A Variable Threshold for an Energy Detector Using GNU Radio

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As the candidate's supervisor, I have approved this dissertation for submission.

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Declaration

I declare that this minor dissertation is my own work. Where collaboration with other people has taken place, or material generated by other researchers is included, the parties and/or materials are indicated in the acknowledgements or are explicitly stated with references as appropriate.

This work is being submitted for the Master of Engineering with a specialization in Telecommunications Engineering at the University of Cape Town. It has not been submitted to any other university for any other degree or examination.

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Dedication

To The Holy Trinity,

The Lechesa Family, and

Makeratile Mary Lechesa,

Your invaluable support has given me the strength and courage to reach this point and the blessings the future has to offer.

Abstract

Spectrum is a natural resource and should be treated as such. Spectrum has dual use applications that range from short distance communication links such as Bluetooth to health, power systems, transport, smart city applications and space communications and exploration. Next Generation Networks (NGNs) are designed to connect millions of devices seamlessly and with high throughput rates in the aforementioned sectors and others not mentioned. The use of spectrum has to be efficiently utilized and appropriated. Cognitive radio communications serve to improve use of dwindling spectrum availability.

Spectrum sensing is the first and critical technology in cognitive radio meant to determine radio parameters. Energy Detection (ED) is a spectrum sensing technology that has a low computational and operational complexity, a relatively fast spectrum sensing technique to other spectrum sensing technologies, and requires no knowledge of the primary user's transmit signal properties such as modulation or error correction schemes. In its classical case, ED compares the signal energy received with a fixed detection threshold, estimated with an expected noise level. Noise however in practice varies randomly due to thermal variations, non-uniform movement of electrons, imperfections of semiconductor materials and external noise sources to mention a few. This creates a noise uncertainty phenomenon which negatively affects the fixed threshold approach used in classical ED.

Development of an out-of-tree module for a variable threshold energy detector using the estimated noise power at each sample point is presented in this dissertation. GNU Radio software and Ettus Universal Software Radio Peripheral (USRP) hardware were used to simulate the performance of the proposed variable threshold energy detector. The Neyman-Pearson theory was adopted in achieving the proposed variable threshold energy detector. The variable threshold energy detector successfully sensed the presence of a primary user signal at 1.25% less the spectrum sensing time of the constant threshold. An ROC curve plot also showed that the proposed variable threshold energy detector had a better performance in general as opposed to the constant threshold energy detector at low signal-to-noise ratio levels.

Acknowledgements

To God, I make my life what I want it to be. Without You in my life I am incomplete, I believe without you that I am nothing. “I have come that they may have life, life in all its fullness.”

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To His Majesty’s Government of Lesotho for funding my studies and making me a better citizen, *Ha e nne e sise, e sisetse Basotho ka ho fela. Khotso, Pula, Nala.*

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Abbreviations:

CR: Cognitive Radio

DSA: Dynamic Spectrum Access

EB: Exabyte

FFT: Fast Fourier Transform

GHz: Gigahertz

HetNet: Heterogeneous Network

ISM: Industrial, Scientific and Medical

MIMO: Multiple-input Multiple-output

NGN's: Next Generation Networks

OFDM: Orthogonal Frequency-Division Multiplexing

PU: Primary User

QoS: Quality of Service

SCADA: Supervisory Control and Data Acquisition

SDR: Software Defined Radio

SU: Secondary User

SNR: Signal-to-noise Ratio

VANET: Vehicular Ad Hoc Network

WSN: Wireless Sensor Network

Chapter 1

1 Introduction:

Next generation networks (NGNs) in general are expected to be better than the preceding networks through different metrics that define the performance of a network. One main difference from the 1st generation network to the current network has been in the improvement of the physical interfaces used. Today however, the sheer amount of projected mobile and fixed devices are expected to be far greater than are today. The situation is exacerbated by the demand for higher throughput to be introduced in NGNs. The main drivers for this demand are projected to be high definition (HD) video streaming, rapid mobile device proliferation at 1 billion in sales and device applications uptake at 270 billion, all these in 2017 [1]. It is estimated that global mobile traffic per month is estimated to be 543 EB and 4 394 EB in 2025 and 2030 respectively [1], it follows that efficient spectrum use is paramount in the design of NGNs.

Fixed spectrum allocation is an inefficient spectrum allocation method for a number of reasons, thus the introduction of dynamic spectrum access (DSA) has been deemed necessary [2]. Temporal and geographical variations of use of fixed spectrum that are in the range of 18% to 85% have characterized the inefficient use of spectrum in 2006 alone in the United States of America [3]. High throughput NGNs will have to use DSA to overcome the inefficiency caused by fixed spectrum allocation; this need necessitates the application of cognitive radio in DSA.

The concept of a cognitive radio (CR) was introduced in 1998 and published in an article the following year [4]. A CR is an intelligent radio that adapts dynamically and automatically to environmental and parameter changes around itself [2]. CR is viewed as an extension of the ever-evolving software defined radio (SDR) that should follow network and end user demands. SDR and CR are independent technologies that can be combined or used independently [2], [4]. A CR first has to determine if a spectrum is occupied or not by what is called a primary user (PU), while the radio doing the sensing is called a secondary user (SU), this is the first and most critical step in CR systems [2]. The SU's have to detect the presence of PU's with a high probability and vacate the channel by changing some radio parameters within a certain amount of time with the goal of avoiding interfering with the PU. A change in these radio parameters could be reducing the transmit power, changing the modulation scheme or remaining idle until spectrum is available. A number of standards that employ CR for the NGN's have stringent specifications.

The upcoming IEEE 802.22 standard for example, requires that the SU detect the television (TV) and wireless microphone signals and vacate the channel within two seconds once they become active. Furthermore, for TV signal detection, it is required to achieve 90% probability of detection and 10% probability of false alarm at signal-to-noise ratio (SNR) level as low as -20 dB and sensitivity levels of -120 dBm [5]. CR specifications may be stringent, but application of CR's can present a number of benefits that necessitates the application of CR technology.

Cellular wireless technologies can be used for rescue and safety operations in unfortunate situations like building collapses, riots, earthquakes, hurricanes and other natural disasters without using the assigned spectrum for public safety and rescue bands [6]. As an example, the lack of radio interoperability between public safety organizations has been identified as a major problem in disasters such as 9/11 terror attacks and Hurricane Katrina tragedies. Using software platforms with redundant wireless architectures and protocols has been suggested where for example, a mobile device with the IEEE 802.11 standard and Bluetooth can form local networks that can solve communication problems in such times [7]. CR technology can use cellular signals of victims who are trying to reach out for help to estimate their locations even when core cellular infrastructure has shut down. Increased congestion caused by overwhelming communication requests and drastic changes in the air interface because of weather conditions during natural disasters have also characterized such events. There is also no common infrastructure or technology defined to cover all more than 74000 public safety organizations using various wireless technologies [6]. Encryption should be employed to provide safety for such communications. Wireless Sensor Networks which are applicable in smart city applications, health care telemetry, Supervisory Control and Data Acquisition (SCADA), and Industrial, Scientific and Medical (ISM) band applications can benefit from CR applications as described later in the Chapter 2.

1.1 Problem Statement

Spectrum assignment policy has been a fixed spectrum assignment policy until the introduction of Dynamic Spectrum Access (DSA) [1], [2]. The fixed spectrum is regulated by the International Telecommunications Union (ITU), a United Nations arm responsible for all telecommunication matters. In turn, government telecommunications agencies locally regulate spectrum by assigning license holders or services on a long-term basis. Spectrum is a natural commodity that is very scarce. The United States of America's (USA) Federal Communications Commission (FCC) had projected that spectrum will run out in America by 2013, even though currently not exhausted, this emphasizes the need to efficiently use the radio spectrum [8].

The first step in use of a Cognitive Radio is spectrum sensing. The proliferation of millions of unlicensed spectrum devices is expected to be cheap thus creating massive competition for limited spectrum. Energy Detection (ED) is an attractive spectrum sensing technique for NGNs because of the fast, low computational complexity, low operational complexity and no need for PU's transmit signal properties such as modulation or error correction schemes. ED in it's classical case has a fixed threshold which is inefficient due to noise uncertainty. A reasonable conclusion is that an energy detector need only know the noise power of the PU. This dissertation is aimed at investigating use of a variable threshold in ED under noise power variations and the subsequent reduction of the spectrum sensing time.

1.2 Hypothesis

An out-of-tree (OOT) module for the GNU Radio software implementing a variable threshold Energy Detection (ED) will enable spectrum sensing for an orthogonal frequency-division multiplexing (OFDM) based technology (e.g. IEEE 802.22/ IEEE DySPAN/ IEEE 80.15.4e).

1.3 Research Objectives

The goal of the research is to,

Establish a variable threshold for the energy detector taking into consideration the noise variation and the number of signal samples taken in realizing the detector.

1.4 Methodology

The ability of the variable threshold to vary with the noise variance while optimizing the sampling size under a set probability of false alarm will be used to measure the performance of the variable threshold detector. The received signal strength indicator (RSSI) and the binary hypothesis testing problem (BHTP) will also be used as a measure of a presence of a signal, while the spectrum sensing times will be used to compare between the constant and variable thresholds of an energy detector.

Cognitive radios (CRs) can be modelled as a BHTP:

$$H_0: y[n] = w[n] \qquad n = 1,2,3, \dots, N \tag{1}$$

$$H_1: y[n] = x[n] + w[n] \qquad n = 1,2,3, \dots, N \tag{2}$$

Where N is the number of samples on the signal of interest in a CR. H_0 represents the first hypothesis when there is no primary signal detected but only noise $w[n]$, while H_1 represents the second hypothesis when there is a presence of a primary signal $x[n]$ and noise $w[n]$.

Another critical factor to take into consideration when modelling an energy detector is the SNR wall. The SNR wall is an SNR value at which no matter the number of samples N taken by the energy detector in determining if the hypothesis test H_1 is true or not, will not increase the robustness of the energy detector. This means that N, is a crucial parameter in making signal-processing times shorter once the SNR value is determined in conjunction with the noise variance [9].

1.5 Scope of Research and Assumptions

Parameters taken into account are the sampling size N, probability of false alarm (P_{fa}), the noise uncertainty, the signal-to-noise ratio and an OFDM modulated signal rather than a specific wireless communication standard. A single antenna transmitter (no MIMO), P_{fa} of 0.1, and N that was optimized using P_{fa} , P_d and an SNR for the constant and variable threshold energy detector were used. A 1024 Fast Fourier Transform of an OFDM modulated signal was also used in the implementation of a constant and variable threshold energy detector were used for reasons detailed in Chapter 4 and Chapter 5. The transmitted power of the USRP N210 software defined radios were the same for both the constant and threshold energy detector in the GNU Radio environment. The simulation was carried out at a frequency unoccupied by any licensed users at the simulation location. Variation of the threshold with the noise variance, spectrum sensing times and RSSI were used to determine the CR performance. A brief discussion on the CR cycle is discussed in this dissertation too.

1.6 Research Justification

The lack of spectrum necessitates the use of more efficient, cheap, small-form factor and low power CR's. Moore's Law that states that there is a doubling in density of transistors in integrated circuits annually calls for better algorithms to employ spectrum sensing to keep up with the law. Moore's Law is said to not be consistent in the decade after 2015, but nonetheless, the rate at which computing power is developing is cumulative [10].

5G is envisioned to have native support for massive, low data rate and latency machine-to-machine (M2M) communications. The possibility of using millimeter waves (mmWaves) means a shift in using GHz frequency ranges (3 to 300 GHz) previously not entirely used, but even so, that spectrum needs to be efficiently utilized. Device-to-Device communications require communication nodes to use low power device-centric architectures while Massive-MIMO when used in conjunction with CR can free up a lot of spectrum while also increasing throughput [11].

1.7 Dissertation Outline

Chapter 1 presents an introduction, the problem statement, research objectives and general methodology, and the assumptions made. A hypothesis is established based on the challenges posed by fixed threshold ED threshold. Constraints to the research are set to narrow the scope of the research to easily identifiable metrics.

Chapter 2 presents the literature review regarding cognitive radios (CR's) by stating the CR cycle. Spectrum sensing, spectrum management, spectrum mobility and spectrum sharing characterize the CR cycle. Emphasis is exerted on ED under spectrum sensing techniques since it is the focal research point of this research when a variable threshold is applied. Applications of the CR are also detailed in this chapter.

Chapter 3 outlines the different thresholding techniques that are considered in this research. Comparisons between the thresholding techniques are also presented with key focus being the classical fixed threshold technique used in the classical ED which is adapted to the proposed variable threshold technique. Autonomous thresholding techniques are also reviewed and compared with one another.

Chapter 4 describes in detail the methodology used in comparing the performance of the constant and the proposed variable threshold.

Chapter 5 analyses both constant and variable threshold technique performance metrics, which includes the ability to sense a PU and determine the spectral sensing times. Plots of the probability of detection against signal-to-noise ratio plots were made for the classical ED technique. The BHTP and receiver operating characteristics curves were evaluated for both thresholding techniques.

Chapter 6 deals with a deep analysis of the results presented in chapter 4 and concludes the research. Recommendations and possible further research is also outlined in this chapter.

Chapter 2

2 Background and Literature Review: Cognitive Radio

2.1 Introduction

Cognition in the normal day-to-day use refers to the mental action or process of acquiring knowledge and understanding through thought, experience and the senses. A parallel approach to this definition enables Next Generation Networks (NGNs) to sense, process and use network parameters through myriad methods in ensuring efficient use of the spectrum and other network resources. A basic framework governs the cognitive radio network (CRN) cycle to ensure that an efficient CR exists. This framework is presented and each element within it described in detail, but with emphasis on the spectrum sensing element [3].

2.2 Cognitive Radio Networks

"*Cognitive Radio System (CRS): A radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives; and to learn from the results obtained*" [12].

The steps of the cognitive cycle can be modelled as *spectrum sensing*, *spectrum analysis, and spectrum decision.* This is referred to as the Dynamic Spectrum Management Framework (DSMF) [3], [13].

CRN's can provide high bandwidth for mobile users in heterogeneous wireless architectures and improve spectral efficiency without interfering with existing users. In attaining the best available channel, the cognitive radios in NGNs should collectively allow for *spectrum sensing, spectrum management, spectrum mobility,* and *spectrum sharing* [3].

- *“Spectrum sensing*: Detecting unused spectrum and sharing the spectrum without harmful interference with other users.
- *Spectrum management*: Capturing the best available spectrum to meet user communication requirements.
- *Spectrum mobility*: Maintaining seamless communication requirements during the transition to better spectrum.
- *Spectrum sharing*: Providing the fair spectrum scheduling method among coexisting NGN’s users.” [3].

Dynamic spectrum may have a negative impact on the performance of fixed spectrum protocols that have been developed if other radio source spectrum parameters do not match the available spectrum thus causing interference to each other. Radio users that have higher priority and rights to occupy spectrum are called PU’s, while radio users that can be replaced by PUs or other radio users with higher rights and priority of spectrum use are called secondary users (SUs) [14]-[18].

CR’s exploit inefficient use of the spectrum by using time, frequency, power or distance to access unused spectrum called spectrum holes or white spaces of licensed or unlicensed users [3]. If the hole is to be further used by the PU, the SU should vacate to another spectrum hole or stay in the same band changing its parameters to avoid interference. Figure 1 below describes how a CR can exploit the spectrum environment. The CR is faced with challenges due to the wideband RF antenna that receives signals from different locations, at different power levels and bandwidths. As a result the CR should be able to detect weak signals in a large dynamic range and thus a requirement of a multi-GHz analogue-to-digital converter (ADC) with a high resolution, which in practice is not readily feasible.

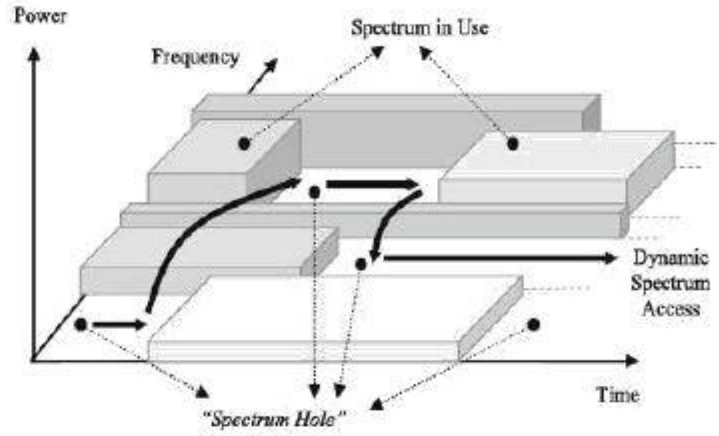

Figure 1 – Illustration of available spectrum holes for Dynamic Spectrum Access [3], [19].

The Binary Hypothesis Testing Problem stated in Equation 1 and 2 describes the hypotheses H_0 and H_1. The H_0 represents the first hypothesis that there is no primary signal detected, only noise *w[n]*, while the H_1 represents the second hypothesis that there is a presence of a primary signal *x[n]* and *w[n]* in the spectrum. The probability of deciding that a primary signal is present when the primary signal is actually present is called the probability of detection, $P_d = P\{Y > \lambda | H_1\}$, while the probability of declaring the presence of a primary signal when it is actually absent is called the probability of false alarm, $P_{fa} = P\{Y > \lambda | H_0\}$. The threshold λ determines the performance matrices, P_d and P_{fa} of the system. Stochastic methods apply in spectrum sensing, in particular, the Neyman-Pearson theorem which is the basis of the variable threshold used in this dissertation that states that the Likelihood Ratio Test (LRT) maximizes the detection probability. The test statistic of the LRT that is used to decide or reject the null hypothesis is defined as

$$Z(n) = \frac{p(Y|H_1)}{p(Y|H_0)} \tag{3}$$

where $p(*)$ is the probability density function [5], [20], [21].

Noise uncertainty makes the Energy Detector inefficient [5], [20], [21]. This means that the Energy Detector is not robust in detecting a presence of a signal in an occupied band as efficiently as it would when noise is explicitly known, especially when there is a low SNR value of the PU. The radio environment changes over time and space, and thus for an occupied hole, the CR should keep track of the radio environment changes. "Any environmental change during the transmission such as PU appearance, user movement or traffic variation can trigger this adjustment." [3]. It is this environmental change that was employed to change noise power in the dissertation.

Let the noise power be $\widehat{\boldsymbol{\sigma}_{\boldsymbol{n}}}^{\mathbf{2}} = \boldsymbol{\alpha}\boldsymbol{\sigma}_{\boldsymbol{n}}^{\mathbf{2}}$ where $\boldsymbol{\alpha}$ is the noise uncertainty factor and $\boldsymbol{\sigma}_{\boldsymbol{n}}^{\mathbf{2}}$ is the expected noise power. The noise uncertainty bound $\boldsymbol{\rho}$ gives the lower and upper bounds in dB of $\boldsymbol{\alpha}$ given by,

$$\rho = 10\log_{10}(\alpha) \tag{4}$$

In practice, the noise uncertainty bound of a receiving device is below 2 dB while the environment noise uncertainty can be larger. The noise power varies within the limits $[\boldsymbol{\alpha}^{-\mathbf{1}}\boldsymbol{\sigma}_{\boldsymbol{n}}^{\mathbf{2}}, \boldsymbol{\alpha}\boldsymbol{\sigma}_{\boldsymbol{n}}^{\mathbf{2}}]$ in a communications system [22] - [24]. If the threshold $\boldsymbol{\lambda}$ is determined using the lower limit $\boldsymbol{\alpha}^{-\mathbf{1}}\boldsymbol{\sigma}_{\boldsymbol{n}}^{\mathbf{2}}$ as the expected noise power, then there is a higher likelihood of the false alarm rate that is directly proportional to the noise uncertainty. Alternatively, if the threshold $\boldsymbol{\lambda}$ is set with the upper limit $\boldsymbol{\alpha}\boldsymbol{\sigma}_{\boldsymbol{n}}^{\mathbf{2}}$ as the expected noise power, the probability of detection will decrease as the SNR decreases and the uncertainty increases. The use of both thresholds using both bounds of noise power $\widehat{\boldsymbol{\sigma}_{\boldsymbol{n}}}^{\mathbf{2}}$ is discussed in Chapter 2 and Chapter 3 under thresholding techniques.

It is also worth noting that when the SNR is very low, the attenuated power of the primary signal does not represent a significant component in the received signal, therefore the low SNR value cannot be enough to compensate the fluctuating noise power. A very low SNR value thus results in a low probability of detection, which is not desirable in CRN's [5], [20], [21]. A high probability of detection is the wanted result.

A parametric plot of the P_d versus P_{fa} called the receiver operating characteristic (ROC) describes the effects of P_{fa} on P_d. The ROC curve depicted in Figure 2 is always concave-down to achieve a higher P_d and always exceeds the equality line, that is, the diagonal line when P_{fa} equals P_d. The degree of separation of the ROC from the equality line depicts the distinctiveness between the binary hypotheses. The P_{fa} and P_d must decrease monotonically as the threshold is increased [25]. It is worth noting that the P_d and the P_{fa}do not imply equality, thus a change in the P_d does not necessarily mean an equal change in P_{fa}. The interest is usually to have P_d to grow more rapidly than P_{fa}. The relationship between P_{fa} and P_d is depicted in Figure 2.

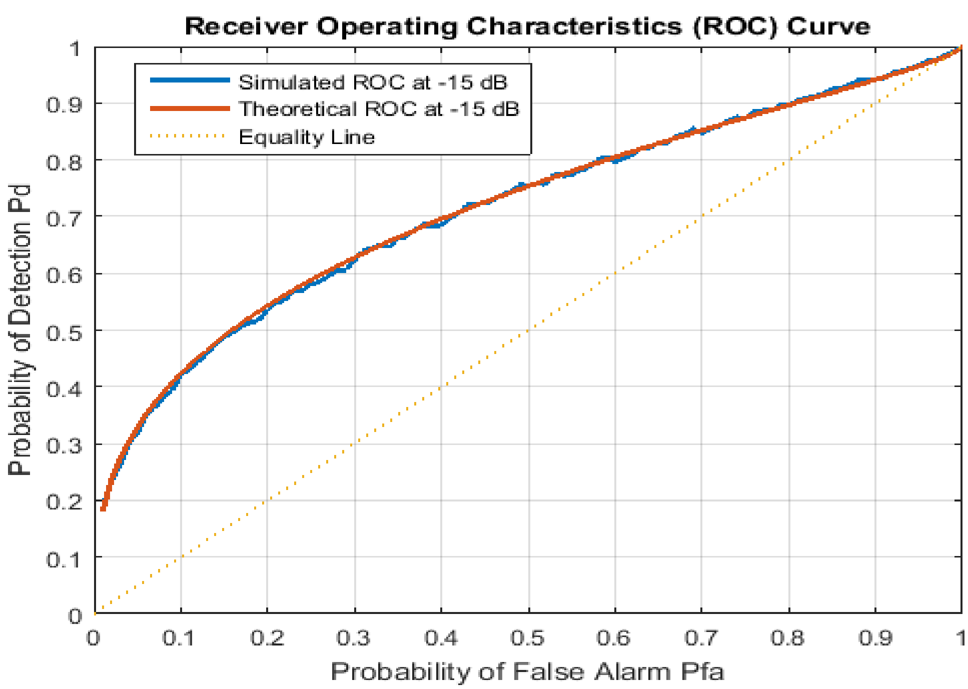

Figure 2 – Receiver Operating Characteristic (ROC) curves example.

Popular spectrum sensing techniques are ED, Matched Filter and the Cyclostationary Feature spectrum sensing method. Other spectrum sensing techniques include but not limited to Multi-taper spectral estimation, Wavelet Transform based estimation, Hough Transform, and time-frequency analysis [26]. ED in comparison to these other spectrum sensing techniques is that it has a low computational and operational complexity, is the fastest spectrum sensing technique, and requires no knowledge of the PU's transmit signal properties such as modulation or error correction schemes make as opposed to aforementioned spectrum sensing methods [2], [26]. These properties make ED a likely candidate for fast, cheap, low computational and energy efficient CRs for heterogeneous networks (HetNets). On the other hand, ED is susceptible to low SNR and noise variances, thus the research is squarely based on the interaction of these factors on making an efficient energy detector [26].

2.3 Spectrum Sensing

Spectrum sensing is the first step in a cognitive radio cycle. It is classified into three primary methods being Non-cooperative spectrum sensing (transmitter detection), Cooperative spectrum sensing and Interference-based spectrum sensing. Three schemes are generally used for the transmitter detection. These are Matched Filter detection, Energy Detection, Cyclostationary Feature and the Wavelet Packet Transform spectrum sensing techniques.

2.3.1 Non-cooperative Spectrum Sensing (Transmitter Detection)

This is a spectrum sensing technique where the cognitive radio determines if a signal from a primary transmitter is locally present in a certain spectrum or not. The techniques commonly used for non-cooperative spectrum sensing are described below.

2.3.1.1 Matched Filter Detection:

"When the information of the primary user signal is known to the next generation user, the optimal detector in stationary Gaussian noise is the matched filter since it maximizes the received SNR. While the main advantage of the matched filter is that it requires less time to achieve high processing gain due to coherency, it requires a priori knowledge of the PU signal such as the modulation type and order, the pulse shape, and the packed format. Hence, if this information is not accurate, then the Matched Filter performs poorly. However, since most wireless network systems have pile, preambles, synchronization word or spreading codes, these can be used for the coherent detection" [3].

2.3.1.2 Energy Detection:

If the receiver cannot gather enough relevant information about the PU, for example, such as the modulation type or transmit power, the optimal detector is known as the energy detector. ED is one of the methods requiring only noise power information (semi-blind detection), another being Wavelet Based detection to be discussed later in this dissertation [5]. The energy of the received signal is measured by taking the output signal of a bandpass filter of bandwidth *W* and squared through a square law device and integrated over the observation period *T*. The output of the integrator *Y* called the test statistic is compared with a threshold $\boldsymbol{\lambda}$ to decide if a licensed user is present or not through the hypotheses H_0 and H_1 [3], [26]. Figure 3 and Figure 4 depict an energy detector both in the time and frequency domain respectively through Parseval's theorem [27]

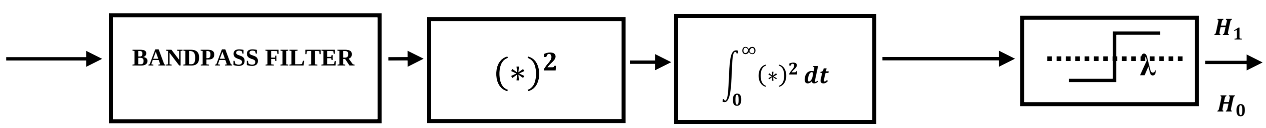

Figure 3 - Time domain representation of the Energy Detector

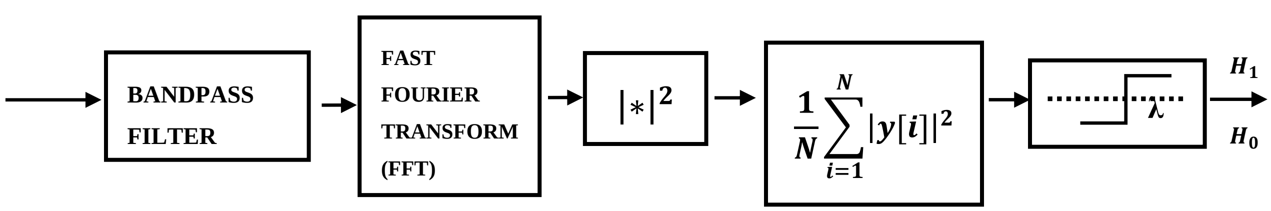

Figure 4 - Frequency domain representation of the Energy Detector

If Y is greater than the threshold λ, the hypothesis H_1 is the decision taken, which means that the PU occupies the spectrum. The decision H_0 which denotes the idle state of the spectrum occurs if Y is less than the threshold λ. The SU will transmit data only if the decision H_0 hypothesis is satisfied [26]. The output of the integrator Y follows the chi-square distribution under both hypotheses H_0 and H_1 [26]. If the number of samples used for detection is large enough, one can make use of Central Limit Theorem (CLT) to approximate the distribution of the test statistic as Gaussian, with a specific mean and variance [18]. This dissertation makes use of the CLT, thus the distribution of the Y was deemed Gaussian. The probability that the SU transmitter may incorrectly make a decision of H_0based on $Y < \lambda$ and transmit data even though there is a PU occupying the spectrum is known as the missed detection probability given by

$$P_m(\xi) = P_r\{Y < \lambda / H_1\} \tag{5}$$

The detection probability $P_d(\lambda) = P_r\{Y \geq \lambda / H_1\}$ denotes the probability that the busy state of the spectrum can be correctly detected by the PU [26]. The probability of the transmitter making a false alarm is the probability that Y is greater than the threshold when nothing actually occupies the spectrum, $P_{fa}(\lambda) = P_r\{Y \geq \lambda | H_0\}$. If the energy detection can be applied in a nonfading environment of the channel, the P_d and $P_{fa}$are given as follows,

$$P_d = P\{Y > \lambda | H_1\} = Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda}\right), \tag{6}$$

$$P_{fa} = P\{Y > \lambda | H_0\} = \frac{\Gamma(N,\ \lambda/2)}{\Gamma(N)} \tag{7}$$

where γ is the SNR,

$\Gamma(a)$ is the complete gamma function for a variable a,

N is the sample size,

$\Gamma(a, b)$ is the incomplete gamma function for variables a and b, while

Q_m is the generalized Marcum Q-function.

From the above equations, while a low P_d would result in missing the presence of the PU which in turn increases the chance of interference to the PU, a high P_{fa} would result in low spectrum utilization since false alarms increase the number of missed opportunities. A balance between the two probabilities has to be optimized for efficient spectrum sensing in a CR [3].

For fading and multipath propagation, when the amplitude gain of the channel varies due to shadowing or fading, the probability of the detection conditioned on instantaneous SNR is as follows:

$$P_d = \int_x^{\infty} Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) f_\gamma(x) dx \tag{8}$$

where $f_\gamma(x)$ is the probability distribution function of the SNR under a fading environment [3].

A number of ways are employed to realize an efficient CR that employs ED. Implementation of an adaptive SNR estimation based energy detector that leads to an adaptive threshold has been used to improve the spectrum sensing performance and efficiency in low SNR environments [28]. An ED scheme employing consecutive energy detection averaged out has also been investigated titled the Three Event Energy Detection (3EED) [29]. An energy detector that uses the knowledge of the magnitudes of the fading gains has been tested too, although it requires a longer time to process, while still maintaining the low complexity of ED. A similar approach using the knowledge of beamforming and the number of antenna elements has been used to determine a variable threshold energy detector [30], [31]. A two-stage double threshold ED scheme has been also proposed for better spectrum sensing under low SNR environments [32]. A fuzzy threshold scheme using "OR", "AND" or "K-out-of-N" fusion rules using multiple nodes aimed at improving P_d has been proposed [33]. Consideration of the SNR wall thus optimization of the sample size N thus leading to a shorter spectral sensing time was not considered in these autonomous adaptive threshold ED methods, which is what this dissertation seeks to address.

A double (two-stage) threshold has also been proposed to improve decision ruling in a cooperative spectrum-sensing scheme. This method improves decision making at the fusion center by setting the lower threshold value for determining the probability of detection P_d while the other determines the P_{fa}. In this method it was not specified on how to determine the individual thresholds for SU's in a CR [22]. Threshold adaptation to overcome noise variance estimation errors has also been considered where noise samples from a reference channel to estimate noise power are taken with errors also taken into consideration, however, the investigation was for an indoor environment [37]**.** These methods aim at improving a fixed threshold for a constant false alarm rate (CFAR) (also known as the Neyman-Pearson criterion) as a metric for determining the threshold to maximize P_d. This energy detector is known as the Classical Energy Detection technique (CED) [15]-[17], [22]. The concept of the CFAR was adopted for the proposed variable threshold energy detector.

2.3.1.2.1 Decision Threshold:

The decision threshold and the noise uncertainty (in turn the SNR and SNR Wall) are key parameters in the performance of the energy detector [34]. The value of the decision threshold λ can be chosen for an optimal compromise between P_{fa} and P_d with the goal of having a greater P_d over P_{fa} as depicted in Figure 2 [35]. This method requires prior knowledge about the noise and detected signal power, both of which are not easy to determine. Detected signal power is difficult to estimate primarily because of transmission and propagation characteristics which include fading possibly due to user movement and interference. Setting the threshold just above the noise floor is typically employed for fixed threshold purposes, but this is not ideal since noise can change due to various reasons. Noise power is primarily due to white noise that varies with temperature fluctuations, inefficient low noise amplifiers in receivers and filters, or leakage of signals with small variations. High noise power that lead to low SNR values can cause sharp degradations in the energy detector performance due to the SNR wall [35], [36]. Pilot tones from the primary transmitter can be used to help improve the accuracy of the energy detector by estimating the SNR. The energy detector's limitation is that it cannot differentiate signal types but can only determine the presence of the signal, therefore, the energy detector is prone to the false detection triggered by the unintended signals [36].

The P_{fa} and P_d are related to each other through decision regions and likelihood functions as stated in Equation 9 as,

$$P_{fa} = \int_{R_1} p_{X|M_0}(X|M_0)\, dx, \quad P_d = \int_{R_1} p_{X|M_1}(X|M_1)\, dx, \tag{9}$$

The decision region R_1which means that when X (the random variable) lies within the decision region R_1, then the hypothesis H_1 is selected. When R_1 tends to zero, both the conditional probabilities in Equation 9 tend to zero. Conversely, as R_1 expands to enclose the whole range, both conditional probabilities tend toward unity, however, P_d increases more rapidly than P_{fa} [25]. A compromise in selecting P_{fa} and P_d must be made since an ideal case where the P_{fa} equals zero and P_d equals unity is not possible when the conditional probabilities overlap as is the case in spectrum sensing [25]. The threshold value describes the decision regions where P_{fa} is specified for reasonable performance of the CR. The relationship between the P_{fa}, P_d and the threshold can be shown in Figure 5 below.

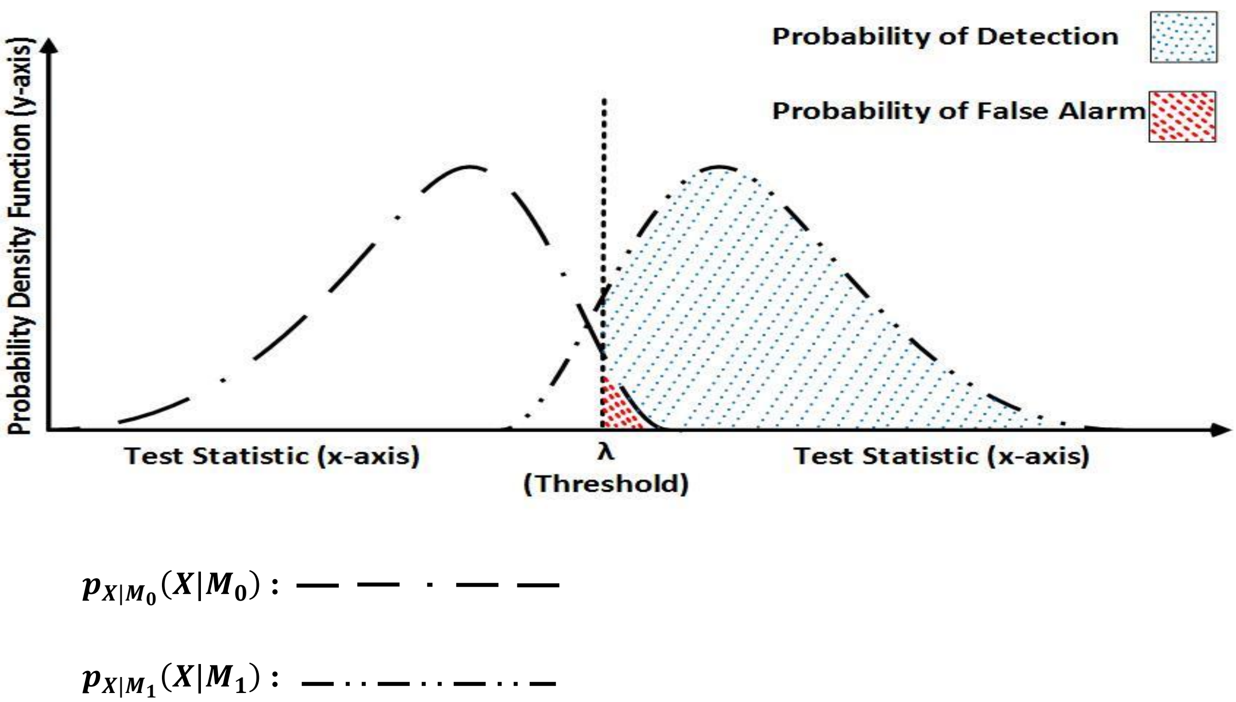

Figure 5 - Stochastic threshold selection using the binary hypothesis test.

Moving the threshold value on either side essentially manipulates P_{fa} and P_d depicted in shaded areas. A higher P_d is desired, but stringent SNR values must be considered when setting the threshold. Consider the IEEE 802.22 standard with specifications for CR to have as low SNR values as -22 dB and sensitivity levels as low as -116 dBm. These signals, along with spread spectrum signals which are used in some of the communication standards for security and higher throughput targets are either embedded in the noise floor or well below the noise floor, thus the robustness of the energy detector has to be high. Chapter 3 is dedicated to the thresholding techniques employed in ED and are discussed in depth therein.

2.3.1.2.2 SNR Wall

The SNR wall which depends on the noise variance (or noise uncertainty factor) is an SNR value at which no matter the number of samples *N* taken by the energy detector in determining if the hypothesis test H_1 is true or not, will not increase the robustness of the energy detector. This means that this value is key in making signal processing times shorter and more efficient once that value is determined in conjunction with the noise variance [9], [36]. The lower the SNR value the more the number of samples required to efficiently determine the existence of a PU [9]. This performance is described in Figure 9.

2.3.1.3 Cyclostationary Feature

One other method for spectrum sensing classified under Non-cooperative spectrum sensing is the Cyclostationary Feature spectrum sensing method. In this method, modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading, hopping sequences, or cyclic prefixes, which result in built-in periodicity. These features are detected by analyzing a spectral correlation function. The main advantage of the spectral correlation function is that it differentiates the noise energy from modulated signal energy, which is a result of the fact that the noise is a wide-sense stationary signal (WSS) with no correlation, while modulated signals are cyclostationary. The spectral cyclostationary feature detector can perform better than the Energy

Detector in discriminating against noise due to its robustness to the uncertainty in noise power. However, it is computationally complex and requires significantly long observation times [3].

2.3.1.4 Wavelet Packet Transform (WPT) Spectrum Sensing

Wavelet Packet Transform technique is based on the breakdown of frequency bands into lower and higher bands at different levels. The lower frequency signal is approximation (A) coefficient and the higher one is detail (D) coefficient. The latter contains much noise. Typically, the signal of interest is primarily of low frequency and noise is of high frequency due to modulation as an example, discrete WPT decomposes the received signal which is a pure sinusoid with high frequency noise into different frequency bands by successive high and low pass filtering in time domain. After filtration, half of the samples can be neglected according to Nyquist criterion. The signal can be downsampled by 2 by discarding every other sample which produces two sequences *cA* and *cD* [18]. For a particular level *m*, the received signal is decomposed into *2m* sub-bands. A 3-level packet decomposition is presented below in Figure 6 [19], [38].

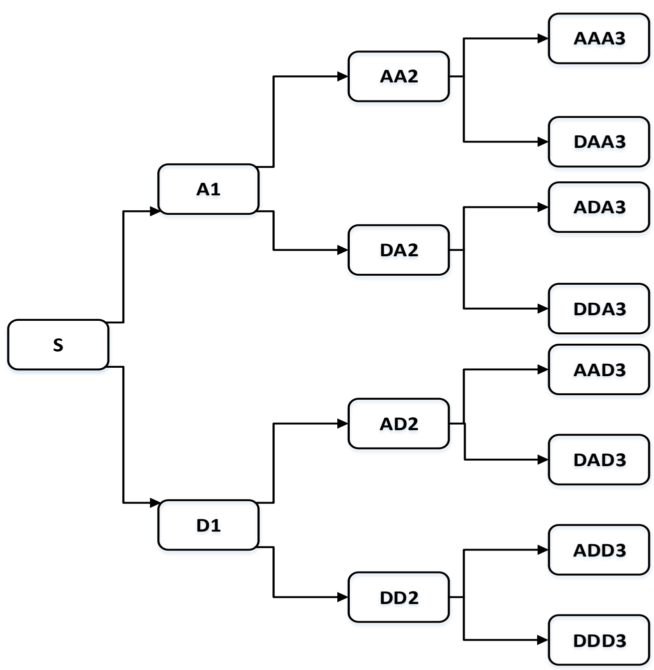

Figure 6 - Figure describing the wavelet packet transform method for spectrum sensing.

2.3.1.5 Eigenvalue Based Detection Method:

Eigenvalue Based detection method is based on the computation of the sample covariance matrix of the received signal. It works on a known noise level. The eigenvalues of the sample covariance matrix are calculated to compute two test statistics proposed by Zeng and Liang [39] based on the maximum and the minimum eigenvalues. Maximum Eigenvalue detection method (MME): In this method, the accurate noise variance is required to make a decision. A ratio of largest eigenvalue to the noise variance is taken, therefore the decision based on the hypothesis is a function of noise and is called semi-blind detection method. Minimum-Eigenvalue detection method (EME): In this method the ratio of minimum Eigenvalue of the covariance matrix to the noise variance is calculated and compared with the set threshold value and decision is made on the different test hypothesis [19], [38]. The algorithm for MME and EME are presented in [38]. The threshold can also be pre-computed based only on a smoothing factor, number of samples N and P_{fa}, irrespective of signal and noise power when eigenvalues method for selecting a threshold is used as opposed to the CED method [39].

2.3.2 Cooperative Spectrum Sensing

In the case of non-cooperative detection, next generation users detect the primary transmitter signal independently through their local observations. Cooperative detection refers to spectrum sensing methods where information from multiple NGN's users is incorporated for PU detection. Cooperative spectrum sensing can be centralized or in a distributed manner. In the centralized method, the NGN's base-station plays a role to gather all sensing information from the NGN's users and then detects the white spaces. On the other hand, distributed solutions require exchange of observations among NGN's users. Cooperative detection among unlicensed users is theoretically more accurate since the uncertainty in a single user's detection can be minimized. Moreover, the multi-path fading and shadowing effect are the main factors that degrade the performance of PU detection methods in hidden user environments. However, cooperative detection schemes allow to mitigate the multi-path fading and shadowing effects, which improves the detection probability in a heavily shadowed environment.

While cooperative approaches provide more accurate sensing performance, they cause adverse effects on resource-constrained networks due to the additional operations and overhead traffic. Furthermore, the primary receiver uncertainty problem caused by the lack of the primary receiver location knowledge is still unsolved in the cooperative sensing [3].

2.3.3 Interference-Based Spectrum Sensing

In NGN’s, interference measurement and control in made from the receiver side as opposed to typically the transmitter side. A model referred to as Interference Temperature proposed by the FCC is considered. The interference temperature model manages interference in the receiver by using a limit called the interference temperature limit which is the absolute limit at which the receiver can tolerate for optimum operation. As long as next generation users do not exceed this limit by their transmissions, they can use this spectrum band. This model describes the interference disrupted by a single next generation user and does not consider the effect of multiple NGN’s users. If next generation users are unaware of the location of the nearby PU’s, the actual interference cannot be measured using this method [3].

Spectrum sensing challenges include interference temperature measurement, sensing in multiuser environments and detection capability [3].

2.4 Spectrum Management

2.4.1 Spectrum Analysis

Spectrum analysis allows for characterization of spectrum bands with the aim of getting the best available and appropriate band to the user requirements. SNR considers only local observations of next generation users, it is not enough to avoid interference at the PU’s.

2.4.2 Spectrum Decision

Once characterization of all available spectrum bands is completed through spectrum sensing and spectrum analysis, an appropriate operating spectrum band should be selected for the current transmission considering quality of service (QoS) requirements and spectrum characteristics. Thus, the spectrum management function must be aware of user QoS requirements and thus select the most appropriate channel parameters.

2.5 Spectrum Mobility

Spectrum mobility arises when current channel conditions become worse or a PU appears, thus rendering a cognitive radio to vacate the spectral band. It is essential for the mobility management protocols to learn in advance about the duration of a spectrum handoff because only tolerable if no interference is allowed by users with higher priority over the band, not just necessarily only PUs. This information should be provided by the sensing algorithm. Consequently, multi-layer mobility management protocols are required to accomplish the spectrum mobility functionalities [3].

2.6 Spectrum Sharing

Spectrum sharing refers to spectrum redistribution based on known rules and service level agreements (SLAs). Spectrum sharing in next generation networks can be classified through three main aspects being Architecture, Spectrum Allocation Behaviour and finally Spectrum Access Techniques.

2.6.1 Architecture

2.6.1.1 Centralized Spectrum Sharing:

A centralized entity controls the spectrum allocation and access procedures. A similar architecture has been proposed in Software Defined Networks (SDNs) where a central entity called the SDN Controller controls all network resources across the network through separation of the control and data plane [40].

2.6.1.2 Distributed Spectrum Sharing:

Distributed solutions are mainly proposed for cases where the construction of an infrastructure is not preferable. Accordingly, each node is responsible for the spectrum allocation and access is based on local (or possibly global) policies [3].

2.6.2 Spectrum Access Techniques

2.6.2.1 Overlay Spectrum Sharing

In this spectrum sharing technique, a node accesses spectral holes where a non-cognitive user shares information to the cognitive user. The cognitive user can transmit at the same time as the PU so long as the overall transmit power of the CR is sufficient for its own communication and does not interfere with the PU [3].

2.6.2.2 Underlay Spectrum Sharing

Underlay spectrum sharing exploits the spread spectrum techniques developed for cellular networks. A next generation node transmits power at a level that a PU perceives it as noise. Spread spectrum techniques are used and can use increased bandwidth relative to overlay techniques.

Spectrum sharing comes with challenges that include a common control channel (CCC) and the dynamic radio range. CCC facilitates many spectrum sharing functionalities such as transmitter receiver handshake, communication with a central entity, or sensing information exchange. However, due to the fact that next generation network users are regarded as visitors to the spectrum they allocate, when a PU chooses a channel, this channel has to be vacated without interfering. This also applies to the CCC. As a result, implementation of a fixed CCC is infeasible in NGN’s [3].

2.6.2.3 Interweaved Spectrum Sharing

A hybrid of the overlay and underlay spectrum sharing techniques can be used to improve the performance of the cognitive radio. The use of the geographical location of the cognitive radio can be employed in improving the performance of the CR in this spectrum sharing technique [3].

2.7 Applications of Cognitive Radio and Respective Radio Bands

Legislation in some countries provides for use of licensed spectrum by assigned bodies such as the police, fire, safety and rescue equipment. The Public Safety/Private Partnership, states that the Public Safety Broadband Licensee will have priority access to the commercial spectrum in times of emergency, and the commercial licensee will have pre-emptible, secondary access to the public safety broadband spectrum. Providing for shared infrastructure assists in achieving significant cost efficiencies while maximizing public safety's access to interoperable broadband spectrum [6]. Below is a list of CR applications.

- **Wireless Sensor Networks (WSNs)**

WSNs consist of highly dense sensor nodes that sense physical and environmental changes. Critical low capacity data is used by sensor networks in healthcare, metropolitan cities for smart city applications, transportation, Supervisory Control and Data Acquisition (SCADA) applications and disaster response scenarios. WSNs suffer from high performance degradation, and high energy consumption in the ISM band because of coexistence [41]. Cognitive Radio can overcome these challenges in WSNs.

- **Vehicular Ad Hoc Networks (VANETs)**

VANETs allow for traffic information, driver assistance, emergency vehicle warning, control loss warning, system performance information, entertainment, collision warning and public safety mainly during peak hours of traffic and for e-safety applications. The high mobility of vehicles makes VANET topologies very dynamic in nature, that results in very short lived vehicular communication links. Currently the main objective of vehicular industry is to provide better safety and efficiency for users by enhancing vehicular communication capabilities using dedicated short-range communications [41], [42].

- **Smart Grid**

Smart grids add intelligence to Power systems. Changes in environment, connectivity and interference affect the performance of Smart Grids [43]. CR can improve smart grid network performance, for example, by using TVWS for communications resulting in lower communication latencies [41].

- **Healthcare:**

Wireless medical telemetry has emerged as an e-healthcare application that sends patient information and data over the 14 MHz spectrum, however, multimedia data is forbidden, no channelization has been defined and is susceptible to television channel interference, thus CR provides a solution to these setbacks. Some medical devices are sensitive to electromagnetic interference (EMI), but the application of CR can reduce this effect.

- **Public Safety Networks:**

A reliable communication network that supports critical information is required for the Public Safety Network bands. The 700 MHz band (698-806 MHz) is one such band. CR can overcome challenges brought by the fixed spectrum since there is usually lack of interoperability, overloading of traffic, lack of coverage and lack of reliability and robustness during disasters [41].

2.8 Chapter Summary

A critical step within the cognitive radio environment framework is the spectrum sensing phase. The binary hypothesis testing theorem has been a reliable model in cognitive radios, in particular the ED spectrum sensing method. The probability of detection and false alarm which are both dependent on the threshold have been introduced to measure the performance of the ED spectrum sensing method (ROC curves). Noise uncertainty has a direct relationship with the threshold, in turn the performance of the ED spectrum sensing method.

A brief overview of the spectrum sensing methods was presented and a comparison between them analysed. Special emphasis on the literature review and variations of the ED method over other spectrum sensing methods was conducted. Spectrum management, mobility and sharing was briefly touched upon. All the theory is not useful without application, hence a look at the application of cognitive radios which range from wireless sensor networks, vehicular ad-hoc networks, smart grids, healthcare and public safety networks was presented.

Chapter 3

3 Thresholding Techniques

3.1 Introduction

Spectrum Sensing is one of the elements of the Dynamic Spectrum Management Framework (DSMF) and will be the key focus of this chapter [13]. ED will be the focal point of spectrum sensing because this method of spectral sensing need not know the modulation type or transmit power. ED is less computationally complex, thus cheaper and less expensive relative to other spectrum sensing methods. Only the noise power of the detected signal need to be known by the CR for efficient performance [5], [26].

The selection of the threshold value for an ED spectrum sensing method is a crucial component that needs special attention in its own right. Determining the appropriate value of the threshold depends on the noise in the system. This presents a number of challenges since the noise power of any electronic system is not static.

The challenge therefore for the ED method is to determine the appropriate threshold **λ** so as to attain a desired P_d and P_{fa} described in chapter 2. A presentation on different thresholding techniques can reveal which method is better to employ. Thresholding techniques can be broadly categorized as either Fixed or Variable thresholds. A variable thresholding technique based on the Neyman-Pearson theorem was used and is presented in this chapter.

3.2 Fixed Threshold Techniques

The conventional Energy Detector uses a static threshold value that is set just above the noise floor to judge spectrum occupancy. In this case the threshold value is fixed and it does not change based on the perceived SNR. The downfall of this approach is that the system requires a priori knowledge of the noise power and spectrum activity. The fixed threshold techniques in their elementary form requires that the spectrum measurement data be inspected by an operator who then proceeds to set the decision threshold as per the observations made thus making it quite difficult to automate the threshold selection process.

Although the fixed threshold techniques are relatively easy to implement, they are susceptible to erroneous decision making due to the fluctuating nature of noise signals. This leads to higher rates of false alarm and miss detection. Another drawback of the fixed threshold techniques (FTT) comes about when the decision threshold is fixed at a static level above the noise floor. Weak primary signals would go undetected if they fall below the threshold and the secondary transmission may cause harmful interference to the PU.

Some examples of fixed threshold techniques are; empirical analysis of spectrum measurements, receiver noise characteristics thresholding, P-tile based thresholding technique and histogram analysis (Laplacian Threshold) technique [44]. Emphasis will be on the Neyman-Pearson thresholding technique.

3.2.1 Neyman-Pearson Based Thresholding

For a Neyman–Pearson based threshold ED, 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}. 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 detection-threshold is set based only on the distribution of the test statistic under the null hypothesis H_0 where for a given P_{fa}, the threshold λ can be determined [20]. This thresholding method is used in the classical ED method where λ is kept constant just above the noise floor.

3.2.2 Empirical Spectral Analysis

Measurements of the spectrum for a specified time are made in Singapore to determine occupied and unoccupied spectrum [45]-[48] is presented in Figure 7 to illustrate how empirical data can be used to detect spectrum for cognitive use. Figure 7 is an example of the results used to determine spectral holes. This method is not practical because of the large amount of resources such as time and equipment required to get results. The ever changing nature of spectrum makes this method very unreliable too. For example, the 2400 MHz to 2700 MHz band is unoccupied but this lies in the unlicensed band which can become operational at any time when an end user sets up a mobile hotspot on their mobile device for tethering purposes as an example, thus it will not operate at peak performance.

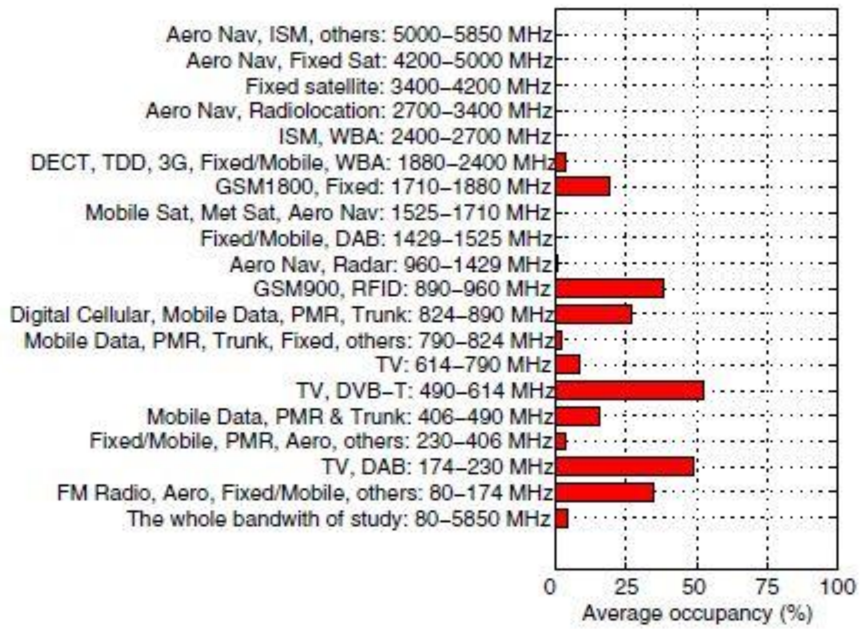

Figure 7 - Average occupancy different bands in Singapore [45].

The application of a CR using ED in public safety bands/channels may be impractical when switching between these channels with different noise levels since ED is ineffective in the presence of noise uncertainty [2]. Public Safety bands are usually dormant but highly active or constantly occupied in special situations such as emergencies and public gatherings.

Machine Learning techniques have been proposed to adaptively set the threshold of Energy Detectors in the public safety band. Machine Learning is used if the precise effects of input on output are unknown, that is, if the input-to-output function is unknown, then learning techniques can predict outputs [49]. For example, to reduce the probability of error over a wireless link by reducing radio parameters, especially SDR, (the coding rate, transmit power, coding scheme, modulation scheme, sensing algorithm, communication protocol, sensing policy, etc.), learning techniques can be applied to estimate the wireless channel characteristics and to determine the specific coding rate that is required to achieve a certain probability of error [49].

Learning algorithms are characterized as either supervised (instruction), unsupervised (reinforcement) or imitation. Unsupervised learning algorithms allow exploring the environment and self-adapting actions accordingly without having any prior knowledge [49]. Using prior knowledge known to the CR is known as supervised learning [49]. Unsupervised Reinforcement Learning, Unsupervised Bayesian Non-parametric approach, Unsupervised Game Theory, Supervised Support Vector Machine and Supervised Artificial Neural Networks are some learning techniques employed in Cognitive Radio [49].

In Air-to-Ground (A/G) communications by civil aircraft, a licensed VHF (30 – 300 MHz) band is utilized to transmit real-time data for Air-Traffic Control (ATC) and Air-Traffic Management (ATM) at sub 5% of the time [49]. In terrestrial CR applications, interference of PU's occurs but it is tolerable, for example, the IEEE 802.22 frame header periodically does this to PU's, but this interference that may cause catastrophic results is unacceptable in aeronautical communications because of stringent safety requirements [50]. This interference does not affect normal mobile or broadcast system operations. A terrestrial direct migration of CR to air-to-ground communications is thus not practical, thus methods such as using non-contiguous bands for aeronautical systems using central station for spectrum management has been proposed where spectrum sensing is performed in each cell and reported to the central station [50].

3.2.3 Other Fixed Threshold Methods

Some methods that have been adapted from the image-processing environment have been proposed for threshold setting. A method called the P-tile based thresholding technique where "an image is assumed to consist of dark objects in a light background. By assuming that the percentage of the object area is known, the threshold is defined as the highest gray level which maps at least (100 - p)% of the pixels into the objects in the thresholded image. For example, suppose an object occupies 20% of an image, then the image should be thresholded at the highest gray level that allows at least 20% of the pixels to be mapped into the object. Obviously, this method is not applicable to images whose object area is not known" [44].

"Another method is the Histogram (Laplacian) threshold technique: For images with distinct objects and background, the histogram of the gray levels will be bimodal. In this case, a threshold can be chosen as the gray level that corresponds to the valley of the histogram. The technique is called the mode method. Though this method is simple, it cannot be applied to images with extremely unequal peaks or to those with broad and flat valleys. For images with distinct objects and background it is possible to select the threshold from the gray level histogram using the mode method. For some images where valleys may not be found in their gray level histogram, it is often possible to define a good threshold at the "shoulder" of the histogram. Since both valleys and shoulders correspond to the concavities in the histogram, a threshold can be determined by analyzing the concavity of the histogram" [44]. This method can be translated to set a threshold at a gray level for either hypothesis in the BHTP.

3.3 Autonomous Threshold Techniques

3.3.1 Double-Threshold Adaptive Threshold

Noise in a telecommunication system is caused by thermal noise, aliasing from leakage signals and front end filters, therefore using a constant noise approach to detect spectrum allocation is impractical. Noise is measured using the noise uncertainty measure which adversely affects conventional ED resulting in the SNR wall. Below the SNR the conventional energy detector fails to be robust no matter the number of samples made or duration of observation.

The double threshold method is used to mitigate the noise uncertainty factor effects on ED. The smaller threshold is used to maximize the P_d while the higher threshold is used to maximize the P_{fa}, these two thresholds are evaluated using the noise uncertainty factor [36]. The two thresholds are toggled such that when the PU is predicted to be present the smaller threshold is used while the larger threshold is used when the PU is predicted to absent in the spectrum of interest. When the detected energy level lies below the lower threshold, no PU is said to not occupy the channel. In the case when the energy is above the higher threshold, a PU is said to occupy the channel. In the case where the detected energy lies between the two threshold levels, the spectrum sensing is applied again until the detected energy lies on the outer bounds of the two thresholds [51]. Adaptive double thresholding techniques which employ a two-stage detection strategy has been proposed where the first stage detection is carried out by designing the two detection threshold, while the second stage detection is implemented for the centre portion of the double threshold where the final result is given [51].

3.3.2 Otsu's Threshold Technique

Otsu's algorithm computes an optimum threshold that results in the maximum separation between the histograms of the signal and noise samples in the data. This technique was popularly used for binary image segmentation [52]. Otsu's algorithm assumes that an image contains two classes of pixels namely the foreground and the background pixels. These can be compared to the two classes of the spectral measurement components; the noise components and the signal components. A bimodal histogram with two peaks can be generated out of the data. These two peaks represent the object and the background respectively. With regard to the CR environment, these peaks represent either the null hypothesis or the occupied state hypothesis. The optimum threshold can be calculated by separating the two classes of components and minimizing the intra-class variance. The threshold is then determined as the lowest point between the two peaks [52]. Otsu's threshold is non-parametric, adaptive and relatively simple to most threshold estimation techniques, however this method tends to introduce sensing delays because of the need of several spectral sweeps before implementation of Otsu's algorithm [53], [54]. This delay has been shortened by using fewer sweeps thus decreasing the spectral sensing time and improving the probability of detection [53], [54].

3.3.3 Other Adaptive Threshold Techniques

Other adaptive threshold techniques exist such as the Recursive One-sided Hypothesis Testing (ROHT), and Maximal Normal Fit techniques [44]. A single adaptive energy detector used simultaneously with a double threshold energy detector has been proposed [55]. The periodicity of PU's activity in the time domain which is exponentially distributed is exploited by using a double threshold. The sensing time in the two latter models has be reduced [56]. A proposal into an adaptive threshold is presented for this dissertation in Chapter 4.

3.4 Chapter Summary

This chapter dealt with thresholding techniques employed in spectrum sensing for CR's. The first thresholding technique category is called the fixed threshold technique, it is used in a conventional energy detector that is set just above the noise floor to judge spectrum occupancy. The second thresholding technique category is called the adaptive threshold technique. It can be based on the exclusive knowledge of the noise power, which in practice is rather hard to establish since noise has various sources. The requirement that the ED needs knowledge of the noise power makes the fixed threshold technique not ideals since it does not vary with the noise power.

Chapter 4

4 Methodology

4.1 Introduction

Two USRP kits that emulated CR’s acting as a PU and SU respectively were setup to test the hypothesis of this dissertation. Apparatus used for the determination of the variable threshold energy detector in a noise induced environment was:

- Two USRP N210 radios
- Compaq CQ58 Notebook PC, 1.8 GHz Intel Celeron, 2 GB RAM
- Ubuntu 16.06 OS
- GNU Radio Companion
- 4 Port Ethernet Switch Netgear

4.2 Experimental Theory and Setup

The fixed and variable threshold energy detector setup for GNU Radio was as depicted in Figure 8 in conjunction with a Linux Ubuntu PC.

Figure 8 – Setup used in investigating the variable threshold energy detector using GNU Radio.

In modelling the variable threshold ED, the primary signal and the noise are assumed to be an independent and identically distributed (i.i.d.) random process with zero mean and of variances, ${\sigma_X}^2$ and ${\sigma_w}^2$ respectively. When we let the SNR be γ, then,

$$\gamma = \frac{{\sigma_X}^2}{{\sigma_w}^2} \tag{10}$$

The test statistic is given by,

$$Z(y) = \frac{1}{N}\sum_{n=1}^{N}|y[n]|^2 \tag{11}$$

As N gets large, according to the central limit theorem, the test statistic $Z(y)$ has a normal distribution with mean μ_i and variance σ_i under the hypothesis H_i for $i = 0,1$ [27]. The mean and variance of the test statistic have been shown to be

$$\mu_0 = {\sigma_n}^2 \tag{12}$$

$$\sigma_0 = \frac{{\sigma_n}^2}{\sqrt{N}} \tag{13}$$

$$\mu_1 = {\sigma_n}^2 * (1 + \gamma) \tag{14}$$

$$\sigma_1 = \sigma_0 * \sqrt{(2\gamma + 1)} \tag{15}$$

The probability of false alarm is given by,

$$P_{fa} = P\{Y > \lambda | H_0\} = \frac{\Gamma(m,\lambda/2)}{\Gamma(m)} = Q\left(\frac{\lambda - \mu_0}{\sigma_0}\right) \tag{16}$$

$$P_d = P\{Y > \lambda | H_1\} = Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) = Q\left(\frac{\lambda - \mu_1}{\sigma_1}\right) \tag{17}$$

where *Q(x)* is defined by the complementary distribution function of the standard Gaussian [39], [57].

An energy detector based on a threshold calculated for a target P_{fa} works well in high SNR conditions, but when the SNR is less than -15 dB, the performance of the energy detector results in high a P_{fa} and low P_d [57]. The ROC simulations for the fixed and variable threshold energy detector will therefore be for the SNR range -15 dB and -7 dB in MATLAB® software and GNU Radio.

Using (16) and (17) and substituting the mean and variance values from (12) to (15), it can be shown that the sensing time, or in other words, the number of samples, *N*, is related to P_{fa} , P_d and SNR, γ shown below as [9], [23], [24], [57].

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

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

$$= 2\left[Q^{-1}(P_{fa}) - Q^{-1}(P_d)\right]^2 * \left[\gamma - \left(\rho - \frac{1}{\rho}\right)\right]^{-2} \tag{18}$$

N approaches infinity in the above equation as the SNR, γ approaches $\left(\rho - \frac{1}{\rho}\right)$, where ρ is called the noise uncertainty. Figure 9 describes the characteristics of ρ as it approaches the SNR wall with $x = 10 \log(\rho)$.

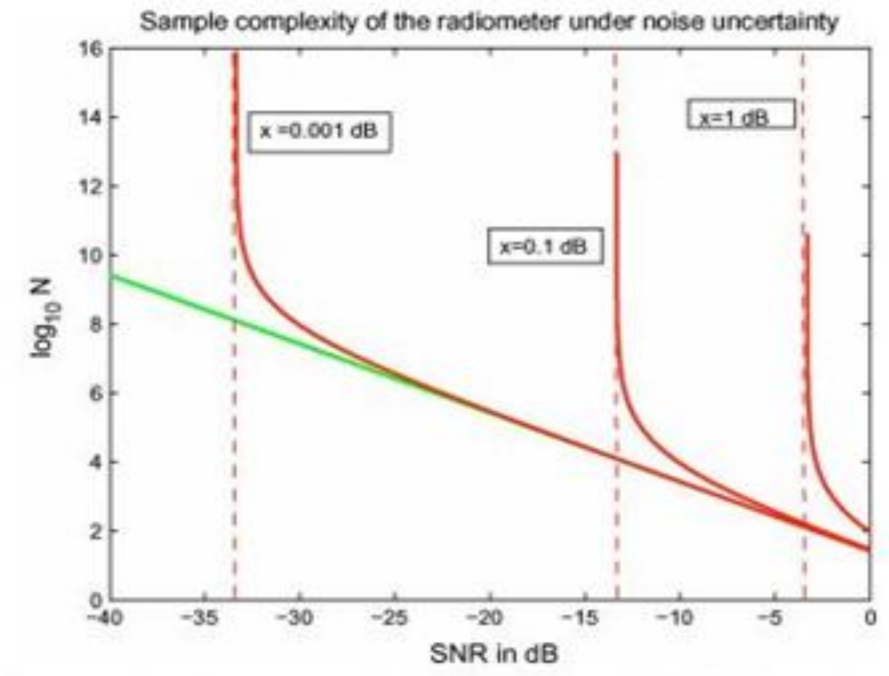

Figure 9 - Sample complexity *N* variation with the SNR approaching the SNR wall

Figure 9 shows that as the SNR decreases, the CR has to increase the number of samples *N* taken to sense the spectrum, however, below SNR values below -20 dB, *N* increases substantially by powers of 10 for the CR to efficiently perform spectral sensing. *N* was optimized in making the proposed variable threshold more efficient based on the SNR and P_{fa} as per Equation 18.

For a Neyman–Pearson detector used in the classical fixed threshold energy detector, the detection-threshold is set based only on the distribution of the test statistic under H_0, where for a given probability of false alarm P_{fa}, *M* is the number of antennas and *N* being the number of taps (samples), the threshold λ can be found as [20]

$$\lambda = \sigma_n{}^2\left(1 + \sqrt{\frac{2}{MN}}Q^{-1}(P_{fa})\right) \tag{19}$$

4.3 Chapter Summary

The research setup and the methodology followed in simulating the performance of the constant and variable threshold is discussed in this chapter. Equation 18 and 19 set the pinnacle of the analysis, with a threshold value that is dependent on the noise uncertainty. The crux of the dissertation is to optimize the sample size N when sensing the spectrum using Equation 18, then applying the result into Equation 19. This essentially was expected to reduce the spectrum sensing time.

The later part of this chapter dealt with the mathematical analysis of developing a variable threshold for an Energy Detector. The noise uncertainty variable was the only variable in Equation 19 that expressed the dependency of the threshold on the noise uncertainty while other terms were optimized. The simulation parameters were described and general constraints stated in this chapter. Exact numbers of the parameters used are described in Chapter 5.

Chapter 5

5 Experimental Results and Analysis

5.1 Introduction

An Energy Detector (ED) is used to determine if a spectral hole is occupied or not using the Binary Hypothesis Testing Theorem (BHTT) and RSSI levels. In order to determine whether or not one hypothesis is satisfied or not, a threshold has to be set. In Chapter 3, it is shown that Fixed and Variable Thresholds are two main thresholding technique categories [44], [52].

An analysis and comparison of a fixed and variable threshold energy detector was presented using the RSSI, the time required to sense the spectrum and outputs from the comparison of the test statistic with the threshold. The ROC curves were also presented for the constant and proposed variable threshold of the Energy Detector in MATLAB R2015a. The constant and proposed variable thresholds were simulated using GNU Radio software in conjunction with two Universal Software Radio Peripheral (USRP) kits that produce an outcome based on the BHTT in the presence of noise. The results and analysis of either energy detectors present important differences between the two energy detectors.

5.2 Simulation Software and Hardware

GNU Radio is a UNIX based modular framework that allows flow-path oriented designs, simulations, and deployments of real-world radio environments. The reusable blocks used in GNU Radio allow scalability, provides open source libraries for different algorithms and standards that can also be created from the scratch. GNU Radio works on digitized signals thus allowing manipulation using general computers. GNU Radio uses two programming languages: Python and C++. At high-level, Python is used for organizing and connecting signal processing blocks, while all the performance-critical signal-processing blocks are implemented in C++. Python uses simplified wrapper and interface grabber (SWIG) for interfacing C++ routines with python. Consequently, python codes of most GNU Radio applications are short and neat [58].

On the other hand, the USRP product architecture includes a Xilinx® Spartan® 3A-DSP 3400 FPGA, 100 MS/s dual ADC, 400 MS/s dual DAC and Gigabit Ethernet connectivity to stream data to and from host processors. A modular design allows the USRP N210 to operate from DC to 6 GHz, while an expansion port allows multiple USRP N210 series devices to be synchronized and used in a MIMO configuration. Users can implement custom functions in the FPGA fabric, or in the on-board 32-bit RISC softcore. The USRP2 has a field programmable gate array (FPGA) and a RF transceiver board connected to the FPGA. The design of USRP2 allows all signal-processing jobs (modulation and demodulation, filtering etc.) in the computer. All general-purpose tasks including decimation, interpolation, and digital up and down conversion are performed inside the FPGA [58].

The USRP N210 takes care of the ADC and DAC thus the processing occurs beyond those stages as shown in Figure 10.

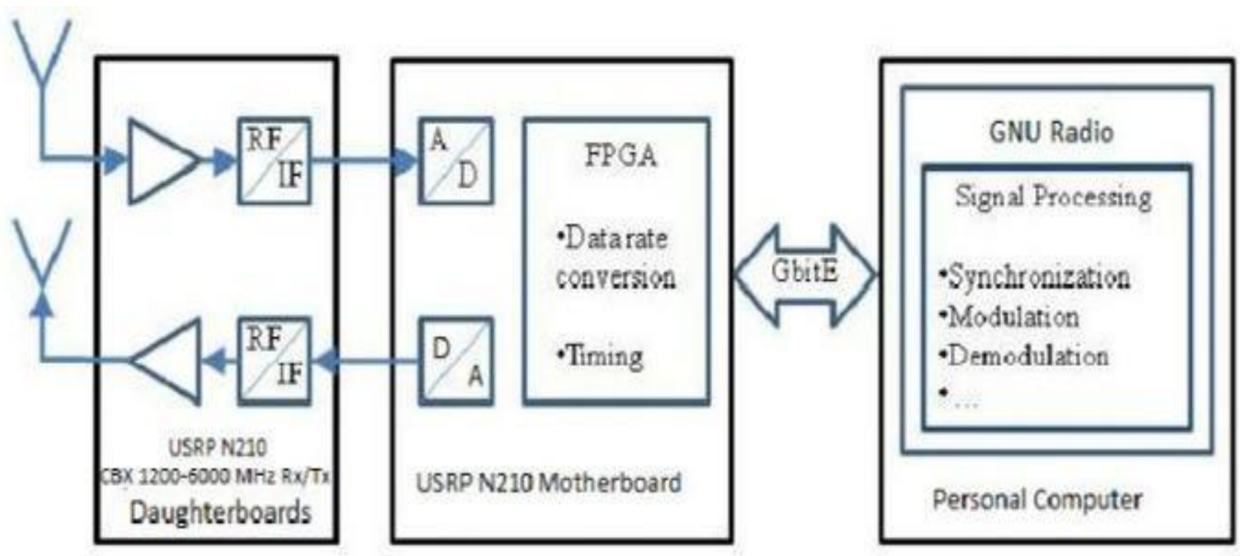

Figure 10 - Functional blocks of the Universal Software Radio Peripheral (USRP)

The proposed algorithm to be used in the implementation of the variable energy detector is described in Figure 11. This algorithm is based on the ED process described in Figures 3 and 4 to continuously determine the threshold as noise levels fluctuate.

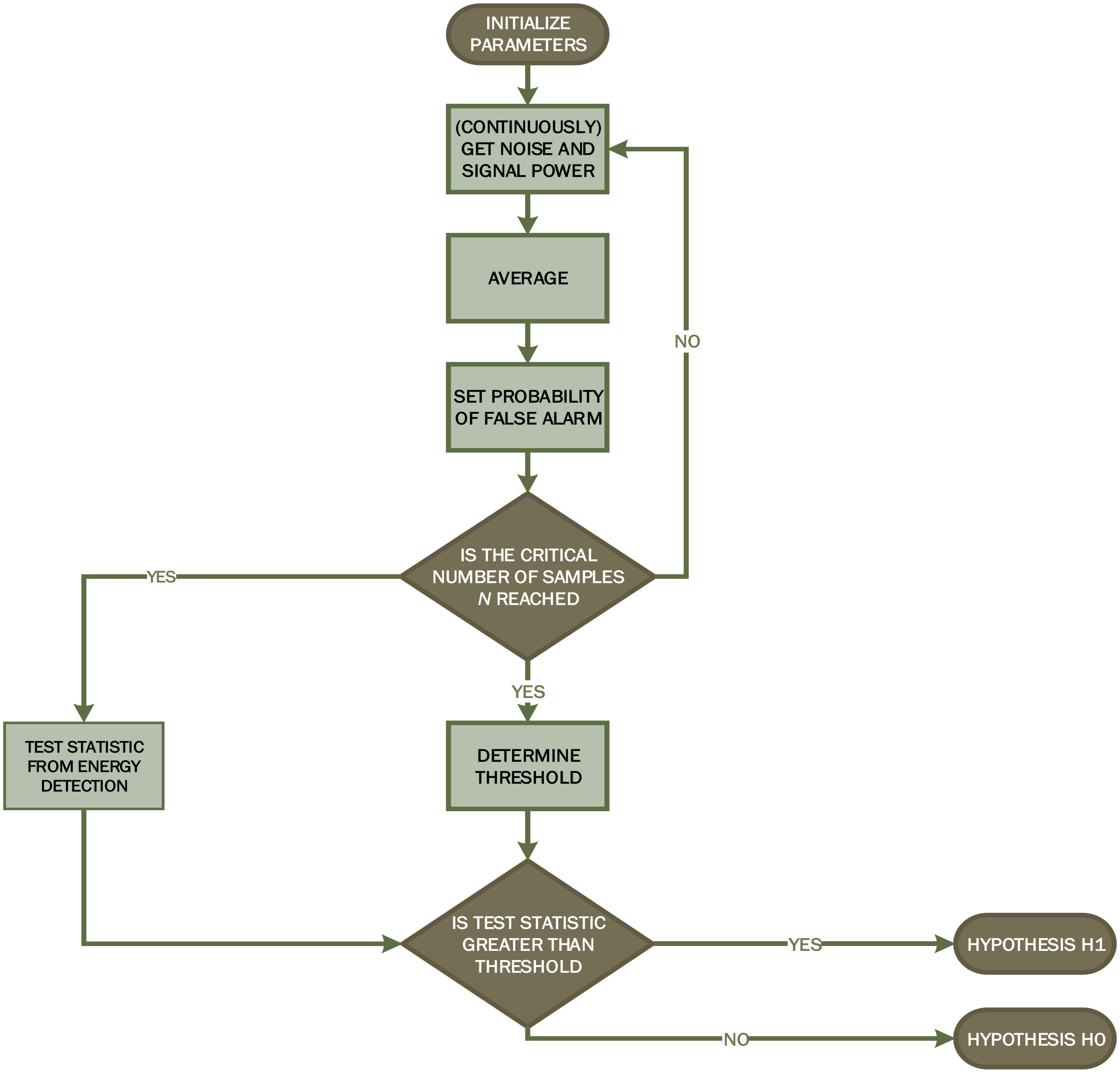

Figure 11 - Algorithm used for executing the variable threshold detector.

The effect of noise uncertainty in the GNU Radio setup was based on the intrinsic noise variations of the USRP development kits while the noise variation in the MATLAB simulation was altered in steps to note the effect on probability of detection and false alarm. A Monte Carlo simulation of the fixed and proposed variable threshold energy detector using the CFAR at -7 dB to -15 dB was used for ROC curve comparisons using MATLAB R2015a. The reason for using the range for -7 dB and -15 dB for simulations is that the performance of a CR below -20 dB creates an ROC curve resembling an equality line (P_{fa} and P_d equal) which is not the desired outcome, while any dB value above -7 dB is too high a receive sensitivity level for many practical applications.

5.3 Constant Threshold

A MATLAB R2015a Monte Carlo simulation for a theoretical and simulated constant threshold through 10000 iterations using an SNR of -15 dB and -7 dB was made using a probability of false alarm from 0.01 to 1 in steps of 0.01. -15 dB and -7dB were selected and with additive white Gaussian noise (AWGN) with mean 0 and noise variance 1 is presented in Figure 12 and Figure 13 below.

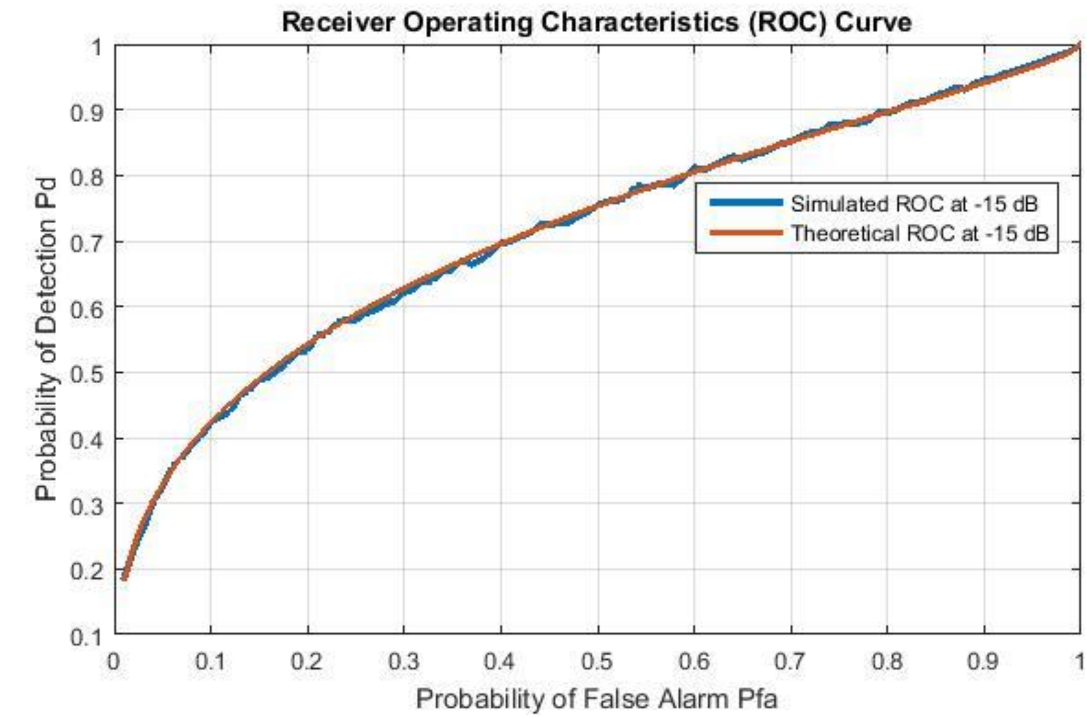

Figure 12 - ROC curve of a constant threshold Energy Detector at -15 dB.

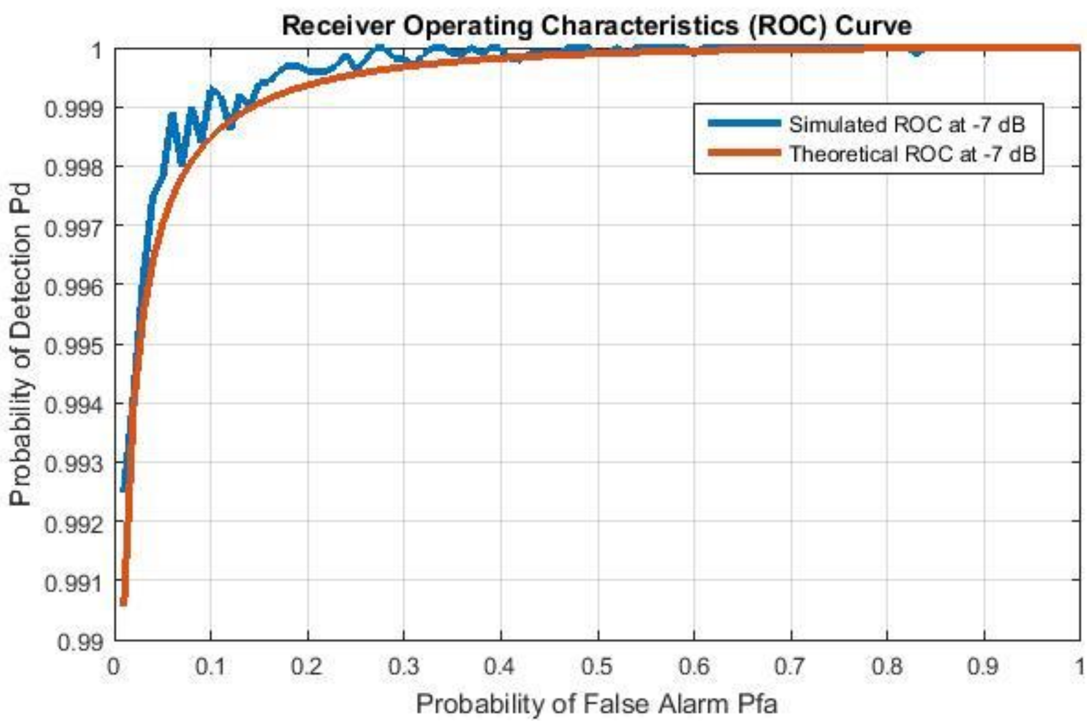

Figure 13 - ROC curve of a constant threshold Energy Detector at -7 dB.

The ROC curve results shown in Figure 12 and Figure 13 show that in general, a high SNR value, results in a high P_d. There is a close correlation between the simulated and theoretical ROC curves. The results for the fixed threshold used in ED show that the higher the SNR value, in this case -7 dB, the higher the P_d at a particular corresponding P_{fa} relative to a lower SNR, in this case -15 dB. This is a desired performance characteristic of a SU receiver since there is a higher probability of detecting a PU signal thus avoiding interference to the PU. The lower the SNR value, in this case -15 dB, the lower the P_d with a close correlating P_{fa} relative to the P_d, which is not a desired performance characteristic of a CR, since the SU will most likely interfere with the PU (low P_d) and also deduce that a spectral hole is non-existent while in fact it exists (low P_{fa}). A lower P_d means that there is a higher risk of PU interference while a higher P_{fa} means that there is an even higher chance of not occupying a vacant spectral hole. This leads to spectral inefficiency which is not a desired result.

A comparison of the ROC curves for the constant and the proposed variable threshold energy detector is shown in Figure 23 and Figure 24 under SNR levels of -10 dB and -20 dB were made.

Figure 14 and Figure 15 below show a plot of a constant false alarm rate at 0.01 and 0.2 for SNR values within the range of -15 dB to 0 dB. One expects the SU to opportunistically use a vacant spectral hole at a lower P_{fa}, however the results for the plot of SNR against the probability of detection at a constant P_{fa} draw an interesting picture in Figure 14 and Figure 15. Both simulated and theoretical outputs of the Monte Carlo simulations are presented.

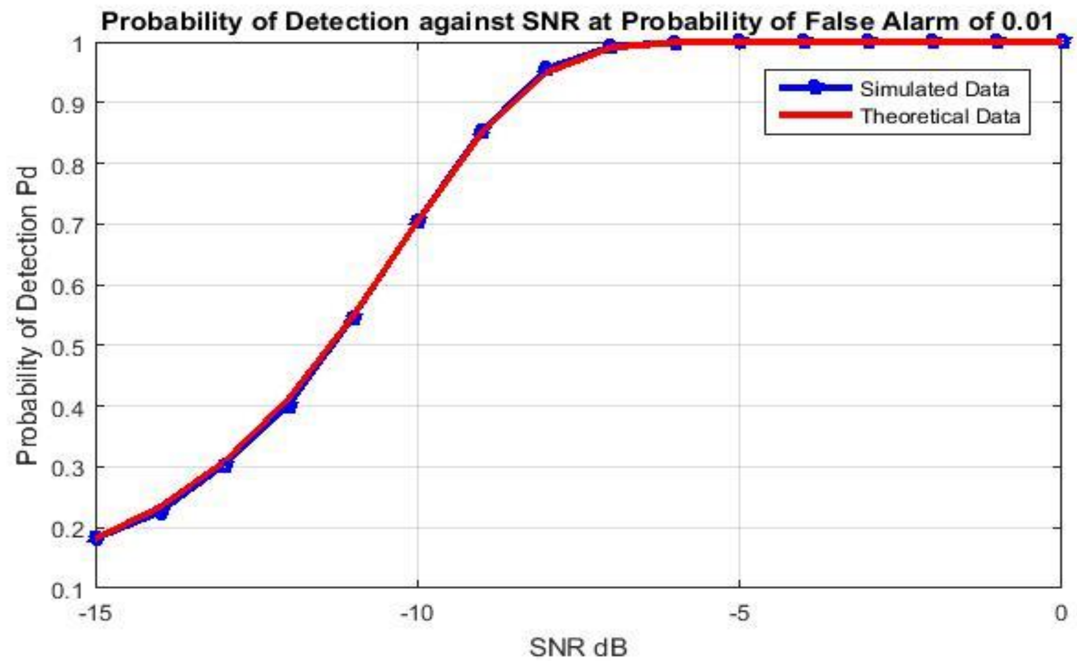

Figure 14 - SNR against probability of detection at a constant probability of false alarm of 0.01.

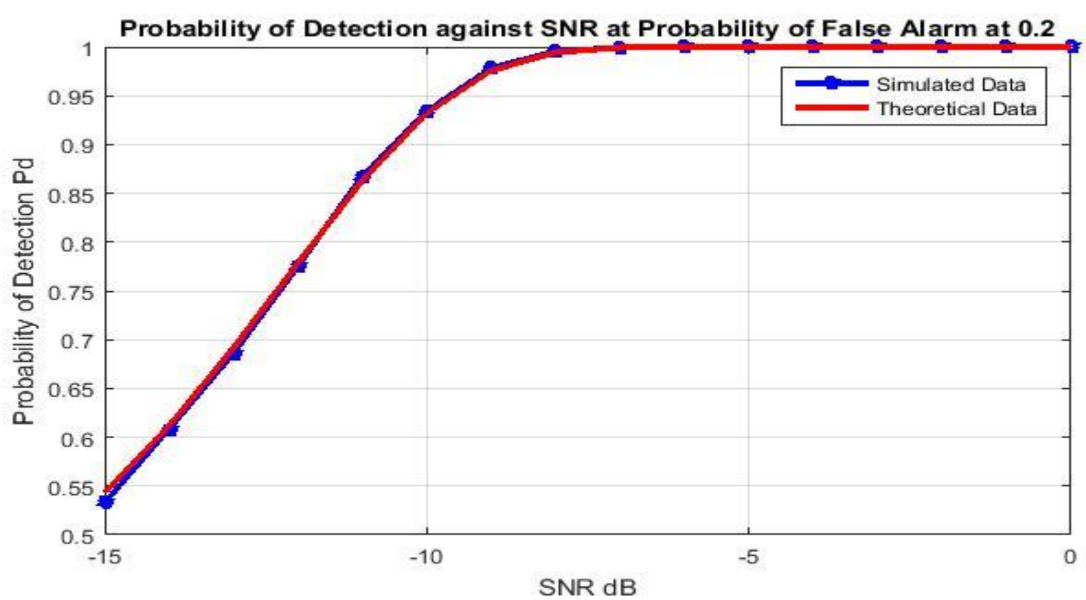

Figure 15 - SNR against probability of detection at a constant probability of false alarm of 0.2.

The results show that a relatively higher constant P_{fa} at a specific SNR value, results in a higher P_d. For instance, if we consider an SNR value of -10 dB in Figure 14 where a lower P_{fa} is used, one notes that a P_d of 0.7 corresponds to -10 dB. However, the same SNR value of -10 dB at a constant probability of false alarm of 0.2 in Figure 15, a probability of detection of approximately 0.94 is achieved, which is a more preferable outcome in CR systems. This leads to a conclusion that a compromise between the probability of false alarm and probability of detection has to be maintained in CR systems. Basically, if we also decrease the threshold λ, P_{fa} and the P_d go up, and the converse is true. This means that the threshold has to be chosen such that P_{fa} is as small as possible under the Neyman-Pearson constraint while trying to achieve a high P_d at the same time. The difference in the change of P_{fa} and P_d theoretically is not a linear relationship, which the results presented in Figure 14 and Figure 15 also affirm.

Figure 16 shows the implementation of a constant threshold energy detector in GNU Radio based on the setup shown in Figure 8. The upper half of Figure 16 shows the PU setup while the lower half shows the SU trying to access the available spectrum.

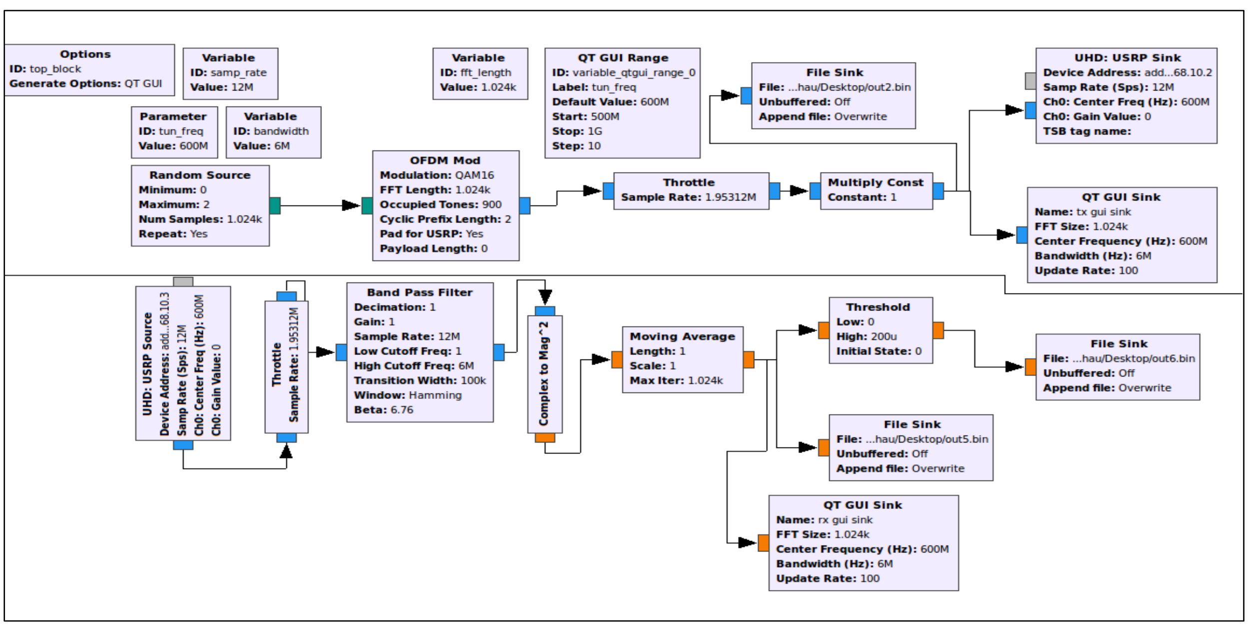

Figure 16 - GNU Radio blocks showing the transmitter and receiver used to simulate the constant threshold energy detector using two USRP N210 hardware modules.

Results of the constant threshold setup presented in Figure 16 are presented in section 5.5. The hardware setup is exactly the same as the proposed variable threshold energy detector described in section 5.4.

5.4 Variable Threshold

Two USRP N210 hardware were used in the implementation of the variable threshold detector in testing the BHTP and determining RSSI values. One was used as a transmitter, in this case a PU and the other was used as a receiver performing the role of a SU. Equation 18 allows for the determination of the number of samples *N* for a specified SNR. *N* was used in Equation 19 to determine the threshold as the noise varies. It is worth noting that as the noise power varies, so does the SNR and the noise uncertainty ρ of the communication channel. A P_{fa} of 0.1 was used in the analysis of both the constant and variable threshold energy detector. Optimization of *N* was expressed in the variable threshold block in GNU Radio C++ code as shown in Appendix B.2. *N* in this dissertation was determined to be equal to 724.34 samples as the bare minimum for spectrum sensing required for an SNR level of -20 dB, P_{fa} of 0.1 and P_d of 0.9.

Equation 19 shows that the threshold λ is a function of *N*, P_{fa}, number of antennas *M*, and the noise variance $\sigma_n{}^2$. The number of antennas *M* and P_{fa} were kept constant to unity and 0.1 respectively, while *N* was optimized so that the processing time and the CLT was applied to the test statistic. This meant that λ is directly proportional to $\sigma_n{}^2$, and this proportionality was used to develop the variable threshold. The varying nature of the noise uncertainty shown in Equation 19 was used to fabricate the variable threshold block shown in Figure 17 below titled as “Edvthr”. The variable threshold GNU Radio block was modelled on the SU side. The upper half of Figure 17 represents the PU while the lower half represents the SU.

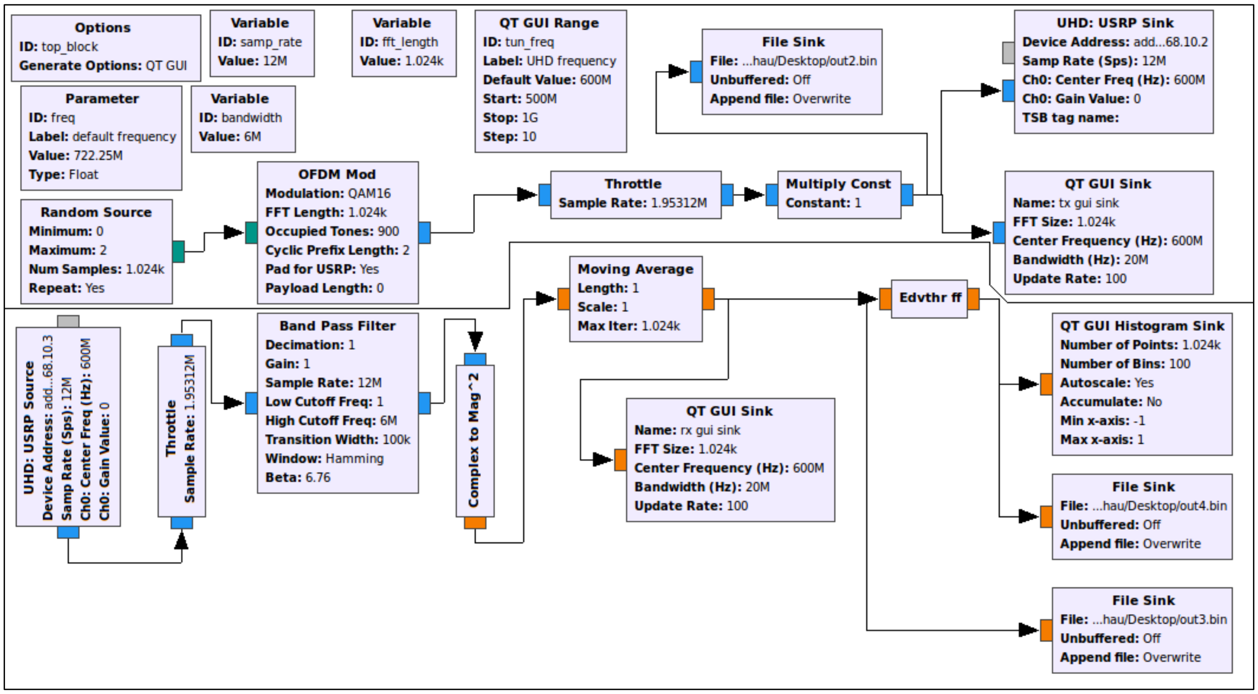

Figure 17 - GNU Radio blocks showing the transmitter and receiver used to simulate the variable threshold energy detector using two USRP N210 hardware modules.

Figure 18 to Figure 20 shows that the SU was able to detect the PU signal that was transmitting an OFDM signal under the proposed variable threshold energy detector. A 1024 FFT-size OFDM signal was transmitted with a 600 MHz center frequency and spectral plot as shown in Figure 18. Figure 19 shows the received signal when the variable threshold energy detector was employed at 600 MHz. The 600 MHz band was selected for the simulation because it was unoccupied when a spectral analyser sweep was conducted. This band selected was within the ITU Region 1 television white spaces (TVWS) band, where the digital switch over (DSO) had to have been completed in 2015 [13].

Figure 18 - Figure showing CR receiver and PU transmitter (OFDM) frequency displays respectively.

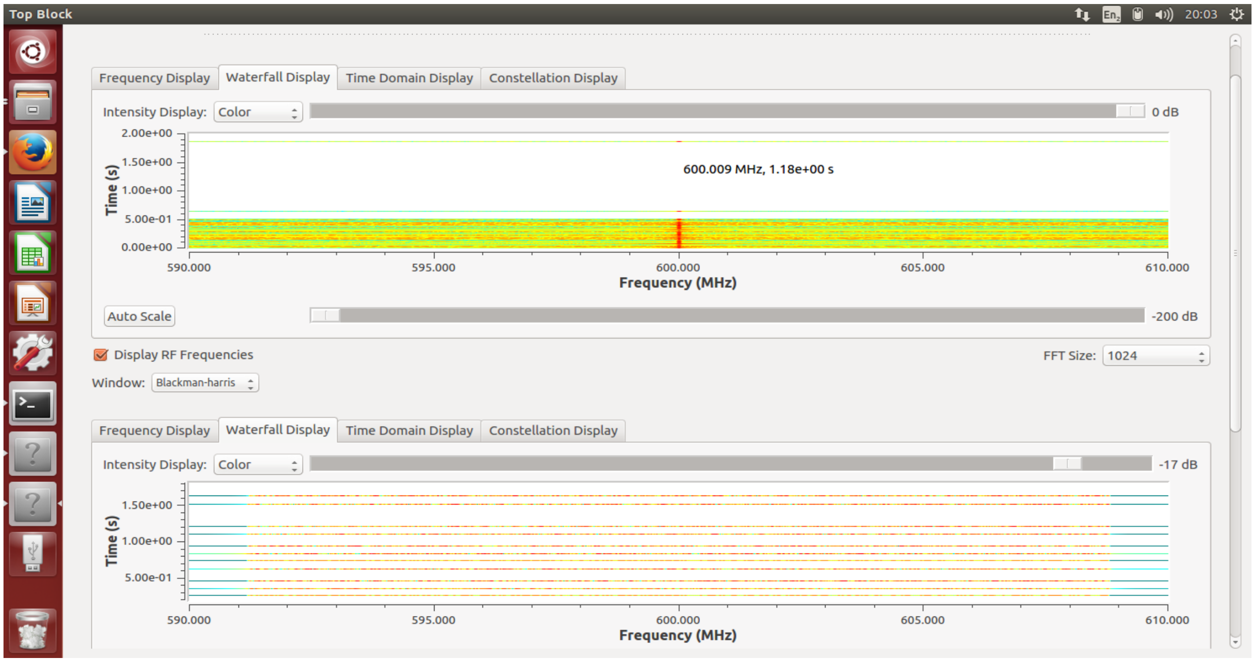

Figure 19 – SU and PU waterfall displays showing OFDM transmission and reception respectively.

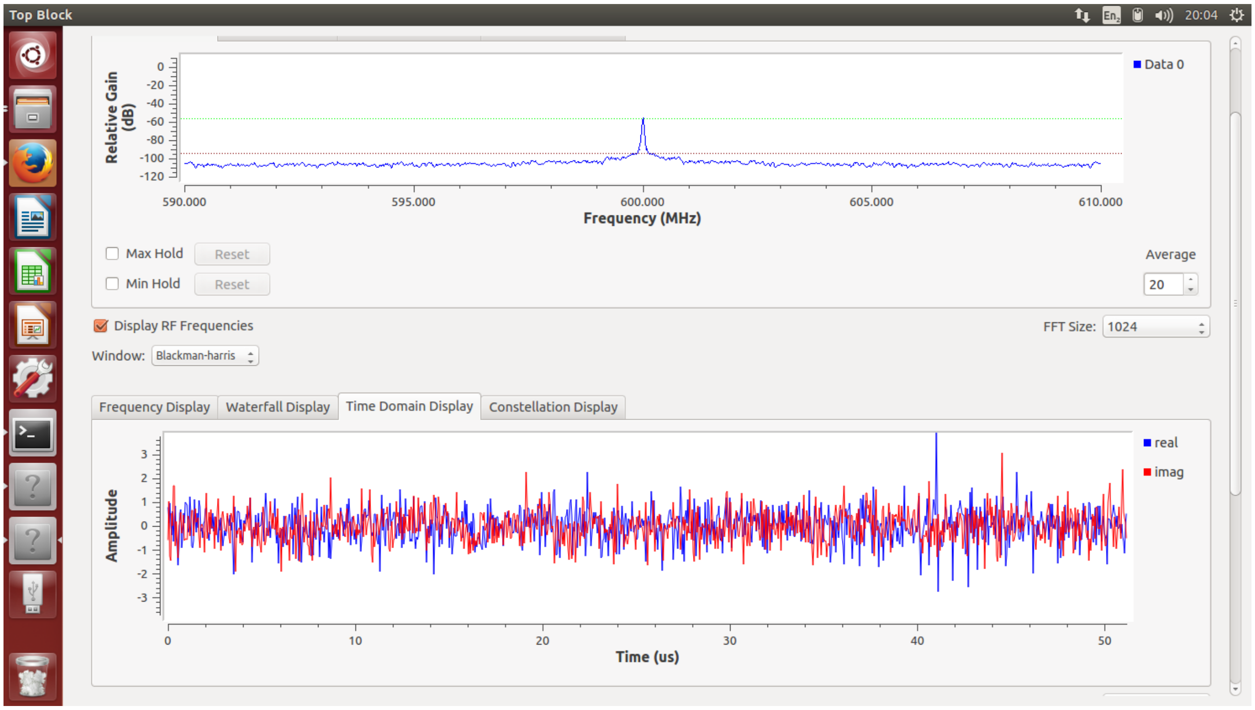

Figure 20 - Figure showing the time domain representation of the transmitted signal used to be detected at 600 MHz.

Figure 20 shows the SU using CR time domain representation of the detected PU signal. The RSSI was approximately -55 dBm which is well within the scope of detection of any receiver. The SU can process and use this information to make decisions on whether or not it can occupy a spectral hole. For instance, -55 dBm is well above the noise floor, which would result in an H_1 hypothesis being selected. The “Edvthr” GNU Radio block can detect PU signals very near the noise floor of -120 dBm as shown in Figure 20.

5.5 Performance Comparison

The performance comparison between the constant threshold energy detector and variable threshold detector in GNU Radio is presented in this section. The expectation for the constant threshold ED is that when the test statistic is above the threshold, the H_1 hypothesis represented by “1” in the output binary file, in this case “out6.bin” from the GNU Radio software output would be observed. The observation for the constant threshold depicted in Figure 21 was meant to detect a PU. When there is a spectral hole available, a string of zeroes “0”s would be observed from the binary file.

Figure 21 - Output from the binary file titled “out6.bin” used to determine the CR performance that uses a constant threshold.

The sequence started with a string of “0”s indicating a null hypothesis, that is, no presence of a PU in the spectrum of interest initially because the CR was initiating the spectrum sensing and calculating the parameters set out in the proposed sensing algorithm set out in Figure 11. For when the test statistic was greater than λ for the constant threshold implementation, the string of “0”s instantaneously changed to “1”s indicating that there was a PU present in the spectrum, in this case, there was a PU at 600 MHz which was true since that was also verified by the spectrum analyser output.

The variable threshold ED implemented in GNU Radio was expected to vary directly with the noise variance, that is, when noise sources jump above the noise floor, the threshold was expected to respond with an increase in the random increase of the noise level thus making the P_d more likely to occur.

Figure 22 - Output from the binary file titled "out4.bin" used to determine the Cognitive Radio performance that uses a variable threshold.

Figure 22 shows the variable threshold was able to detect an H_1 hypothesis indicating a presence of a PU at 600 MHz. The binary output file "out4.bin" shows that a string of "0"s indicating a null hypothesis was initially present, but this was due to the GNU Radio setup and parameter initialization. The H_1 hypothesis was detected when the test statistic was greater than λ. When the noise variance was introduced in the GNU Radio blocks by moving the receiver thus changing the channel environment temporarily, the λ changed with the noise introduction. This λ variation was seen in the temporary shift from "1"s to "0"s and back to "1"s in Figure 22 above.

The spectral sensing time for the proposed variable threshold energy detector was determined to be 1.25% less than the constant threshold energy detector. This result was based on the number of sample outputs depicted in Figure 21 and Figure 22. The variable threshold energy detector on average sensed that a PU had occupied the spectrum after 48 initial samples while the constant threshold energy detector did so in 57 initial samples out of 723 samples. The reason for the difference in the spectral sensing times was due to the optimization of the sampling size *N* and the variable threshold energy detector being more sensitive to noise fluctuations. It is worth noting that in both simulations, parameters were kept the same, the only difference being the threshold blocks that either responded to the noise variance or not in GNU Radio. The RSSI of both the constant and variable threshold of the energy detector was found to be equal at -55 dBm. This is because P_d and P_{fa} are influenced by λ while the RSSI is not, thus expecting a different RSSI from either the constant or the variable threshold was not observed.

A MATLAB simulation of the ROC curves for the constant and proposed variable threshold energy detectors was carried out. It was expected that the ROC curves of the constant threshold and variable threshold would be different with all parameters the same. A higher P_d for each P_{fa} in the variable threshold energy detector plot of each ROC curve was expected. This was generally the case from the MATLAB simulation at low SNR values. Figure 23 shows the ROC curve plots for both thresholds.

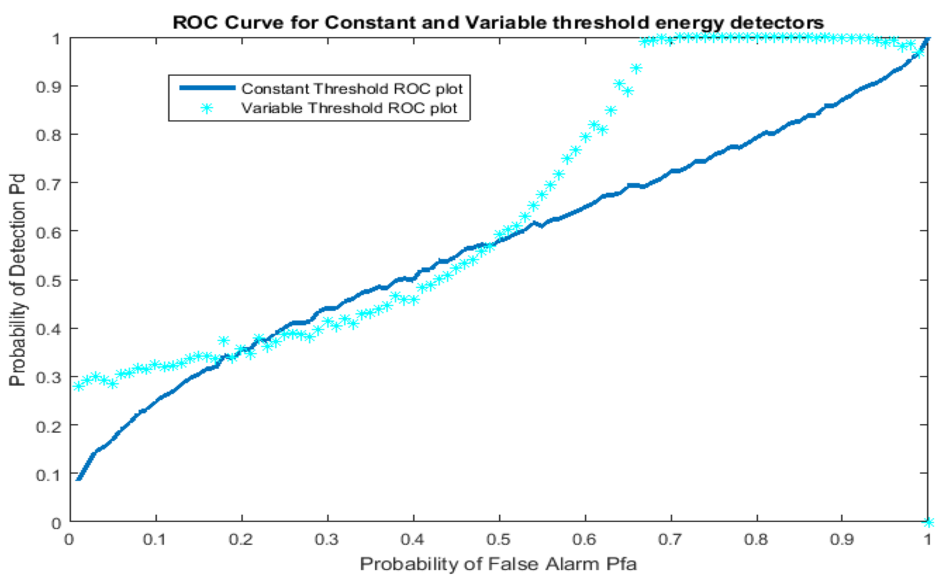

Figure 23 – ROC curves for both constant and variable threshold energy detectors simulated in MATLAB at -20 dB

A P_{fa} value of 0.1 is typically used in CR communications. The proposed variable threshold energy detector outperforms the constant threshold energy detector for P_{fa} values less than 0.2 as depicted in Figure 23. The constant threshold energy detector had a P_{fa} of approximately 0.24, a figure less than the 0.34 for the proposed variable threshold at low SNR values used in the simulation. The ROC curve for the proposed variable threshold did however perform poorly relative to the constant threshold in the P_{fa} range 0.2 to 0.5. This inconsistency could be due to a low SNR value used in the simulation, but it should be noted that the variable threshold energy detector still performs better than the constant threshold energy detector throughout the probability range of 0 to 1. A combination of the variable and constant threshold energy detector could optimize the performance of the CR by selecting either at each desired P_{fa}.

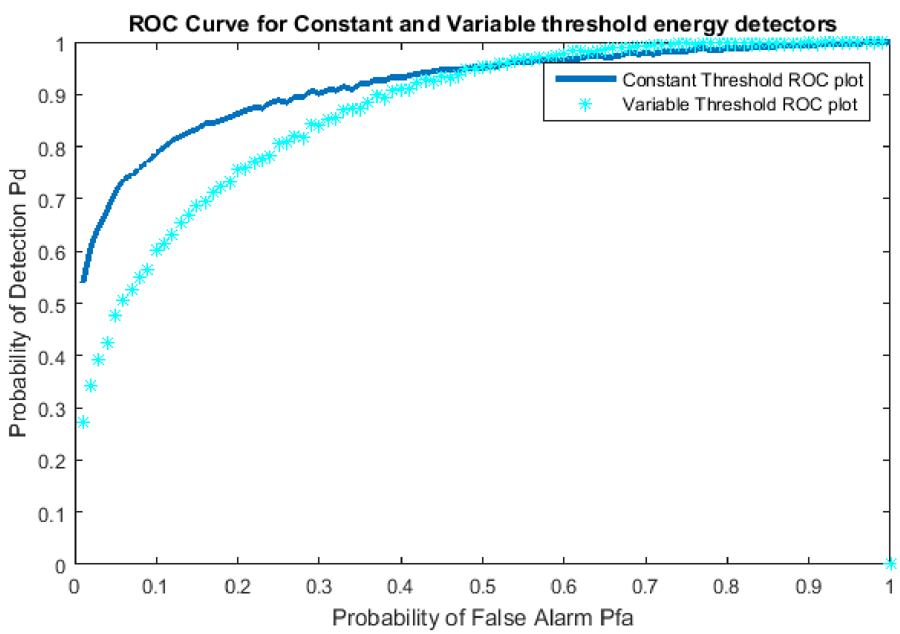

Figure 24 - ROC curves for both constant and variable threshold energy detectors simulated in MATLAB at -10 dB.

Figure 24 shows that for a relatively higher SNR value of -10 dB to a lower SNR value of -20 dB, the constant threshold energy detector outperforms the proposed variable threshold energy detector from 0 to around a P_{fa} of 0.5. In general, the ROC curves of both the constant and the proposed variable threshold energy detector produce better P_d per P_{fa} when a higher SNR value was used for the simulation.

The proposed variable threshold energy detector does however pose a number of challenges. The main challenge of the variable threshold energy detector's performance is that if the communication channel is too noisy, the variable threshold would not give a steady output with regard to an output of either hypothesis. This can result in low power efficiencies and major interruptions in data rates of the CR. The variable threshold energy detector cannot differentiate between noise and communications signals efficiently.

5.6 Chapter Summary

In high SNR scenarios, the fixed threshold energy detector can be considered enough to detect PU signals, however, this is not the case with weaker signals that may be embedded in noise or spread spectrum signals [41].

Variable threshold energy detectors can sense weaker signals better than fixed threshold energy detectors. Noise variance plays a critical role in spectrum sensing with regard to the SNR wall as depicted by Equation 18 and Figure 8. The sensing time can be reduced by using the number of samples presented by Equation 18 rather than using more samples to sense for spectral holes [23], [24], [57]. The variable threshold energy detector outperforms the fixed threshold detector because the variable threshold ED adapts to the noise uncertainty inherent in all electronic systems and communication channels. A 1.25% less spectrum sensing time was observed for the variable threshold energy detector than a constant threshold energy detector.

An RSSI of -55 dBm was determined and sufficient for detection of the PU signal. The proposed variable threshold and the constant threshold energy detector were compared using ROC curves.

Chapter 6

6 Summary, Conclusion and Future Work

6.1 Introduction

5G technology is earmarked to ease communication of billions of wireless devices that will compete for limited spectrum. The emergence of CR networks will make this possible. Determining best spectrum sensing techniques within the CR cycle is key for myriad technological and economic reasons. Research and findings of an alternative more efficient variable threshold energy detector were produced in this dissertation. Use of an optimized number of spectrum samples was crucial in applying a quicker spectrum sensing algorithm.

6.2 Summary

6.2.1 Energy Detection

NGN's are envisioned to have high throughput and spectral efficiencies. CRN's are central in this dissertation at increasing spectral efficiency and throughput in NGN's. The CR cycle was discussed with emphasis on spectral sensing, specifically ED because of its ease of implementation, no need for knowledge of PU signal modulation and error correction schemes, and ease of fabrication. This results in low manufacturing costs for NGN devices equipped with CR's that use ED.

The ROC curve is a plot of P_d against P_{fa}. A P_{fa} of 0.1 at low SNR values is the typical value used in CR's [3]. An expression of the P_d and P_{fa} that depends on the SNR and threshold value was described in section 2.3.1.2. In general, the ED literature performance is centered around changing energy detector arrangements or varying the threshold with a parameter the triggers it's variability [28]-[33].

The classical ED method called the constant false alarm rate is the basic ED method that uses a single static threshold just above the noise floor. Energy detectors using more than one energy detector operating in tandem using logical operators (OR, AND and K-out-of-N) and an averaging mechanism have been presented as non-adaptive thresholds. There have been attempts made to make the energy detector thresholds adaptive.

An adaptive threshold energy detector that varied the threshold using SNR estimation and a reference signal was described. A double-threshold approach has also been proposed to improve either P_d or P_{fa}. A single adaptive energy detector used simultaneously with a double threshold energy detector has been proposed [55]. In this dissertation, an adaptive threshold energy detector that varied the threshold with noise variances was simulated in MATLAB and implemented in GNU Radio having optimized the number of spectrum samples.

6.2.2 Methodology

Emulation of a PU and a SU for a variable threshold energy detector was produced using two USRP radios. A normally distributed test statistic that is an ensemble of the signal energy levels was compared to thresholds to test the BHTT. The threshold being compared with the test statistic was modelled using a constant P_{fa}, the number of PU and SU antennas M, the number of signal taps N, and the noise variance ${\sigma_n}^2$ [20]. N approaches infinity when there is a high noise uncertainty ρ, thus a threat of the SNR wall that retards the spectrum sensing ability of a CR. However, a threshold value nearer to the noise floor can be achieved when MIMO and more signal taps N are used [9], [23], [24].

6.2.3 Experimental Results and Analysis

The RSSI, ROC curves, spectrum sensing times and BHTT outputs were used as indicators to describe the performance of the proposed variable threshold and the CED that uses a static threshold just above the noise floor.

The proposed variable threshold energy detector has a better performance at a lower SNR value of -20 dB in comparison to -10 dB. This means that the proposed variable threshold energy detector can be used in low SNR environments, possibly in conjunction with the fixed threshold energy detector or other variable threshold energy detectors that produce a better P_d at a specific P_{fa} and SNR level.

The RSSI output of the proposed variable threshold energy detector was detected in a noisy environment at an approximate value of -55 dBm when a signal was detected using either thresholds.

The proposed variable threshold energy detector had a 1.25% less spectrum sensing time as opposed to the fixed threshold energy detector because N was optimized using Equation 18. The spectrum sensing time was not considered in the literature referenced.

What was unique with the proposed variable threshold energy detector is that it had a range of P_{fa} values at which it performed better than the CED at specific SNR values and the converse true. GNU Radio was not used in most of the simulations for comparing variable and constant threshold energy detectors [28]-[33], [37].

6.3 Relevancy of Results Presented

The 3rd Generation Partnership Project (3GPP) has outlined potential next generation requirements into massive internet of things (MIoT), critical communications, and enhanced mobile broadband and network operation. Coverage sizes of base stations are limited to small sizes for high end user demands that range from high video quality streaming to a high density of massive connections of a million connections per square kilometer [59].

NGN's will use direct 3GPP and non-3GPP radio access technologies (RAT's) [59]. CR's that use ED can determine if a PU has occupied spectrum regardless of the connectivity model or RAT used. Spread-spectrum based RAT are not easily detected by CR's that employ ED, however for RAT's that are non-spread spectrum based, ED serves as a robust spectrum sensing method.

The proposed variable threshold energy detector used a variation of a CFAR but optimized the sampling size during spectrum sensing. This made it possible to reduce the spectrum sensing time while the threshold varied only with the noise variance as depicted in Equation 19 and subsequent results shown in Figure 22. Some 5G technology devices are also required to have low power dissipation, low cost, possibly device-centric and possess high P_d in the case of CRs, thus ED can meet this requirement because of its ease of implementation [11], [59]. By ease of implementation, one means that the implementation algorithm is relatively easier than other spectrum sensing techniques to execute.

6.4 Conclusion

ED requires knowledge of the noise variation only. The ED spectrum sensing method albeit presents benefits that include no need for knowledge of enough relevant information about the PU such as the modulation type or transmit power, does not perform well in low SNR environments. Low SNR environments for the standard such as the IEEE 802.22 standard that requires a sensitivity as low as -120 dBm would thus require a more robust approach of the ED method. An adaptive autonomous variable threshold ED technique thus presents a solution to the challenge presented by low SNR environments.

In this dissertation, a 1.25% less spectrum sensing time of the proposed variable threshold energy detector against a constant threshold ED technique is achieved. The variable threshold energy detector in GNU Radio is able to detect PU signals very close to the noise floor of -120 dBm, resulting in either hypothesis being selected from the binary hypothesis testing theorem.

ROC curve plots show that the proposed variable threshold energy detector has a better P_d of 0.29 to 0.38 and 0.59 to 1 in the P_{fa} ranges 0 to 0.2 and 0.5 to 1 respectively as opposed to the constant threshold energy detector at a low SNR of -20 dB. On the other hand, the classical energy detector has a better P_d of 0.55 to 0.92 in the P_{fa} range of 0 to 0.5 at an SNR value of -10 dB when compared to the proposed variable threshold energy detector.

6.5 Recommendations

Using multiple energy detectors in tandem in CR’s using an averaging mechanism or logical operators can be used to improve the overall performance of a CR. Most of the research done so far has been to determine which combination of energy detectors produces the best results [28]-[33]. One energy detector could be the proposed variable threshold energy detector that can be used in low SNR environments, but switched back to the classical energy detector for higher SNR values in order to get a higher P_d in either cases. An investigation into the behaviour of both energy detectors and how each can be used in varying SNR environments is crucial.

This behaviour can also be investigated in the internet of things (IoT) sphere where multiple SU’s and PU’s with sufficient separation exist, and a channel environment is quickly changing, especially when one of the end users is moving is worth investigating. An OFDM modulated signal was used in this dissertation. The behaviour of the variable energy detector would be of interest in this environment using specific standards such as the IEEE 802.22, IEEE DySPAN or IEEE 80.15.4e and spread spectrum signals (since ED performs poorly in spread spectrum signals) in software-defined networks (SDN’s) environments. This can be implemented by having a CR that has both the data plane and control plane as is the case in SDN’s. The control plane could use this metadata (possibly the SNR level, desired P_d and P_{fa}, or RSSI level) to employ the variable threshold energy detector. These can serve as possible research areas for the variable threshold energy detector.

A better spectrum sensing timing mechanism can also be improved upon by using the unit measure of time being the seconds as opposed to a percentile measure when comparing both ED methods simulated.

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Appendix A: Code for ROC curves for Energy Detection

A.1 Fixed threshold Energy Detector using MATLAB

```
close all
clear all
L = 1000;
snr_dB = -8;              % SNR in decibels
snr = 10.^(snr_dB./10); % Linear Value of SNR from definition
Pf = 0.01:0.01:1;        % Pf = Probability of False Alarm
%% ROC curves simulation via Monte Carlo simulation using a fixed threshold
for Energy Detection
for step = 1:length(Pf)
    step
    i = 0;
for kk=1:10000            % Number of Monte Carlo Simulations
 n = randn(1,L);          % AWGN noise with mean 0 and variance 1
 s = sqrt(snr).*randn(1,L); % Real valued Gaussina Primary User Signal
 y = s + n;               % Received signal at SU
 energy = abs(y).^2;      % Energy of received signal over N samples
 energy_fin =(1/L).*sum(energy); % Test Statistic for the energy detection
 thresh(step) = (qfuncinv(Pf(step))./sqrt(L))+ 1; % Theoretical value of
Threshold
 if(energy_fin >= thresh(step))  % Compare received energy against threshold
and make decision
     i = i+1;
 end
end
Pd(step) = i/kk;
end
plot(Pf, Pd, 'Linewidth',1.5)
hold on
%% Theroretical ecpression of Probability of Detection; refer above
reference.
thresh = (qfuncinv(Pf)./sqrt(L))+ 1;
Pd_the = qfunc(((thresh - (snr + 1)).*sqrt(L))./(sqrt(2).*(snr + 1)));
plot(Pf, Pd_the, 'Linewidth', 1.5)
hold on
xlabel('Probability of False Alarm Pfa')
ylabel('Probability of Detection Pd')
title('Receiver Operating Characteristics (ROC) Curve')
legend('Simulated ROC at -7 dB', 'Theoretical ROC at -7 dB')
```

A.2: Code for SNR against Probability of Detection for an Energy Detector. (fixed threshold)

```
clc
close all
clear all
L = 1000;
snr_dB=-15:1:0;
snr= 10.^(snr_dB./10);
for i=1:length(snr_dB)
Detect=0;
Pf=0.1;
for kk=1:10000 % Number of Monte Carlo Simulations
%-----AWGN noise with mean 0 and variance 1-----%
Noise = randn(1,L);
%-----Real valued Gaussian Primary User Signal------%
Signal = sqrt(snr(i)).*randn(1,L);
Recv_Sig = Signal + Noise; % Received signal at SU
Energy = abs(Recv_Sig).^2; % Energy of received signal over N samples
%-----Computation of Test statistic for energy detection-----%
Test_Statistic =(1/L).*sum(Energy);
%-----Theoretical value of Threshold-----%
Threshold = (qfuncinv(Pf)./sqrt(L))+ 1
% Check whether the received energy is greater than threshold, if
so,(Probability of detection) counter by 1
if(Test_Statistic >= Threshold)
Detect = Detect+1;
end
end
Pd4(i) = Detect/kk;
Pm4(i)=1-Pd4(i);
Pd_the4(i) = qfunc(((Threshold - (snr(i) + 1)).*sqrt(L))./(sqrt(2).*(snr(i) +
1)));
%Pm_the4(i)=1-Pd_the(i);
end
plot(snr_dB,Pd4,'-kh')
xlabel('SNR dB')
ylabel('Probability of Detection Pd')
hold on
plot(snr_dB,Pd_the4,'-r')
hold on
```

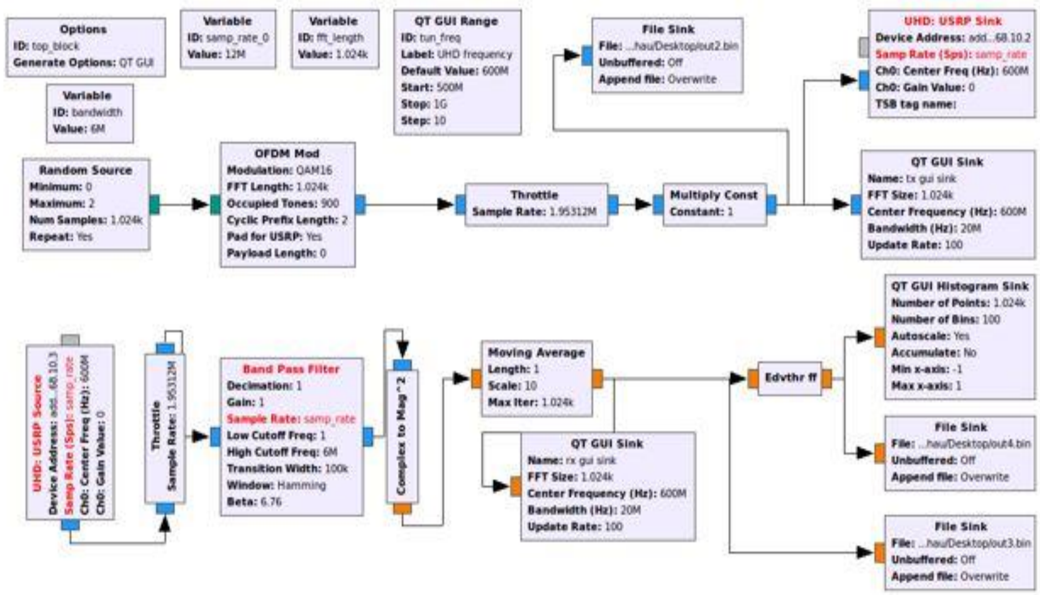
A.3: ROC Curve Plot for Constant and Variable Threshold ED

```
clc
close all
clear all

L = 1000;               % number of samples
snr_dB = -20;           % SNR in decibels
snr = 10.^(snr_dB./10); % Linear Value of SNR from definition
Pf = 0.01:0.01:1;       % Pf = Probability of False Alarm
%% ROC curves simulation via Monte Carlo simulation using a fixed threshold
for Energy Detection
for step = 1:length(Pf)
    step
    i = 0;
for kk=1:10000          % Number of Monte Carlo Simulations
 n = randn(1,L);        % AWGN noise with mean 0 and variance 1
 s = sqrt(snr).*randn(1,L); % Real valued Gaussina Primary User Signal
 y = s + n;             % Received signal at SU
 energy = abs(y).^2;    % Energy of received signal over N samples
 energy_fin =(1/L).*sum(energy); % Test Statistic for the energy detection
 thresh(step) = (qfuncinv(Pf(step))./sqrt(L))+ 1; % Theoretical value of
Threshold

 if(energy_fin >= thresh(step))  % Compare received energy against threshold
and make decision
     i = i+1;
 end
end
Pd(step) = i/kk;
End


%modification area
for step = 1:length(Pf)
    step
    j = 0;
for kk=1:10000          % Number of Monte Carlo Simulations
 n = randn(1,L);        % AWGN noise with mean 0 and variance 1
 s = sqrt(snr).*randn(1,L); % Real valued Gaussina Primary User Signal
 y = s + n;             % Received signal at SU
 energy = abs(y).^2;    % Energy of received signal over N samples
 energy_fin =(1/L).*sum(energy); % Test Statistic for the energy detection
 Nc = 1/(snr^2)*(qfuncinv(Pf(step))-(qfuncinv(Pd(step))*(1+snr)))^2;  %
Number of Samples for an SNR Wall
 sqrt1 = sqrt(2/Nc);
 prod1 = sqrt1 * qfuncinv(Pf(step));
 thresh2(step) = 1 + prod1; % Variable Threshold Proposed

 if(energy_fin >= thresh2(step))  % Compare received energy against threshold
and make decision
     j = j+1;
```

```
 end
end
%other part below
Pd1(step) = j/kk;
end

plot(Pf, Pd, 'Linewidth',3.0)
hold on
plot(Pf, Pd1, 'c*')
hold on
title('ROC Curve for Constant and Variable threshold energy detectors')
xlabel('Probability of False Alarm Pfa')
ylabel('Probability of Detection Pd')
legend('Constant Threshold ROC plot', 'Variable Threshold ROC plot')
```

Appendix B: GNU Radio Setup

B.1: Path setup at Ingress



B.2: C++ code for Variable threshold implementation in GNURadio Software

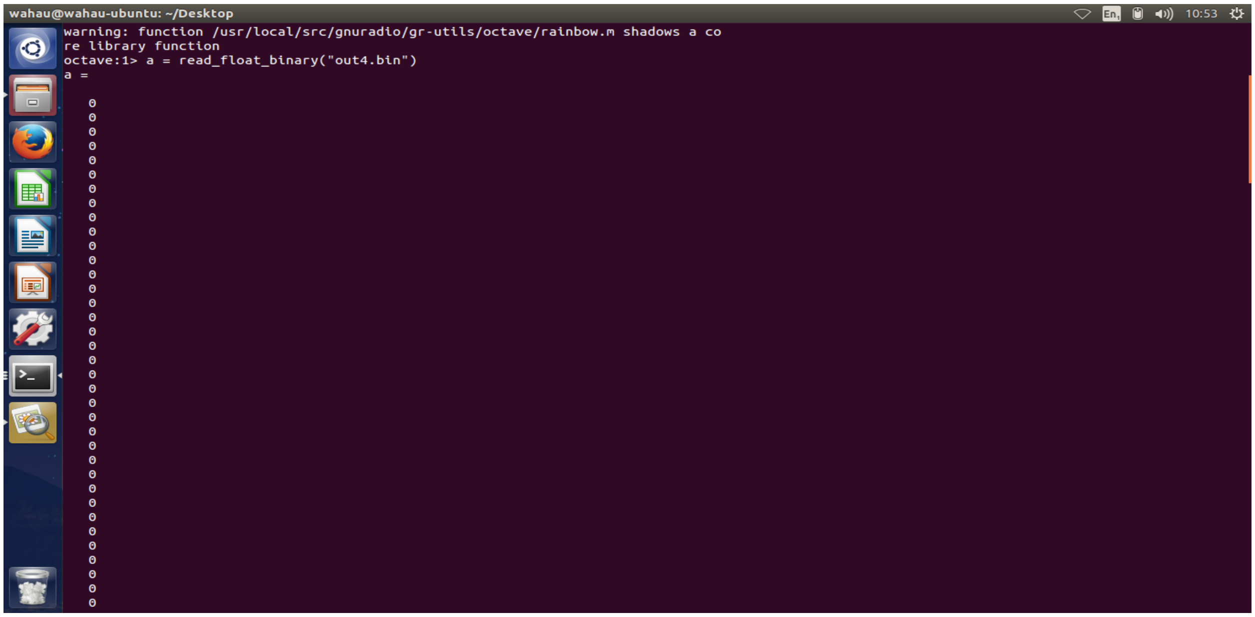
```
/* -*- c++ -*- */
/*
 * Copyright 2016 <+YOU OR YOUR COMPANY+>.
 *
 * This is free software; you can redistribute it and/or modify
 * it under the terms of the GNU General Public License as published by
 * the Free Software Foundation; either version 3, or (at your option)
 * any later version.
 *
 * This software is distributed in the hope that it will be useful,
 * but WITHOUT ANY WARRANTY; without even the implied warranty of
 * MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the
 * GNU General Public License for more details.
 *
 * You should have received a copy of the GNU General Public License
```

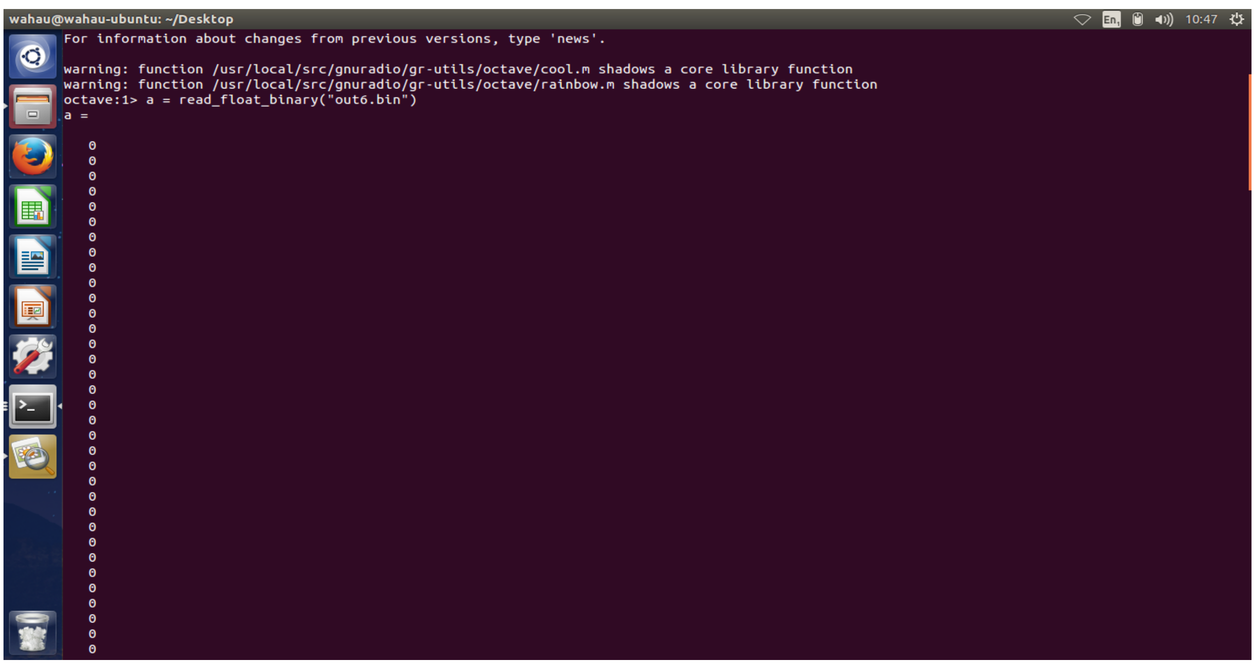
```
 * along with this software; see the file COPYING.  If not, write to
 * the Free Software Foundation, Inc., 51 Franklin Street,
 * Boston, MA 02110-1301, USA.
 */

#ifdef HAVE_CONFIG_H
#include "config.h"
#include <math.h>
#endif

#include <gnuradio/io_signature.h>
#include "edvthr_ff_impl.h"

namespace gr {
  namespace zis {

    edvthr_ff::sptr
    edvthr_ff::make()
    {
      return gnuradio::get_initial_sptr
        (new edvthr_ff_impl());
    }

    /*
     * The private constructor
     */
    edvthr_ff_impl::edvthr_ff_impl()
      : gr::block("edvthr_ff",
              gr::io_signature::make(1, 1, sizeof(float)),
              gr::io_signature::make(1, 1, sizeof(float)))
    {}

    /*
     * Our virtual destructor.
     */
    edvthr_ff_impl::~edvthr_ff_impl()
    {
    }

    void
    edvthr_ff_impl::forecast (int noutput_items, gr_vector_int &ninput_items_required)
    {
      ninput_items_required[0] = noutput_items;
    }
```

```
int
edvthr_ff_impl::general_work (int noutput_items,
                  gr_vector_int &ninput_items,
                  gr_vector_const_void_star &input_items,
                  gr_vector_void_star &output_items)
{
  const float *in = (const float *) input_items[0];
  float *out = (float *) output_items[0];

  float prob_fa = 0.1;                           //probability of false alarm
  float prob_d  = 0.9;                                                   //probability of
                                                         detection
  int sample_num = 1024;                                                 //number of samples
                                                         to determine threshold and critical
                                                         number of samples for snr wall
  float qfuncinv_pfa = sqrt(2) * pow(erf(1-(2*prob_fa)),-1);// q^-1(x) = sqrt(2) * erf^-1(1-2x)
  float qfuncinv_pd  = sqrt(2) * pow(erf(1-(2*prob_d)),-1); // q^-1(x) = sqrt(2) * erf^-1(1-2x)
  float threshold = (qfuncinv_pfa/sqrt(sample_num))+1;      // theoretical threshold value
  float snr = pow(10,-3);                                                      // assuming an
                                                         snr of -30 db is used (snr estimation
                                                         techniques are alt)
  float sqr_snr = pow(snr,2);                                            // snr squared
  float critical_sample_num = pow(qfuncinv_pfa-(qfuncinv_pd*(1+snr)),2)/sqr_snr; //critical
                                                         number of samples for snr wall

  if (critical_sample_num < sample_num)
  {
     sample_num = critical_sample_num;
  }


  for(int i=0;i<noutput_items;i++)
  {
   if (in[i]>=threshold)
     out[i]=1;
   else
                                                           out[i]=0;
  }
  // Tell runtime system how many input items we consumed on
  // each input stream.
  consume_each (noutput_items);

  // Tell runtime system how many output items we produced.
```

```
    return noutput_items;
  }

 } /* namespace zis */
} /* namespace gr */
```

B.3 Binary File Reading Commands and Outputs in Determining Spectrum Sensing Times





ADDENDUM 1:

Proposal

A Variable Threshold for an Energy Detector Using GNU Radio

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Abstract: A proposal for development of an out of tree module being a variable threshold energy detector for the GNU Radio Software is made using the USRP software defined radio starter kits.

1. Introduction: The current policy on spectrum assignment is a fixed spectrum assignment policy. This is regulated by the International Telecommunications Union, a United Nations arm responsible for all telecommunication matters. In turn, government telecommunications agencies locally regulate spectrum by assigning license holders or service providers on a long term basis. This has resulted in inefficient use of the spectrum, with temporal and geographical variations of use of fixed spectrum in the range of 18% to 85% [1]. Use of dynamic spectrum access is proposed to overcome the inefficiency caused by fixed spectrum allocation.

Cognitive radio networks can provide high bandwidth and spectral efficiencies for mobile users through heterogeneous wireless architectures and dynamic spectrum access techniques. Opportunistic access to the licensed spectrum can improve efficiency without interfering with existing users. Cognitive radios achieve this and as such investigations as to how they achieve this is investigated.

1.1 **Research problem**: Current networks use very limited channel widths while on the other hand more demand for faster data rates and lower latency applications has been on the rise. Regulations have been set in place by the International Telecommunications Union to control the radio spectrum, however, fixed spectrum allocation is inefficient. Cognitive radios are meant to increase the efficiency of the spectrum by using temporal and geographical variations in spectral use. The main challenge is, "how does a cognitive radio in the first place detect that a channel is unoccupied or not?".

The telecommunications industry is also faced with an ever increasing trend to use software as a main driver for better Next Generation Networks, from optimization using Traffic Engineering, to software defined networks and software defined radios. The challenge is that most software defined radios have built-in functional blocks, but not all blocks satisfy the user requirements due to the lack of tools and resources through coding. Open software systems usually have myriad modular blocks that are free and have a lot of documentation and support as opposed to proprietary software packages that are expensive and lack readily available and free documentation.

1.2 Hypothesis and Objectives of Research:

Hypothesis: An out of tree module for the GNU radio software implementing Energy Detection will enable spectrum sensing for an OFDM based technology (IEEE 802.22/ IEEE DySPAN/ IEEE 80.15.4e). A variable detector threshold is proposed for the research and optimization of the spectrum sensing technique.

1.3 Contribution:

The research will add value to users of the GNU radio that is an open platform that will add spectrum sensing as a feature for research and a building block to more complex architectures.

Energy detection is a simple yet effective spectrum sensing technique, this in turn means low costs, low power and high spectral efficiency for particularly software defined radios.

1.4 Research Scope:

- GNU radio: Software used to control and set radio parameters. An out of tree module will be installed here.
- USRP 210N kit: Software defined radio controlled by the GNU radio.
- OFDM based standard: 802 or any standard that will be in the Next Generation Network.

2. Lit Review

In attaining the best available channel, the cognitive radios in next generation networks should allow *spectrum sensing, spectrum management, spectrum mobility,* and *spectrum sharing* [1].

- *"Spectrum sensing*: Detecting unused spectrum and sharing the spectrum without harmful interference with other users.
- *Spectrum management*: Capturing the best available spectrum to meet user communication requirements.

- *Spectrum mobility*: Maintaining seamless communication requirements during the transition
  to better spectrum.
- *Spectrum sharing*: Providing the fair spectrum scheduling method among coexisting next generation users." [1].

Cognitive radios should enable usage of temporally and geographically unused spectrum of licensed or unlicensed users which is called a spectrum hole or white space [1]. If the hole is further used by the primary user, the cognitive radio should vacate to another spectrum hole or stay in the same band changing its parameters to avoid interference. The cognitive radio is faced with challenges due to the wideband RF antenna that receives signals from different locations, power levels and bandwidths. As a result the CR should be able to detect weak signals in a large dynamic range and thus a requirement of a multi-GHz A/D converter with a high resolution which is infeasible. The steps of the cognitive cycle are *spectrum sensing, spectrum analysis, and spectrum decision.* This is referred to as the Dynamic Spectrum Management Framework (DSMF) [3].

The radio environment changes over time and space, and thus for an occupied hole, the CR should keep track of the radio environment changes. "Any environmental change during the transmission such as primary user appearance, user movement or traffic variation can trigger this adjustment." [1].

Spectrum sensing Methods: Non-cooperative spectrum sensing (transmitter detection), Cooperative spectrum sensing and Interference-based spectrum sensing are spectrum sensing classifications. Three schemes are generally used for the transmitter detection which are: matched filter detection, energy detection and cyclostationary feature detection techniques.

- **Matched filter detection:** "When the information of the primary user signal is known to the next generation user, the optimal detector in stationary Gaussian noise is the matched filter since it maximizes the received signal-to-noise ratio (SNR). While the main advantage of the matched filter is that it requires less time to achieve high processing gain due to coherency, it requires a priori knowledge of the primary user signal such as the modulation type and order, the pulse shape, and the packet format. Hence, if this information is not accurate, then the matched filter performs poorly. However, since most wireless network systems have pilot, preambles, synchronization word or spreading codes, these can be used for the coherent detection." [1].

- **Energy detection:** If the receiver cannot gather enough relevant information about the primary user, for example, such as modulation type or transmitter power, the optimal detector is known as the energy detector. The energy of the received signal is measured by taking the output signal of a bandpass filter of bandwidth W squared and integrated over the observation period T. The output of the integrator Y is compared with a threshold λ to decide if a licensed user is present or not [1].

  If the energy detection can be applied in a nonfading environment, the probability of detection P_d and false alarm P_{fa} are given as follows,

$$P_d = P\{Y > \lambda | H_1\} = Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda}\right),$$

$$P_{fa} = P\{Y > \lambda | H_0\} = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)}$$

Where γ is the SNR,

$\Gamma(*)$ is the complete gamma function,

$\Gamma(*,*)$ is the incomplete gamma function

And Q_m is the generalized Marcum Q-function.

From the above functions, while a low P_d would result in missing the presence of the primary user with high probability which in turn increases the interference to the primary user, a high P_{fa} would result in low spectrum utilization since false alarms increase the number of missed opportunities. Since it is easy to implement, the recent work on detection of the primary user has generally adopted the energy detector" [1]

For fading and multipath propagation, "…while P_{fa} is independent of *C*, when the amplitude gain of the channel, *H*, varies due to the shadowing/fading, P_d gives the probability of the detection conditioned on instantaneous SNR as follows:

$$P_d = \int_x^{\infty} Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) f_\gamma(x)\, dx$$

where $f_\gamma(x)$ is the probability distribution function of SNR under fading."[1].

The performance of energy detector is susceptible to low signal-to-noise ratios and uncertainty in noise power. In other words, the variance in noise degrades the performance of the Energy Detector. Variances in noise of the energy detector could be due to thermal noise which varies with temperature, spurious RF leakages, and inefficient receiver filters. Variances in SNR could be due to multipath fading and differences in either transmit powers, pathloss or varying objects in the propagation environment. Pilot tones from the primary transmitter can be used to help improve the accuracy of the energy detector. The energy detector's other limitation is that it cannot differentiate signal types but can only determine the presence of the signal, therefore, the energy detector is prone to the false detection triggered by the unintended signals. [1]

- **Cyclostationary feature:** Modulated signals are in general coupled with sine wave carriers,

  pulse trains, repeating spreading, hopping sequences, or cyclic prefixes, which result in built-in periodicity. These modulated signals are characterized as cyclostationarity since their mean and autocorrelation exhibit periodicity. These features are detected by analyzing a spectral correlation function. The main advantage of the spectral correlation function is that it differentiates the noise energy from modulated signal energy, which is a result of the fact that the noise is a wide-sense stationary signal with no correlation, while modulated signals are cyclostationary with spectral correlation due to the embedded redundancy of signal periodicity. Therefore, a cyclostationary feature detector can perform better than the energy detector in discriminating against noise due to its robustness to the uncertainty in noise power. However, it is computationally complex and requires significantly long observation time."[1].

3. Methodology:

CRs can be modelled as a Binary Hypothesis Testing Problem:

$$H_0:\ y[n] = w[n] \qquad\qquad n = 1,\ 2,\ 3, \dots,\ N$$

$$H_1:\ y[n] = x[n] + w[n] \quad n = 1,2,3, \dots, N$$

Where n is the number of samples on the signal of interest in cognitive radios. The H_0 represents the first hypothesis that there is no signal detected only noise *w[n]*, while the H_1 represents the second hypothesis that there is a presence of a signal *x[n]* and noise *w[n]*.

The SNR wall is an SNR value at which no matter the number of samples n taken by the energy detector in determining if the hypothesis test H_1 is true or not, will not increase the robustness of the Energy Detector (ED). This means that this value is key in making signal processing times shorter and more efficient once that value is determined in conjunction with the noise variance [5].

The probability of detection and the probability of false alarm will be used as the main indicators of the efficiency of the cognitive radio for a fixed threshold ED through Receiver Operating Characteristic curves given in Figure 1, the SNR wall, noise variance and SNR values. In totality, statistical methods will be used to measure the performance of the variable threshold detector which is selected using the probability distribution functions of the binary hypothesis test theorems H_0 and H_1 as depicted in Figure 2.

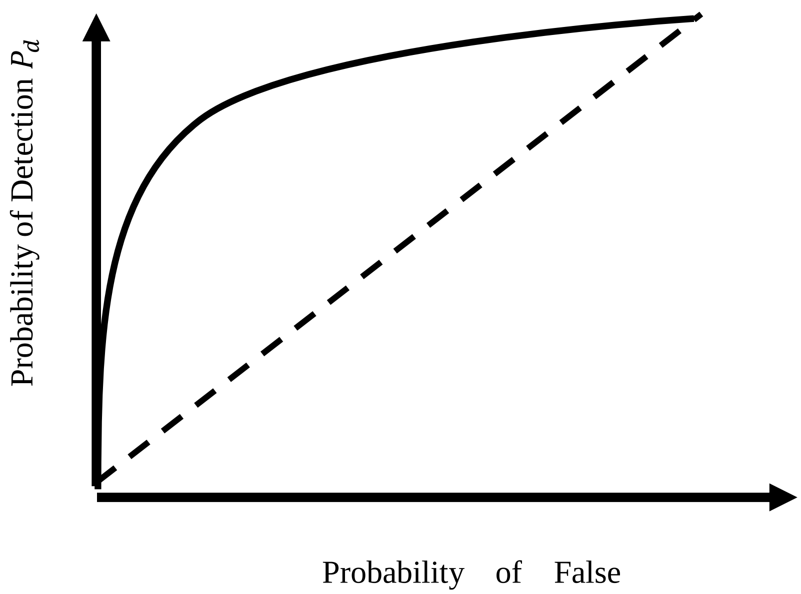


Figure 1 - Receiver Operating Characteristic (ROC) curves for an Energy Detector used for performance measurement of the Spectrum Sensing Technique (Energy Detection).

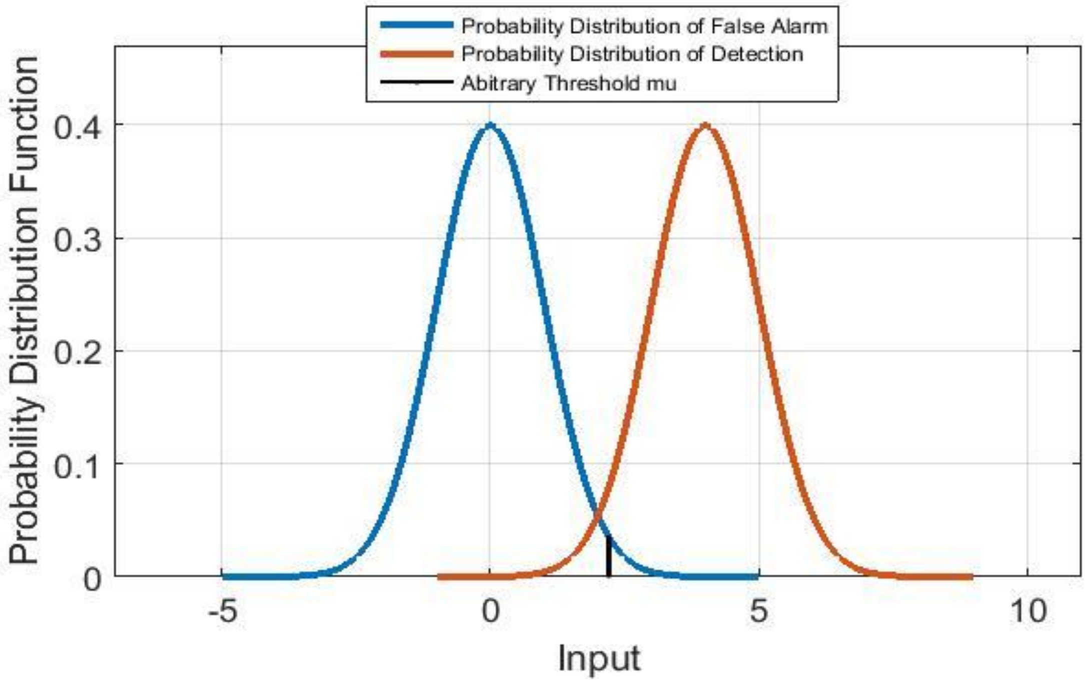


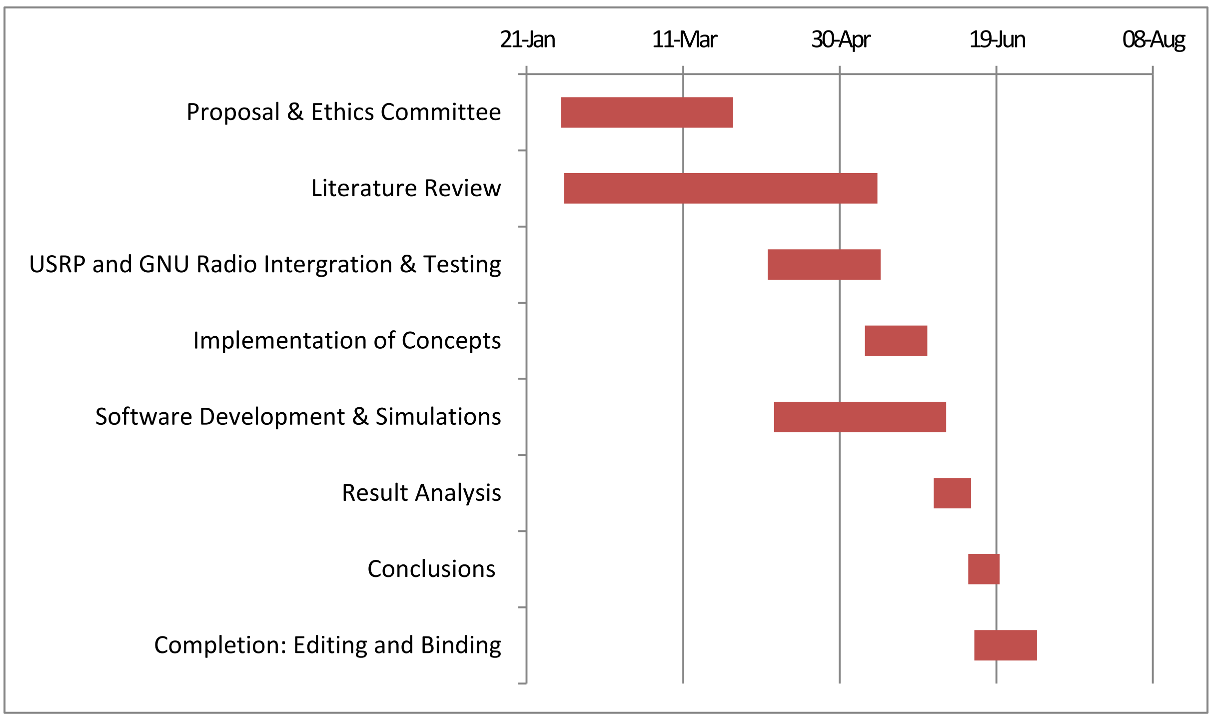
Figure 2 - Figure showing how the threshold is selected statistically using the probability distribution functions of binary hypothesis tests H_0 and H_1.

A number of methods have been proposed to make the Energy Detector more efficient. Some of these methods include using a fixed threshold, a constant false alarm rate (CFAR), a double threshold method in which the lower threshold value is used for determining the probability of detection P_d while the other determines the P_{fa}. Threshold adaptation to overcome noise variance and Cooperative ways to maximize P_d have also been proposed [6]-[8].

4. Analysis and Evaluation:

Verification of existence and non-existence of a signal or spectrum hole will be empirically made and compared with the statistical and mathematical model used to determine the success of the energy detector of the GNU Radio.

5. Time frame (Gantt charts)



6. Conclusion

The proposed variable threshold Energy Detector will be an efficient spectrum sensor that will add to the open source community that uses the GNU Radio that operates under the free GNU License. A sequential, scientific method will be used in deriving the variable threshold detector using first principles of digital signal processing and fundamental concepts of software defined radio.

7. Future work

More complex software modules that add value to spectrum sensing, spectrum management, spectrum mobility, and spectrum sharing.

References:

[1] Ian F. Akyildiz, Won-Yeol Lee, Mehmet C. Vuran, Shantidev Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey", *Computer Networks*, vol. 50, May 2006, pp. 2127–2159

[2] Electronic Communication Committee (ECC), "Technical and Operational Requirements for the Possible Operation of Cognitive Radio Systems in the White Spaces of the Frequency Band 470-790", *European Conference of Postal and Telecommunications Administrations (CEPT), Technical Report: ECC Report 159*, Jan. 2011, [online], available: http://www.ietf.org/mail-archive/web/paws/current/pdf6LNQT4Lb6S.pdf.

[3] M. T. Masonta, M. Mzyece and N. Ntlatlapa, "Spectrum decision in cognitive radio networks: a survey," *IEEE Communications, Survey and Tutorials*, Vol. 15, no. 3, Nov. 2012, pp. 1088-1107.

[4] T. Yücek and H. Arslan, "A survey of spectrum sensing algorithms for Cognitive Radio applications", *IEEE Communications, Surveys And Tutorials*, Vol. 11, no. 1, First Quarter 2009, pp. 116-130.

[5] R. Tandra and A. Sahai, "SNR Walls for Signal Detection", IEEE Journal Of Selected Topics in Signal Processing, Vol. 2, No. 1, February 2008

EBE Faculty: Assessment of Ethics in Research Projects (Rev2)

Any person planning to undertake research in the Faculty of Engineering and the Built Environment at the University of Cape Town is required to complete this form before collecting or analysing data. When completed it should be submitted to the supervisor (where applicable) and from there to the Head of Department. If any of the questions below have been answered YES, and the applicant is NOT a fourth year student, the Head should forward this form for approval by the Faculty EIR committee: submit to Ms Zulpha Geyer (Zulpha.Geyer@uct.ac.za; Chem Eng Building, Ph 021 650 4791).
NB: A copy of this signed form must be included with the thesis/dissertation/report when it is submitted for examination

This form must only be completed once the most recent revision EBE EiR Handbook has been read.

Name of Principal Researcher/Student: **Mr.Wahau Simon Lechesa** Department: **Electrical Engineering**

Preferred email address of the applicant: **LCHWAH001@myuct.ac.za**

If a Student: Degree: **M. Eng. Telecoms Engineering** Supervisor: **A/Prof. M. Dlodlo**

If a Research Contract indicate source of funding/sponsorship:

Research Project Title: A Variable Threshold for an Energy Detector Using GNU Radio

Overview of ethics issues in your research project:

Question 1: Is there a possibility that your research could cause harm to a third party (i.e. a person not involved in your project)?		NO
Question 2: Is your research making use of human subjects as sources of data? If your answer is YES, please complete Addendum 2.		NO
Question 3: Does your research involve the participation of or provision of services to communities? If your answer is YES, please complete Addendum 3.		NO
Question 4: If your research is sponsored, is there any potential for conflicts of interest? If your answer is YES, please complete Addendum 4.		NO

If you have answered YES to any of the above questions, please append a copy of your research proposal, as well as any interview schedules or questionnaires (Addendum 1) and please complete further addenda as appropriate. Ensure that you refer to the EiR Handbook to assist you in completing the documentation requirements for this form.

I hereby undertake to carry out my research in such a way that

- there is no apparent legal objection to the nature or the method of research; and
- the research will not compromise staff or students or the other responsibilities of the University;
- the stated objective will be achieved, and the findings will have a high degree of validity;
- limitations and alternative interpretations will be considered;
- the findings could be subject to peer review and publicly available; and
- I will comply with the conventions of copyright and avoid any practice that would constitute plagiarism.

Signed by:

	Full name and signature	Date
Principal Researcher/Student:	Wahau Simon Lechesa Lechesa	13/01/2017

This application is approved by:

Supervisor (if applicable):	Prof. M. E. Dlodlo Mqhele Dlodlo	13/01/2017
HOD (or delegated nominee): *Final authority for all assessments with NO to all questions and for all undergraduate research.*	[signature]	~~13/01/2017~~ 25/1/17

It is assumed that you have read the UCT Code for Research involving Human Subjects (available at http://web.uct.ac.za/depts/educate/download/uctcodeforresearchinvolvinghumansubjects.pdf) in order to be able to answer the questions in this addendum.

2.1 Does the research discriminate against participation by individuals, or differentiate between participants, on the grounds of gender, race or ethnic group, age range, religion, income, handicap, illness or any similar classification?		NO
2.2 Does the research require the participation of socially or physically vulnerable people (children, aged, disabled, etc) or legally restricted groups?		NO
2.3 Will you not be able to secure the informed consent of all participants in the research? (In the case of children, will you not be able to obtain the consent of their guardians or parents?)		NO
2.4 Will any confidential data be collected or will identifiable records of individuals be kept?		NO
2.5 In reporting on this research is there any possibility that you will not be able to keep the identities of the individuals involved anonymous?		NO
2.6 Are there any foreseeable risks of physical, psychological or social harm to participants that might occur in the course of the research?		NO
2.7 Does the research include making payments or giving gifts to any participants?		NO

If you have answered YES to any of these questions, please describe below how you plan to address these issues:

ADDENDUM 3: To be completed if you answered YES to Question 3:

3.1 Is the community expected to make decisions for, during or based on the research?		NO
3.2 At the end of the research will any economic or social process be terminated or left unsupported, or equipment or facilities used in the research be recovered from the participants or community?		NO
3.3 Will any service be provided at a level below the generally accepted standards?		NO

If you have answered YES to any of these questions, please describe below how you plan to address these issues:

ADDENDUM 4: To be completed if you answered YES to Question 4

4.1 Is there any existing or potential conflict of interest between a research sponsor, academic supervisor, other researchers or participants?		NO
4.2 Will information that reveals the identity of participants be supplied to a research sponsor, other than with the permission of the individuals?		NO
4.3 Does the proposed research potentially conflict with the research of any other individual or group within the University?		NO

If you have answered YES to any of these questions, please describe below how you plan to address these issues: