNR level of the ED. It has also been shown that this does not cause any loss of performance. In other words, when the channel SNR is good, the results of the ED can be trusted and if the ED does not detect any PU, then no further analysis is done and the band is judged as to be vacant. If the proposed algorithm is implemented for the technique in [42], it could help in saving the mean detection time by as much as 86% at high SNRs where the ED is sufficient for detection purposes.

The chapter also shows the hardware implementation of the ED and PACD techniques to understand the resource utilization of the two stages. It has been found that the dynamic power requirement of the PACD is five times that of the ED. Hence switching off the PACD stage leads to enormous savings in power consumption. Thus the modified two-stage detector presented in this chapter not only leads to savings in the mean detection time of the CR, it consequentially

leads to the lowering of the overall power requirements of the CR device which is a limiting factor for any battery-operated device. As shown in the paper, an 84% savings in dynamic power can be obtained by switching the PACD stage off at high SNR regimes.

In the next chapter, real time signals are captured with the help of universal software radio peripheral2 (USRP2) signals and their power and frequency spectrum plotted to ascertain the behavior of real signals. The captured signals are plotted using the inbuilt python script, suitably modified for purposes of this thesis, and also are given as input signal to the ED algorithm.

Chapter 5

Spectrum sensing using USRP2

The preceding chapters discussed about the algorithms that can be used for estimating the presence or absence of primary user in the licensed spectrum. The random data used for the performance evaluation were generated using Matlab codes. In this chapter, it will be shown as to how real data in I & Q format can be captured from the surroundings using the universal software radio peripheral2 (USRP2) board and given as input to the Matlab code to plot the power spectrum of the captured signal.

5.1 Overview:

To capture and analyze the signals, an USRP2 board with a WBX daughter board has been used. The relevant features of the USRP2 board are

1. Two 100MS/s Analog to Digital Converters.
2. Two 400MS/s Digital to Analog Converters.
3. Gigabit Ethernet Interface.
4. Capability to process signals as wide as 50MHz in bandwidth.
5. The RF range varies from 0 to 5.9GHz as is limited by the antenna module used.

The WBX daughter board can operate from 50 MHz to 2.2 GHz band and hence offers an excellent choice for testing wide range of signals (like GSM signals captured from the environment and also signals generated from a standard signal generator).

In the USRP2, high sample rate processing, like digital up- and down conversion, takes place in the field programmable gate array (FPGA). The data can then be transferred to the host PC over the gigabit ethernet interface and the low sample rate operations can be then performed on the host computer. Alternatively the FPGA can be used to do some amount of user desired processing for which there is free space available in the FPGA to insert custom modules. This flexibility due to the increased size of FPGA allows the USRP2 to be used as a standalone system. To make the

programming easier, the configurations and firmware of the USRP2 are stored in a secure digital (SD) flash card.

In the setup used for capturing signals at the lab, the antenna module fetches the RF signal from sensing environment and shifts the signals to an Intermediate Frequency (IF). The down shifted IF signal is then sent to the FPGA where the ADC and digital down converter (DDC) convert the data to baseband. The DDC also does the decimation of the incoming data to moderate the data rate so that the data rate at which it has to be passed through the gigabit Ethernet interface can be obtained without any loss of information.

Figure 5.1. USRP2 front and top view.

The digital output from the ADC is then mixed with a digitized sine and cosine component for the Q channel and I channel respectively which will produce the sum and the difference components.

The unwanted components are then filtered by passing through digital filters. The post processed data (complex I and Q) is then transferred by the FPGA module to the host computer via the gigabit Ethernet controller.

5.1.1 Inside the USRP FPGA

The FPGA present in the USRP boards performs the complex signal processing tasks which involve high level of computation along with high levels of throughput. Operations such as digital up conversion, digital down conversion, decimation and interpolation are thus handled by the FPGA resident in the USRP. The control of the various analog components present in the USRP board is also done by the FPGA. The first generation USRP had a high speed USB interface with the host machine while the later ones of the family namely the USRP2, USRP N210 and USRP E100 use a Gigabit Ethernet Interface to communicate with the host machine. This allows a higher data rate for data transfer purposes. The Gigabit Ethernet interface is used for exchanging the configuration as well as signal data and it is capable of handling simultaneously up to 50 MHz of RF bandwidth in and out of the USRP. The configuration data for setting the required parameters such as RF frequency, decimation and interpolation rates, ADC and DAC configuration is provided by the host machine to the USRP module. The recent USRPs also come with a MIMO interface for interfacing with other USRPs and as well as other FPGAs. Also to enable precise synchronization operations, an output to an external reference is provided. The important thing to realize is that the FPGA code of USRP2 cannot be altered. Only the later versions of the USRP family allow FPGA code modifications.

5.1.2 ADC and DAC

The first generation USRP had four high speed 12-bit Analog to Digital Converters (ADCs) with a sampling rate of around 64M samples per second. There were four Digital to Analog Converters (DACs) each capable of handling sampling rate up to 128M samples per second. Also these ADCs and DACs were preceded by a programmable gain amplifier which could be used to control the gains of the converters in order to utilize the entire range of the ADCs especially in the case of a weak signal. USRP2 on the other hand has two 14 bit ADCs with a sampling rate of 100 MS/s and another two 16 bit DACs with a very high sampling rate of 400 MS/s.

5.1.3 Daughterboard

The task of managing the RF front end is dedicated to daughterboards which can be mounted on the USRP. A variety of daughterboards are available which operate across a wide range of frequencies ranging from around DC to 6 GHz to support a wide range of applications. Figure 5.1 shows the USRP motherboard with a WBX daughterboard attached to it. The daughterboards usually come equipped with the EEPROM which allows the host software to setup the USRP according to the daughterboard connected. An error is reported in case this EEPROM is not programmed. The daughterboard consists of the antenna along with the synthesizer, mixer and local oscillators. The USRP2 has two daughterboard slots which can be used in receive-only, transmit-only and transceiver type daughterboards. The receive-only and transmit-only daughterboards take up only one slot whereas the transceiver type daughterboards take up two slots. Thus both transmit and receive can be performed using one USRP2 module.

5. 2 GNU Radio Framework

The work presented in this thesis has used the framework provided by the GNU radio project to integrate the USRP2 board with the host computer. As seen from the Fig. 5.2 [73], the high sample rate operations are carried out in the FPGA by the USRP2 board and then the data is passed over to the host via the gigabit ethernet. The GNU radio framework has built in modules to do many of the signal processing tasks that are required for our purposes. The GNU Radio tool kit provides an all encompassing framework to use software modules to realize radio functionalities. The framework of GNU radio provides the necessary libraries of signal processing blocks like modulators, demodulators, filters, etc which can be used to construct a software defined radio. The structure of the GNU radio's software is organized in a two layered architecture. The blocks used for signal processing, being performance critical, are implemented in C++, while the task of connecting and gluing the signal blocks together is done using Python at the top layer. Figure 5.3 shows the clear linkage between the various layers in a GNU radio platform. Python language is used to create the flow graph of the blocks which are configured with the correct parameters. The signal source blocks are connected to the sinks via the processing blocks. The signal processing blocks are used to process the streams of data from their input port to their output port.

Figure 5.2. Block diagram of a USRP2 operating in GNU Radio framework.

The input and output ports of a signal processing block are variable. So a block can have multiple outputs and multiple inputs. The signal processing blocks are written in C++. Python and C++ are interfaced together using the Simple Wrapper and Interface Generator (SWIG). SWIG is the wrapper for the C++ modules and generates the corresponding Python code and library so that these classes and functions can be called from Python.

Figure 5.3. Software architecture of GNU Radio.

The GNU Radio project has already created a large repository of signal processing blocks very similar to the blocks available in Matlab Simulink. If necessary, customized signal processing blocks written in C++ can be created and integrated to the framework [74]. There is also a graphical environment available to create a custom radio. This is called GNU Radio Companion (GRC). This helps in building the flow graph with ease by avoiding the need to write the Python

script. The GRC generates the python script required to execute the data flow graph. In this chapter, the use of GRC is mentioned briefly since no pre defined blocks were available to achieve the task in hand i.e. to get the sensing data samples in I & Q format. Hence existing python scripts had to be modified to get I & Q data values.

5.3 Hardware Setup

The hardware setup required to capture the signal are summarized in Table 5.1.

Table 5.1. Hardware Configuration for Data Acquisition

Host Configuration

Processor	Intel Pentium 3.17 GHz (Core 2 Duo)
OS	Ubuntu 10.10
GNU Radio	3.3 or later

Data acquisition equipment

SDR RF hardware	USRP2
USRP Daughterboards	WBX

Test Measurement equipments

Signal generators	Agilent E4438C
Spectrum analyzer	Rohde & Schwarz FMU 36
Mobile Device	Nokia N 73

The Fig. 5.4 and Fig. 5.5 show the setup to generate and capture signals for various modulation formats like QPSK, QAM, BPSK, etc. A Signal Generator is used to generate the modulated signal with AWGN added to it. This is passed to the USRP2 board where I & Q values are demodulated and decoded and written to a text file.

Figure 5.4. Setup to capture GSM signals.

Figure 5.5. Setup to generate predefined modulated signals and capture using USRP2.

5.4 Installing and Building GNU Radio

This section lists out the general procedure to be followed to install GNU radio on the host and use it to communicate with the USRP2 board.

1. Install the dependencies for GNU radio:

The basic packages which form the pre requisites can be obtained from the website of GNU radio <http://gnuradio.org/redmine/wiki/gnuradio/UbuntuInstall>. Depending on the version of the Operating System (OS) installed on the host, a desired package must be chosen.

2. Download boost

Boost package might be required to be installed for using the C++ libraries. It is advisable to check whether this is already installed which can be done by going through the SPM (Synaptic Packet Manager) in Ubuntu (similar options would exist for other OS as well). If the boost package is not found then it should be downloaded and saved.

3. Install boost

If boost was found to be not installed then the boost package can be installed by changing the directory to the location where boost packages were saved and executing the following

- a) `./bootstrap`
- b) `sudo ./bjam install`

4. Download GNU Radio

The GNU Radio source can be downloaded from the repository called the git. To download the relevant link can be found at <http://gnuradio.org/git/gnuradio.git>. Alternatively if a stable version of GNU radio is available in the host or at some other PC, then it can be copied and used.

5 Setting up the communication path with the board

To start the initial communication with the board, the steps needed to be followed are :

- a) Connect the gigabyte Ethernet and power cable to the USRP2 board. The D&F LED on the USRP2 board should glow indicating that the firmware and FPGA are preloaded.
- b) Download the latest firmware and FPGA images and write them to the SD card. RAW Ethernet images were used, but if the purpose is to use the Universal Hardware Driver (UHD) then the corresponding images need to be used. The command to burn the image are as follows :

- *location of the u2_flash_tool*

`/opt2/gnuradio/usrp2/firmware` (or type `locate u2_flash_tool` in the terminal to know the location)

-Command to flash the firmware

```
sudo ./u2_flash_tool --dev=/dev/sdb -t s/w /home/location of firmware image/usrp2_fw.bin -w
```

- Command to flash the fpga

```
sudo ./u2_flash_tool --dev=/dev/sdb -t fpga /home/location of fpga image/usrp2_fpga.bin -w
```

Care should be taken to know the name of the SD card of the USRP2 in the Ubuntu installation. For instance for the lab setup for this thesis, the SD card was recognized as **/dev/sdb**. Installing and running the software **gparted** can give a list of the names of storage devices in PC.

c) Change the Ethernet port IP address of the host to 192.168.10.1.

d) Setup the LD_LIBRARY_PATH and PYTHONPATH as

```
LD_LIBRARY_PATH = /usr/local/lib
```

```
PYTHONPATH = /usr/local/lib/python2.6/site-packages.
```

It should be noted that the version of python used in the lab setup was 2.6. This can change depending on the package installed.

6. Install GNURadio

Change to the directory where the source for GNURadio has been downloaded (Step 4) and run

a) `./bootstrap`

b) `./configure`

c) `sudo make, make check, make install`

7 Download UHD

To communicate with the USRP2 board using the Universal Hardware Driver (UHD), the relevant driver needs to be downloaded and installed. This is not required if communication with the USRP2 is via the raw Ethernet only (as was in the case of setup used in the lab). Run the command: `git clone git://code.ettus.com/ettus/uhd.git` in a bash terminal to download UHD to the host.

8. Install UHD

Execute the following steps to install the UHD.

- a) cd to uhd/host
- b) mkdir build
- c) sudo apt-get cmake (if cmake is not installed)
- d) cmake ../
- e) sudo make, make test, make install

9) Test Communication with the board.

If all these procedures have been completed without any errors then open any terminal and ping **192.168.10.2** . If the data packets can be exchanged without errors then it indicates that a successful communication with the USRP2 board. If UHD has been installed then executing the command *uhd_find_devices* will also list out the USRP2 connected. Also by executing *find_usrps* it can be ensured that the USRP2 is connected and able to communicate to the board.

5.5 Capturing spectrum

In the previous sections the complete hardware and software requirements and installation procedures to get the USRP2 board to communicate with the GNU radio framework has been explained. In this section, the modifications required to be done in the Python script, the commands required to execute the scripts and the captured data and waveforms will be presented.

As shown in Fig. 5.4 & Fig. 5.5, the spectrums were captured from the environment and also from the signal generator. The signal generator gave the flexibility to create different kinds of signal at various SNRs.

To get I&Q data from the captured signal, two python scripts available in the utility folder (gr-utils) had to be used. Of these, the file *usrp2_rx_cfile.py* was used to capture the spectrum and *gr_plot_fft.py* was modified to extract I & Q data from the captured spectrum. Also the file *usrp2_fft.py* was used to see the FFT of the spectrum captured in real time.

The command used to capture the spectrum is

```
sudo usrp2_rx_cfile.py -e eth1 -d 32 -f 900M -N 8192 file_name.dat
```

The file `usrp2_rx_cfile.py` is a python script to capture the signals. Here *eth1* indicates the interface to which the USRP2 is connected. In the laboratory setup, the Ubuntu 10.10 OS was installed using VMWare and so it was possible to establish a bridge connection and so the default interface `eth0` was not used. In order to narrow down the range of signal, a decimation factor of 32 was applied over the signals to be captured at 900MHz. A total of 8192 samples were captured which were dumped to the `.dat` file name given at the end.

The command used to plot the spectrum is

```
sudo ./gr_plot_fft.py file_name.dat >store_data.txt
```

After the spectrum is captured, the python script `gr_plot_fft.py` is used to obtain the I&Q data of the captured spectrum. This code cannot be used as such to get the I & Q data. The code was studied and suitably modified to dump I & Q data into the text file given as command input. The I & Q data gets stored in the `.txt` file (`store_data.txt` in this example) which can then be used as input values for validating the algorithms developed.

Figure 5.6 to Fig. 5.8 show the output spectrum and I & Q values plotted using the python script for the different signals that were captured or generated using the Signal generator. The noise floor was seen to be -100dBm. The modulate I & Q values can be seen clearly in Fig. 5.6 to Fig. 5.8. Since the bandwidth allotted to each user is very narrow, the output spectrum shows only a small portion of the spectrum as occupied.

5.6 Power spectrum plot

As it can be seen from the FFT spectrum of Fig. 5.6 to Fig. 5.8, the noise power keeps varying and as the signal power is reduced further, it becomes impossible to distinguish between noise fluctuations and signals. Thus, it becomes fairly obvious that an accurate determination by ED is possible only if the SNR is high.

Figure 5.7 shows the communication signal for TETRA communication. The signal generator was used to create this signal. It has a multi tone carrier having 5 carriers. The spectrum shows the 5 carriers distinctly. The modulated I & Q values can also be seen.

Figure 5.6. I & Q values and spectrum plot of a GSM signal.

Figure 5.7. I & Q values and spectrum plot of a TETRA signal.

The captured I & Q values were given as input signal to the ED algorithm. Since a Monte Carlo simulation of real signals is not practical, this thesis restricts the analysis to generation of power spectrum plot of the captured signal. Figure 5.9 shows the power spectrum generated by the ED algorithm developed.

Figure 5.8. I & Q values and spectrum of a customized wideband signal.

Figure 5.9. Power spectrum of a customized wideband signal generated by ED algorithm.

Comparing Fig. 5.8 and Fig 5.9, it can be clearly seen that the ED algorithm is able to detect the occupied signal band correctly. It can be also be observed that the noise fluctuations are rapid and spread over a wide range. Thus a correct estimate of noise floor is difficult to achieve. Hence ED can work only when the SNR is high (as in this case). Otherwise, it becomes very difficult to accurately detect the presence of signal.

To further illustrate the point, Fig. 5.10 shows the GSM spectrum captured when two mobile phones were communicating very near to each other. The peaks are clearly visible in the FFT plot. The signal strength is high enough to enable an ED to decide that the PU (in this case the mobile)

is using the spectrum. Figure 5.11 shows the spectrum plot when the mobile stations are some distance away from the antenna of the USRP2 device.

Figure 5.10. FFT plot using `usrp2_fft.py` to plot the spectrum for GSM signal of mobile kept near to the antenna.

Figure 5.11. FFT plot to plot the spectrum for GSM signal of mobile kept far away from the antenna.

It can be clearly seen that due the fluctuations of the noise floor, the signal gets easily drowned in the uncertain region. This reinforces the limitation of the ED in estimating signals at low SNR regimes where the uncertainty of the noise makes an accurate detection unachievable. Since the Pilot Assisted Cyclostationary Detection (PACD) method discussed in Chapter 4 of this thesis needs customized OFDM packets having modified pilot subcarriers, it could neither be obtained by capturing the wireless spectrum in the lab nor could it be generated using the signal generator. Hence real time signals for testing the OFDM signals could not be obtained.

Chapter 6

Conclusions and Future Work

As more and more wireless devices are invented and the market for wireless devices increases, the spectrum to accommodate all the users would become more scarce and expensive. Recent finding that the licensed spectrum is not being used optimally provides a scope for their efficient utilization. Cognitive Radio (CR) aims to fulfill this need of maximizing the spectrum utilization by making intelligent estimate of the surroundings and using the spectrum left vacant by a licensed user for its own needs.

The aim of this thesis has been to analyze the various algorithms available in the literature which would help the CR in doing an accurate detection of the presence of the licensed user so that no harm is done to the legitimate owner of the spectrum. In this chapter, the conclusion of the analysis is presented. The future scope and direction of work are also listed.

6.1 Conclusions

In this thesis, a comprehensive study of the various methodologies to detect the presence of deterministic signal has been presented. The three basic techniques discussed in the literature are the matched filtering technique, the cyclostationary feature detection (CFD) technique and the energy detection (ED) technique. The study has evaluated the different techniques present in the literature and has identified the merits and demerits of each approach.

From the literature survey in Chapter 2, it has been found that the matched filter technique is the best technique for the detection of a deterministic signal. But the drawback is that the technique requires perfect knowledge about the signal to be detected. Since this may not be possible in all the scenarios, the matched filtering technique was not pursued further for the research. The CFD method involves complex computations but is very robust to noise interferences. But a real time analysis is difficult due to the complexities involved in determining the cyclic frequencies. If the cyclic frequencies are known before hand, then the CFD method can be employed to get accurate results on a real time basis. ED is the simplest of all the known techniques. The energy of the

input signals are calculated and compared with a threshold. The presence or absence of a deterministic signal signifying the presence of a licensed user is established by comparing the calculated energy with a pre-defined threshold.

The major focus of the work in this thesis has been on the ED-based spectrum sensing. This is due to the inherent simplicity and low computational complexity of the technique. However ED is prone to errors in noise estimation and is known to perform below par at low signal to noise ratio (SNR) conditions. It has been established that the setting of threshold is very critical to the performance of an ED based cognitive radio and hence a detailed analysis of the impact of threshold on the probability of detection and probability of false alarm was undertaken.

In this thesis, an analysis of the impact of the threshold on an ED-based CR is presented at a more detailed level. A mathematical representation of the threshold and its impact on the performance metrics is presented. The detailed discussion about the impact of sensing time (samples) and the SNR on the ability of the CR to detect the licensed user accurately has also been presented. It has been found that the performance of an ED deteriorates significantly as the number of samples decreases. The same deterioration in the ability to detect the licensed user is observed when the SNR of the channel is reduced. These deteriorations in performance happens since the threshold is held constant and not changed as per the changing operating conditions of the CR. Chapter 3 presented an algorithm which can be used to adaptively change the threshold based on the sensing time or the SNR of the channel. The threshold thus set acts as a tradeoff between the probability of detection and probability of false alarm. Depending on the operational needs of the CR, the threshold can be changed by changing the adaption parameter and thus a performance suited to the CR can be tailor made. The chapter also presented an in-depth analysis on the existence of SNR Wall for ED. An expression which dictates the minimum SNR required guaranteeing a targeted performance was also presented.

The work presented till Chapter 3 has been confined to a single stage detection technique to identify the presence or absence of the licensed user. A single stage technique, though less complex, need not overcome all the limitations inherent in the chosen spectrum sensing technique. Two-stage detection thus arose from the need to synergize the best of two detection techniques such that the outcome is better than either of the techniques taken individually. However, it was observed that the two-stage detection techniques employed conventionally suffered from inherent redundancy when operating at high SNR regimes. Specifically it was observed that the results of the ED in the first stage were not trusted even when the SNR is high and well above the

theoretical minimum stipulated by the expression presented in Chapter 3. Thus the thesis builds up on the analysis presented in Chapter 3 and uses the information on the theoretical minimum SNR required for guaranteed performance and then decide whether to trust the result of the ED when it is unable to detect any signal.

Since this thesis analyses the algorithms in the presence of noise uncertainty in the estimation of noise power, the second stage of the proposed two-stage detector proposed in this thesis used a pilot assisted cyclostationary feature detector (PACD). The thesis favors boosting of the pilot subcarrier in order to facilitate an easy and faster detection of the cyclic frequencies of the signal. The literature survey done in Chapter 2 presents a detailed analysis of the FFT Accumulation Method (FAM) to calculate the Spectral Correlation Density (SCD) function of a signal. This technique is used in Chapter 4 to obtain the cyclic frequencies present in an OFDM signal. Analysis of the threshold required to distinguish between noise and OFDM signal has also been presented.

Having established a two-stage detection scheme using ED in the first stage and PACD in the second stage, Chapter 4 proposes the algorithm to optimize the usage of the second stage. Thus the second major contribution of this thesis was to make the conventional two-stage detectors presented in the literature faster by removing the redundancy inherently present in them. In other words, the algorithm proposed in Chapter 4 emphasized on trusting the results of the ED when the conditions are favorable to the ED i.e. in a high operating SNR regime. Under those conditions, even if the ED could not find any signal upon doing an analysis, the time and power consuming second stage would not be activated. The second stage is activated only if the operating SNR is lower than that required for guaranteed performance from an ED. This approach does not compromise on the detection performance of the spectrum sensing algorithm while reducing the mean detection time and consequently the power consumed by a large extent. In other words, at high SNRs, the algorithm proposed in Chapter 4 can make the two-stage detector save detection time and power consumed substantially without any loss of detection performance. The results presented in Chapter 4 show that as the spectrum becomes sparser, the savings in mean detection time and power consumed increase as compared to the conventional techniques. Since the proposed algorithm is agnostic to the second stage algorithm chosen, this design philosophy can be extended for other two-stage detection techniques as well like those employing Eigen value based detection instead of CFD in the second stage.

Additionally a study of the USRP2 board, including the setting up procedure of GNU Radio to communicate with the board, has been explained in Chapter 5. The aim of this work was to see how signals operate in real world. The USRP2 board was interfaced with a GNU Radio setup running on the host computer. Both GSM mobile signals and signals generated with the help of a signal generator were captured by the USRP2 board and I & Q complex inputs were obtained. These I & Q values were then passed to the algorithms to plot the power spectrum.

6.2 Future Work

6.2.1 Cooperative Sensing Schemes

In this thesis, the work was focused on non cooperative sensing schemes only. But as briefly mentioned in Chapter 2, cooperative sensing is the best bet against many of the disadvantages of the existing techniques. For example, the ED method suffers from limitations due to multipath, shadowing, etc. These natural effects can affect the performance of the CR significantly. Cooperative sensing offers a clear solution to mitigate these problems by pooling in information from multiple sources.

The two-stage algorithm presented in this thesis can be further extended to a cooperative model wherein the second stage analysis is done at a central processing module (CPM). The decision to activate the second stage at the CPM can be taken based on the weighted SNRs reported by the sensors deployed at multiple locations. These sensors need only transmit their spectrum sensing decision and the estimated SNR to the CPM. Thus the benefits of cooperative sensing and the merits of two-stage sensing can be combined to improve the detection performance and reduce the mean detection time and power of the whole CR system.

Further, to reduce the sample rate of the ED-PACD algorithm, a DFT filter bank can be employed at the IF input to lower the operating frequency. The input signal at RF is down-converted to IF and passed through an ADC before being processed by the DFT filter bank. Thus a polyphase DFT filter bank for 'M' number of subbands can be used to detect the spectrum. This will in effect reduce the computational complexity of the ED-PACD algorithm by a factor 'M'.

6.2.2 Real Time Implementation

As part of the future work, the algorithms developed in this thesis can be implemented in a FPGA to do a real world analysis of the performance of the various techniques. The spectrum of interest

is the DVB-T signal used for terrestrial broadcast of digital TV channels. The DVB-T transmission uses OFDM modulation with the subcarriers modulated using QPSK, 16QAM or 64QAM. A hardware realization of the simulink module presented in this thesis can be done using Xilinx blocksets which can then be downloaded to the FPGA on board the hardware.

The configuration of the system for implementing the prototype is expected to consist of a data acquisition module (DAM) and the FPGA board. The DAM shall consist of a RF antenna having the desired bandwidth and frequency of operation and a hardware board to convert the input complex signal to baseband and to split them into the In-phase (I) or Quadrature (Q) output just like the functionality of the USRP2 module. This output can be sent to the FPGA board. The spectrum sensing algorithm on the FPGA can then process the data to determine the presence or absence of signal in the captured signal samples. The result obtained can then be shown on a on board display unit. Thus a real time performance evaluation of the various algorithms developed will help in narrowing down the desired technique to be used for spectrum sensing for a field deployable cognitive radio system.

Bibilography

- [1] Federal Communications Commission, "Spectrum policy task force report," Washington DC, November 2002.
- [2] M. H. Islam, C. L. Koh, S. W. Oh, X. Qing, Y. Y. Lia, C. Wang, Y. C. Liang, B. E. Toh, F. Chin, G. L. Tan, and W. Toh, "Spectrum survey in Singapore: occupancy measurements and analysis," in *Proc. of the 3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Singapore, May 2008.
- [3] J. Mitola, "Cognitive Radio: An integrated agent architecture for software defined radio," Ph.D. diss., KTH, Stockholm, Sweden, 2000.
- [4] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Communications Surveys & Tutorials*, vol. 11, no.1, pp. 116-130, March 2009.
- [5] R. Tandra and A. Sahai, "SNR walls for signal detection," *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, no.1, pp. 4-17, Feb. 2008.
- [6] A. Sonnenschien and P. M. Fishman, "Radiometric detection of spread spectrum signals in noise of uncertain power," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 28, no.3, pp. 654-660, July 1992.
- [7] Y. Zheng, Y. C. Liang, E. C. Y. Peh, and A. T. Hoang, "Sensing throughput tradeoff for cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 7, no.4, pp. 1326-1337, April 2008.
- [8] S. M. Mishra, A. Sahai, and R. W. Brodersen, "Cooperative sensing among cognitive radios," in *Proc. IEEE International Conference on Communications*, June 2006.
- [9] A. Ghasemi and E. S. Sousa, "Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs," *IEEE Communications Magazine*, vol. 46, no.4, pp. 32-39, April 2008.
- [10] Federal Communications Commission, "Notice of proposed rule making and order: facilitating opportunities for flexible, efficient, and reliable spectrum use employing cognitive radio technologies," vol. ET Docket No. 03-108, Feb. 2005.
- [11] 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, Sept 2006.
- [12] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE Journal of Selected Areas in Communications*, vol. 23, no.2, pp. 201-220, Feb. 2005.
- [13] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proc. IEEE*, vol. 55, no.4, pp. 523-531, April 1967.

- [14] Y. C. Liang, Y. Zheng, A. T. Hoang, and R. Zhang, "A review on spectrum sensing for cognitive radio: challenges and solutions," *EURASIP Journal on Advances in Signal Processing*, January 2010.
- [15] Stevan M Kay, *Fundamentals of Statistical Signal Processing*, Vol. II, Prentice Hall, 1998.
- [16] Z. Ye, G. Memik and J. Grosspietsch, "Energy detection using estimated noise variance for spectrum sensing in cognitive radio networks," in *Proc. IEEE Wireless Communication and Networking Conference*, Las Vegas, April 2008.
- [17] A. Gorcin, K. A. Qaraqe, H. Celebi and H. Arslan, "An adaptive threshold method for spectrum sensing in multi channel cognitive radio networks," in *Proc. IEEE 17th International Conference on Telecommunications*, Qatar, April 2010.
- [18] J. W. Lee, J. H. Kim, H. J. Oh and S. H. Hwang, "Energy detector using adaptive-fixed thresholds in cognitive radio systems," in *Proc. 14th Asia-Pacific Conference on Communications*, Tokyo, Oct. 2008.
- [19] J. W. Lee, J.H. Kim, H. J. Oh and S. H. Hwang, "Energy detector using a hybrid threshold in cognitive radio system," *IEICE transactions on communications*, vol. E92-B, pp. 3079-3083, Oct. 2009.
- [20] Q. Shi, N. S. Correal, S. Kyperountas, Z. Ye, "Signal detection in cognitive radio systems," US Patent No: US 2010/0081387, April 2010.
- [21] H. H. Choi, K. Jang, and Y. Cheong, "Adaptive sensing threshold control based on transmission power in cognitive radio systems," in *Proc. IEEE Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Singapore, May 2008.
- [22] T. Yu, R. Parera, D. Markovic, and D. Cabric, "Cognitive radio wideband spectrum sensing using multitap windowing and power detection with threshold adaptation," in *Proc. IEEE International Communications Conference*, Cape Town, South Africa, May 2010.
- [23] J. Zhu, Z. Hu, F. Wang, B. Huang, and B. Zhang, "Double threshold energy detection of cooperative spectrum sensing in cognitive radio," in *Proc. IEEE Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Singapore, May 2008.
- [24] C. Song, Y. D. Alemseged, T. H. Nguyen, G. Villardi, C. Sun, S. Filin, and H. Harada, "Adaptive two thresholds based energy detection for cooperative spectrum sensing," in *Proc. IEEE Consumer Communications and Networking Conference*, Las Vegas, USA, Jan. 2010.
- [25] N. Hoven, A. Sahai, and R. Tandra, "Some fundamental limits on cognitive radio," in *Proc. of Forty Second Allerton Conference on Communication, Control and Computing*, Monticello, USA, Oct. 2004.
- [26] S. J. Shellhammer, "Spectrum sensing in IEEE 802.22," in *IAPR Wksp. Cognitive Info. Processing*, June 2008.

- [27] H. Tang, "Some physical layer issues of wide-band cognitive radio systems," in *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Baltimore, USA, Nov. 2005.
- [28] P. D. Sutton, K. E. Nolan, and Linda Doyle, "Cyclostationary signatures in practical cognitive radio applications," *IEEE Journal of Selected Areas in Communications*, vol. 26, no.1, pp. 13-24, Jan. 2008.
- [29] W. A. Gardner, "Cyclostationarity in communications and signal processing," *IEEE Press*, Jan. 1994.
- [30] W. A. Gardner, "Spectral correlation of modulated signals," *IEEE Transactions on Communications*, vol. 35, pp. 584-601, 1987.
- [31] Andrea Tani and Romano Fantacci, "A low complexity cyclostationary based spectrum sensing for UWB and WiMAX coexistence with noise uncertainty," *IEEE Trans. On Vehicular Technology*, vol. 59, pp. 2940-2949, July 2010.
- [32] S. R. Schunur, "Identification and classification of OFDM based signals using preamble correlation and cyclostationary feature extraction," Master Thesis, Naval Postgraduate School, Monterey, CA, 2009.
- [33] R. S. Roberts, W. A. Brown, and H. H. Loomis, "Computationally efficient algorithms for cyclic spectral analysis," *IEEE Signal Processing Magazine*, pp. 38-49, April 1991.
- [34] D. Bhargavi and C. R. Murthy, "Performance comparison of energy, matched-filter and cyclostationarity-based spectrum sensing," in *Proc. IEEE Eleventh International Workshop on Signal Processing Advances in Wireless Communications*, Marrakech, June 2010.
- [35] D. Cabric, S. M. Mishra, and R. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in *Proc. Asilomar Conf. on Signals, Systems and Computers*, California, Nov. 2004.
- [36] Y. Zeng and Y. C. Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio," *IEEE Transactions on Communications*, vol. 57, no.6, pp. 1784-1793, June 2009.
- [37] X. Xiao, C. Xuefen, P. Wurong, and W. Yining, "An adaptive spectrum sensing algorithm based on eigenvalue decomposition," in *2nd International Congress on Image and Signal Processing*, Tianjin, Oct. 2009.
- [38] Y. Zeng, C. L. Koh, and Y. C. Liang, "Maximum eigenvalue detection : theory and application," in *Proc. of IEEE International Conference on Communications (ICC)*, Beijing, May 2008.
- [39] Y. Hur, J. Park, W. Woo, K. Lim, C. H. Lee, H. S. Kim, and J. Laskar, "A wideband analog multi-resolution spectrum sensing (MRSS) technique for cognitive radio (CR) systems," in *Proc. IEEE International Symposium on Circuits and Systems*, Greece, May 2006.

- [40] Q. Zhang, A. B. J. Kokkeler, and G. J. M. Smit, "An efficient multi-resolution spectrum sensing method for cognitive radio," in *Third International Conference on Communications and Networking in Hangzhou*, China, August 2008.
- [41] N. M. Neihart, S. Roy, and D. J. Allstot, "A parallel, multi resolution sensing technique for multiple antenna cognitive radio," in *Proc. IEEE International Symposium on Circuits and Systems*, New Orleans, USA, May 2007.
- [42] S. Maleki, A. Pandharipande, and G. Leus, "Two-stage spectrum sensing for cognitive radios," in *Proc. IEEE International Conference on Acoustics Speech and Signal Processing*, Texas, USA, March 2010.
- [43] S. Fazeli-Dehkordy, N. P. Konstantinos, and S. Pasupathy, "Two stage spectrum detection in cognitive radio networks," in *Proc. IEEE International Conference on Acoustics Speech and Signal Processing*, Texas, USA, March 2010.
- [44] Z. Tian and G. B. Giannakis, "Compressed Sensing for wideband cognitive radios," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, Hawaii, USA, May 2007.
- [45] P. T. Boufounos and R. G. Baraniuk, "1 bit compressive sensing," in *42nd Annual Conference on Information Sciences and Systems*, Princeton, USA, March 2008.
- [46] D. D. Ariananda, M. K. Lakshmanan, and H. Nikookar, "A survey on spectrum sensing techniques for cognitive radio," in *Second International Workshop on Cognitive Radio and Advanced Spectrum Management*, Denmark, May 2009.
- [47] Z. Tian and G. B. Giannakis, "A wavelet approach to wideband spectrum sensing for cognitive radio," in *Proc. of International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Greece, May 2006.
- [48] B. Zayen, W. Guibene, and A. Hayar, "Performance comparison for low complexity blind sensing techniques in cognitive radio systems," in *2nd International Workshop on Cognitive Information Processing*, Italy, June 2010.
- [49] Z. Quan, C. Shuguang, and A. H. Sayed, "Optimal linear cooperation for spectrum sensing in cognitive radio networks," *IEEE Journal on Selected Topics in Signal Processing*, vol. 2, no.1, pp. 28-40, Feb. 2008.
- [50] W. Yue and B. Zheng, "Spectrum sensing algorithms for primary detection based on reliability in cognitive radio systems," *Computers & Electrical Engineering*, vol. 36, no. 3, pp. 469-479, May 2010.
- [51] E. C. Peh, Y.C. Liang, Y. L. Guan, and Y. Zeng, "Cooperative spectrum sensing in cognitive radio networks with weighted decision fusion schemes," *IEEE Transactions on Wireless Communications*, vol. 9, no. 12, pp. 3838-3847, Dec. 2010.
- [52] S. M. Mishra, A. Sahai, and R. W. Brodersen, "Cooperative sensing among cognitive radios," in *Proc. IEEE International Conference on Communications*, Istanbul, June 2006.

- [53] D. Cabric, S. M. Mishra, D. Willkomm, R. W. Brodersen, and A. Wolisz, "A cognitive radio approach for usage of virtual unlicensed spectrum," in *Proc. IST Mobile and Wireless Communications Summit*, Dresden, June 2005.
- [54] S. Narlanka, R. Chandra, P. Bahl, and J. I. Ferrell, "A hardware platform for utilizing TV bands with a Wi-Fi radio," in *15th IEEE Workshop on Local & Metropolitan Area Networks*, New York, June 2007.
- [55] S. W. Oh, S. A. A. Naveen, Y. H. Zeng, V. P. Kumar, T. P. C. Le, K. J. M. Lua, and W. Q. Zhang, "White-space sensing device for detecting vacant channels in TV bands," in *Proc. IEEE 3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Singapore, May 2008.
- [56] S. Maharjan and T. Jun-ichi, "Energy detector prototype for cognitive radio system," *Technical Report of IEICE*, 2007.
- [57] V. Turunen, M. Kosunen, A. Huttunen, S. Kallioinen, P. Ikonen, A. Parssinen, and J. Ryynanen, "Implementation of cyclostationary feature detector for cognitive radios," in *Proc. IEEE 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Hannover, June 2009.
- [58] L. Biard, D. Noguet, T. Gernandt, P. Marques, and A. Gameiro, "A hardware demonstrator of a cognitive radio system using temporal opportunities," in *Proc. IEEE 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Hannover, June 2009.
- [59] M. Ghozzi, B. Zayen, and A. Hayar, "Experimental study of spectrum sensing based on distribution analysis," in *18th ICT-MobileSummit Conference*, Spain, 2009.
- [60] G. Thomas, "Fast detection of spectral white spaces for cognitive radio networks," in *Proc. IEEE Military Communications Conference*, Boston, Oct. 2009.
- [61] A. Shukla, E. Burbidge, and I. Usman, "Cognitive radios - what are they and why are the military and civil users interested in them," in *The Second European Conference on Antennas and Propagation*, Edinburgh, Nov. 2007.
- [62] Y. Wang, "Cognitive radio for aeronautical air-ground communications," *IEEE Aerospace and Electronic Systems Magazine*, vol. 25, no. 5, pp.18-23, May 2010.
- [63] H. Arslan, "Applications of cognitive radio," in *Cognitive Radio, Software Defined Radio and Adaptive Wireless Systems*, ed: Springer, 2007, pp. 383-420.
- [64] E. C. Peh and Y.C. Liang, "Optimization for cooperative sensing in cognitive radio networks," in *Proc. IEEE Wireless Communications and Networking Conference*, Kowloon, March 2007.
- [65] Y. Zhou and F. Tian, "A spectrum sensing algorithm based on random matrix theory in cognitive radio networks," in *Proc. IEEE International Symposium on Wireless Communication Systems*, York, Sept. 2010.

- [66] S. Kritchman and B. Nadler, "Determining the number of components in a factor model from limited noisy data," *Chemometrics and Intelligent Laboratory System*, vol. 94, pp. 19-32, Nov. 2008.
- [67] A. Zahedi-Ghasabeh, A. Tarighat, and B. Daneshrad, "Spectrum sensing of OFDM waveforms using embedded pilot subcarriers," in *Proc. IEEE International Conference on Communications (ICC)*, Cape Town, May 2010.
- [68] Zhixin Li, Hua Wang, and Jingming Kuang, "A two-step spectrum sensing scheme for cognitive radio networks," in *Proc. International Conference on Information Science and Technology*, Nanjing, Jiangsu, China, March 2011.
- [69] L. Luo, N. M. Neihart, S. Roy, and D. J. Allstot, "A two stage sensing technique for dynamic spectrum access," *IEEE Transactions on Wireless Communications*, vol. 8, pp. 3028-3037, June 2009.
- [70] Beibei Wang and K. J. Ray Liu, "Advances in cognitive radio networks: a survey," *IEEE Journal of Selected Topics in Signal Processing*, vol. 5, pp. 5-23, Feb 2011.
- [71] Sohn, Sung Hwan Han, Ning Kim, Jae Moun Kim, and Jae Wan, "OFDM signal sensing method based on cyclostationary detection," in *Proc. 2nd International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Orlando, August 2007.
- [72] K. Maeda, A. Benjebbour, T. Asai, T. Furano, and T. Ohya, "Recognition among OFDM based sytems utilizing cyclostationary inducing transmission," in *Proc. 2nd IEEE Int. Symp. New Frontiers in Dynamic Spectrum Access Networks*, Dublin, Ireland, April 2007.
- [73] M. Föhnle, "Software-defined radio with GNU radio and USRP/2 hardware frontend: setup and FM/GSM applications," Bachelor Thesis, Institute of Communication Technology, University of Applied Sciences, Ulm, Germany, 2010.
- [74] A. Verduin, "GNU radio wireless protocol analysis approach," Master Thesis, Universiteit van Amsterdam, 2008.