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Performance Evaluation of Energy Detection Based Spectrum Sensing for Cognitive Radio Networks

by

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Declaration

I hereby declare that this submission is my own work towards the MSc, and that, to the best of my knowledge, it contains no material previously published by another person , nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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Dedication

To my parents, Mr. Samuel W. Oyibo and Mrs. Juliana J. Oyibo. For always sacrificing and pushing me to do my best.

Abstract

The rapid growth of bandwidth demanding wireless technologies has led to the problem of spectrum scarcity. However, studies show that licensed spectrum is underutilized. Cognitive radio technology promises a solution to the problem by allowing unlicensed users, access to the licensed bands opportunistically. A prime component of the cognitive radio technology is spectrum sensing. Many spectrum sensing techniques have been developed to sense the presence or not of a licensed user. This thesis evaluates the performance of the energy detection based spectrum sensing technique in noisy and fading environments. Both single user detection and cooperative detection situations were investigated. Closed form solutions for the probabilities of detection and false alarm were derived. The analytical results were verified by numerical computations using Monte Carlo method with MATLAB. The performance of the energy detection technique was evaluated by use of Receiver Operating Characteristics (ROC) curves over additive white Gaussian noise (AWGN) and fading (Rayleigh & Nakagami-m) channels. Results show that for single user detection, the energy detection technique performs better in AWGN channel than in the fading channel models. The performance of cooperative detection is better than single user detection in fading environments.

Contents

List of Figures

Chapter 1

Introduction

1.1 Background and Motivation

The possibility of electronic wireless communication would not exist without the electromagnetic frequency spectrum. Traditionally, licensed spectrum is allocated over relatively long time periods, and is meant to be used only by licensees [1]. A government agency is responsible for allocating spectrum bands to operators. In Ghana, the National Communications Authority is responsible for this exercise. So is the Nigerian Communications Commission (NCC) and Federal Communications Commission (FCC) of the USA. This approach is termed the Fixed Spectrum Allocation (FSA) scheme.

With this, the radio spectrum is split into bands allocated to distinct technology based services, e.g. mobile telephony, radio and TV broadcast services, on absolute basis. The FSA management framework guarantees that the radio frequency spectrum is exclusively licensed to an authorized party, (i.e. the primary user (PU)) without interference [2].

As a result of the transition from regular voice-only communication to multimedia type application, the need for high data rate has increased. Apparently, the

FSA will not have the capacity for these rapid increase in the number of high data rate technology [3].

However, background studies [4] show that spectrum use is intense on certain portions while a significant amount remains underutilized. High utilization is common in the cellular and FM radio bands, while other bands indicate low usage levels. More so, most of the license owners do not transmit all the time in all geographic locations where the license covers. Records from the FCC indicate that spectrum allocated in the bands below 3GHz have a utilization range of 15% to 85% [5].

Figure 1.1 depicts measurements taken by Shared Spectrum Company (SSC) to determine spectrum occupancy over several localities [6]. Observations from this exercise imply that the average occupancy of spectrum over the seven locations is only about 5.2%. It can be inferred from these measurements that an important part of the radio frequency spectrum is unused or underutilized most of the time, leading to large chunks of "spectrum holes" (whitespaces).

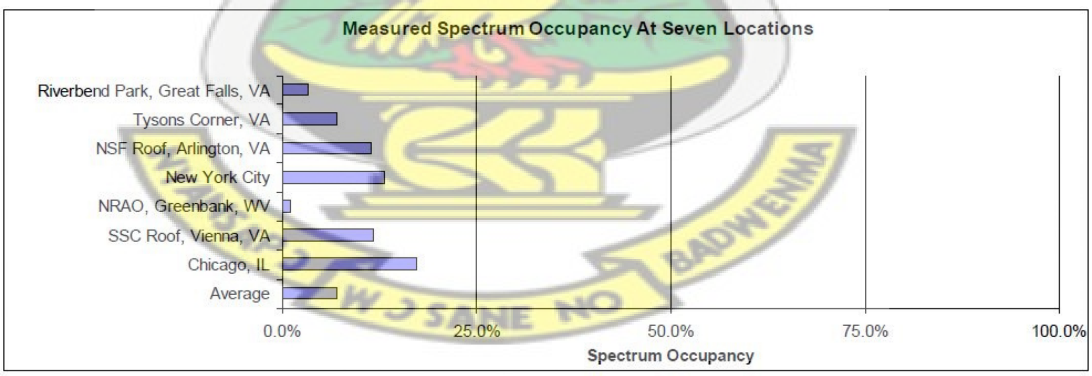

Figure 1.1: Spectrum occupancy measurement over some locations [6].

The static frequency allocation scheme as in place currently will not be suitable, since it creates an artificial shortage. The development of new bandwidth demanding wireless technologies would depend on the availability of radio spectrum [3].

As spectral resources become more limited, the [7] FCC recommends that significant efficiency can be realized by deploying wireless devices that coexist with primary users. Thus the secondary users take advantage of the available resources with minimal interference to the primary users.

Consequently, groundbreaking techniques that provide new ways of exploiting the available spectrum are required. As a result, Dynamic Spectrum Access (DSA) was proposed to solve the inefficiency caused by the static allocation of spectrum. With this concept, use of existing radio spectrum is enhanced by opportunistic spectrum access (OSA) of the frequency bands that are not occupied by the licensed or primary user. The enabling technology for this Next Generation (xG) network is the Cognitive Radio.

A Cognitive Radio (CR) is an intelligent radio platform with the ability to exploit its environment to increase spectral efficiency and capacity. CR's are regarded as transceivers that automatically detect (sense the existence of) available channels in a wireless spectrum and accordingly, change their transmission or reception parameters [8]. The CR technology is envisaged to enable identification, use and management of vacant spectrum, known as *Spectrum Holes* [9]. A spectrum hole is a region of space-time frequency, where a primary user is absent and a particular secondary use is possible [10]. An illustration of this concept is shown in Figure 1.2 below.

By dynamically switching between unoccupied spectrum gaps, CRs take advantage of the locally unused spectrum.

Cognitive radios possess the ability to observe their communication environment and adapt the parameters of their communication scheme to maximize the spectrum, while minimizing interference to the primary users [12] . To do so, [13], asserts that CRs must continuously sense the spectrum in use in order to detect

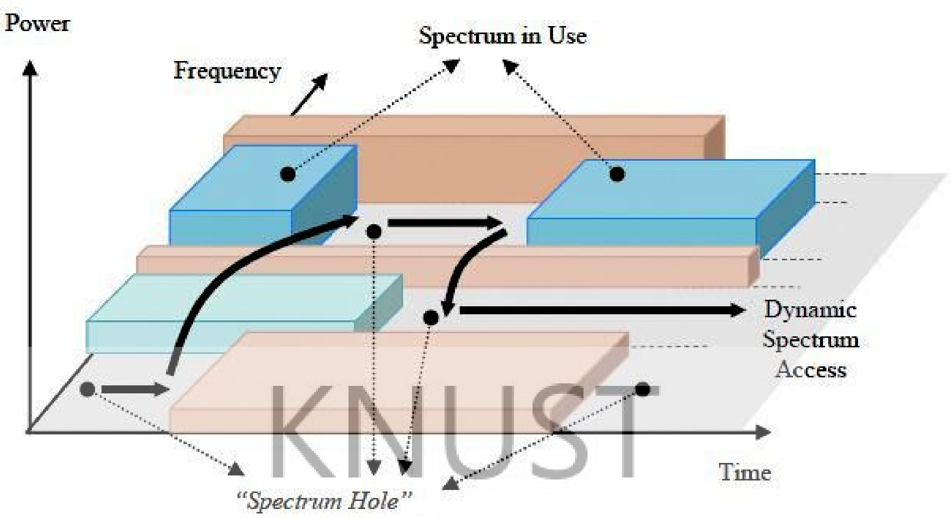

Figure 1.2: Illustration of the Spectrum Hole concept [11].

re-appearance of a primary user. This and other functions of CRs are contained in the basic cognitive cycle shown in Figure 1.3.

When implemented, the CR undergoes the various phases of the cognitive cycle. Thus specifying how the radio learns, as well as responds (adapts) to its operating environment [13].

From this cycle, the radio receives information (senses) it's operating environment by performing direct observation; searching and identifying spectrum holes. The information obtained is then analysed to ascertain characteristics of the environment; i.e. to estimate the spectrum holes. Based on this evaluation, the radio determines its alternatives; selecting an option in a way that improves the evaluation carried out previously [4]. The radio then employs these observations and decisions to improve its operation (adaptation).

As seen from the figure, the initial phase of the cognitive cycle consists of the sensing process. Hence, it is evident that reliable spectrum sensing is the most critical function of the cognitive radio process [14].

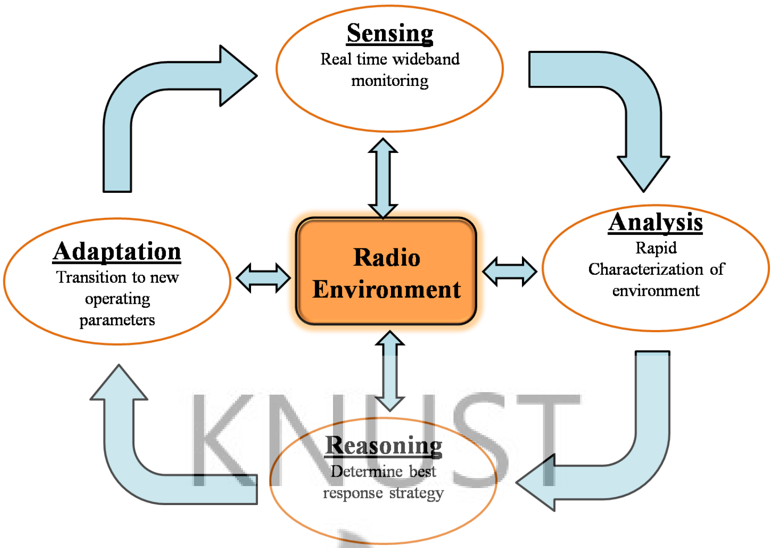

Figure 1.3: The Cognitive cycle [13].

By sensing and adapting to the environment, a cognitive radio will possess the ability to fill in the spectrum holes and serve its users without causing harmful interference to the primary user. Ultimately, a spectrum sensing scheme should give a general picture of the medium over the entire radio spectrum. This allows the cognitive radio network to analyze all parameters (time, frequency and space) in order to ascertain spectrum usage [15].

From the aforesaid, it is essential that there should be efficient spectrum detection techniques that ensure secondary user transmissions, while safeguarding primary users.

The challenge then is that the procedure needs to have as little delay as possible, so that once channels are available, transmission commence immediately. Consequently, one would want as few false detections and missed detections as possible. Three well studied spectrum sensing (SS) techniques are the matched filter, cyclostationary detection and energy detection. Both the matched filter detection and the cyclostationary based detection concern prior knowledge of the primary signal, which is not obtainable in practical scenarios [16] . Heterogeneous wireless communication systems licensed to different primary spectra may overlap within a geographical region. In such events, matched-filter detection or feature detection are too costly for sensing multiple primary spectra [17]. More so, these two techniques require a significant amount of time to detect a signal and there include more complexity in the detection process of the CR. Among them, the energy detection scheme is widely feasible. It does not require *a priori* knowledge of the primary signals and has lower complexity than the other two schemes. The ED method essentially ascertains the energy of a received signal to decide whether a detected signal is noise or a primary user signal. Consequently, the energy detection technique fits well into the general purpose of sensing the spectrum for different wireless communication systems.

1.2 Problem Statement

In opportunistic spectrum access, a failure in the performance of spectrum sensing implies a missed opportunity for secondary users to utilize the whitespace of the spectrum, thereby causing harmful interference to the primary user [17].

The problem considered in this work is to ascertain the performance of a detection scheme that quickly scans a spectrum band to decide on the availability of a primary user. This system will not involve prior knowledge of the primary user signalling scheme and channel information between users.

The performance of a single secondary user (SU) using the energy of a received signal to determine presence of a primary user over fading and non-fading channels is to be investigated. More so, the impact of employing cooperating secondary user nodes over fading channels is also considered.

1.3 Motivation

The challenge of spectrum scarcity and underutilization has gained prospects with opportunistic spectrum access (OSA) and cognitive radio (CR) concepts lately. CR in itself, aside from being a novel concept, presents a worthwhile area of research. This technology offers a solution to the spectral scarcity phenomenon by offering spectral awareness; hence its adaptive application. Since, a radio that identifies its local radio spectral situation to recognize temporarily vacant spectrum has a potential to present higher bandwidth services. It also lessens the need for centralized spectrum management. This, in the long run allows for new technologies in ubiquitous wireless communications. For this reason, spectrum sensing, which involves ascertaining the frequency spectrum for empty bands; and a foremost part of the cognitive cycle, is a stimulating research area.

1.4 Objective

The main objective of this thesis is to assess the performance of the energy detection method for spectrum sensing.

1.4.1 Specific Objectives

The specific objectives of this study are:

1. To study and analyze the performance of the energy detection based spectrum sensing technique in additive white guassian noise (AWGN).

2. To study and analyze the impact of fading channels on the energy detection spectrum sensing technique, viz.;

   (a) Rayleigh

(b) Nakagami,

3. To investigate if cooperative detection has any effect on the performance of the energy detection spectrum sensing technique over fading channels.

1.5 Outline of the study

The rest of this thesis will be as follows. Chapter two presents previous work related to spectrum sensing for oppurtunistic spectrum assess. In chapter three, we discuss the system model for the proposed technique. Chapter four provides an assessment of the method described in Chapter three; by way of simulations. In chapter five, we conclude and put forward recommendation(s) that can lead to further research.

Chapter 2

Review of Literature

In this chapter, the role of spectrum sensing (SS) to the overall opportunistic spectrum access is reiterated. Basic concepts concerning SS are discussed, with a view to deepen understanding. State-of-the-art techniques involved with SS available in literature are described; while identifying research gaps.

2.1 Introduction

The goal of cognitive radio (CR) technology is to improve the spectral efficiency through dynamic access by the unlicensed users [4, 18]. Opportunistic spectrum access (OSA) is one that facilitates exploitation of local spectrum availability without deleterious effect to the primary user [19]. The foundation on which the CR paradigm is built is the OSA. With this paradigm, devices would be capable of sensing the environment over swaths of spectrum to find spectral holes and expeditiously make use of frequency bands that are not occupied by primary users, inducing no harm to the legacy system in the process. Basically, the secondary user identifies "gaps" in the spectrum, known as a *spectrum holes* or *white spaces* and puts them to use. These white spaces originate from partial or no occupations by the incumbent users, i.e primary users (PU) (e.g. Digital TV broadcasters). The secondary communication can be executed once the white spaces are identified in the spatio-temporal domain [20]. The function of spectrum sensing therefore, is to be aware of the spatio-temporal electromagnetic environment by determining the frequencies occupied by the PU.

A number of methods have been proposed for identifying spectrum opportunities in a scanned frequency band. Typically, spectrum sensing is grouped within three main detection approaches, namely, transmitter based detection methods, cooperative detection methods and interference based method. Transmitter detection methods consist of matched filter, cyclostationary and energy detection [21]. These techniques are further classified as [22] coherent, semi-coherent or non-coherent; that is, either having complete, partial or no prior knowledge of the transmitter respectively. Schemes that are cooperative include centralized, distributed and cluster based sensing methods. Whereas transmitter and cooperative detection methods "perceive" spectrum to avoid interference to primary transmitters; interference based detection guarantees minimal primary receiver interference [23]. Figure 2.1 below describes in detail, classification of spectrum sensing techniques. The transmitter and cooperative detection approaches fall under the category of spectrum overlay; wherein SUs only transmit over the licensed spectrum when PUs are not using the band.

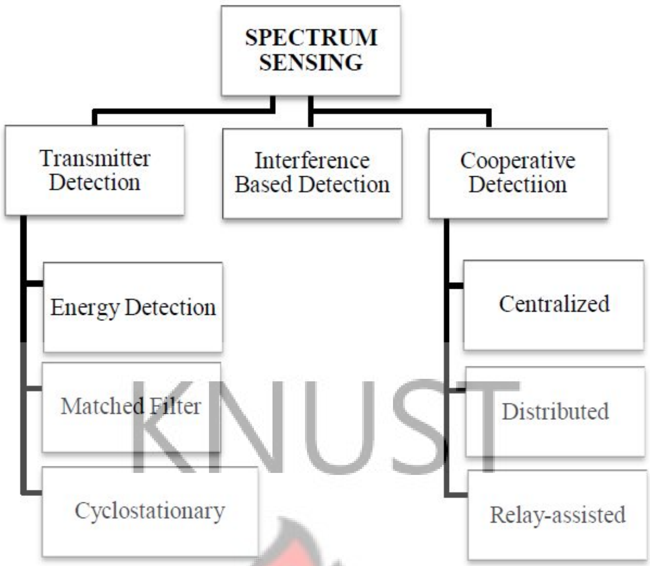

Figure 2.1: Classification of Spectrum Sensing Techniques [21].

In the next section, a review of relevant works undertaken in the area of SS as found in literature is described.

2.2 Transmitter Detection Methods

An efficient approach to identify spectral opportunities with low infrastructure requirement is to detect the primary receiver within operative range of a secondary user (SU). Practically however, this is not feasible as the SU cannot locate a receiver since it is not intelligent enough. Hence, spectrum sensing methods rely on detecting the primary transmitter [21]. With this, a primary user transmitter is detected on the basis of the received signal at the secondary user end. The primary transmitter detection model represents analysis of the received signal at the secondary user. In its simple form, the idea is to find primary transmitters operating at a given time by using local measurements and observations. With these technique, the SU examines the signal strength generated from the PU to exploit the free space (whitespace) within the channel.

Analytically, when the decision on the availability of a primary user is to be made, it is reduced to an identification problem [15]. This is formalized as an hypothesis test as:

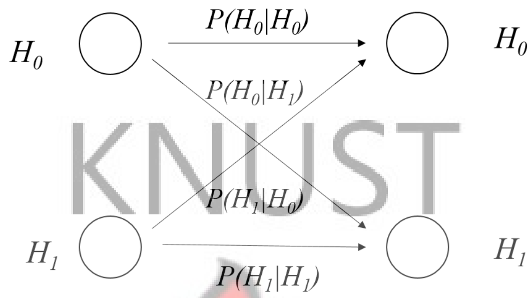

Figure 2.2: Hypothesis test with possible outcomes and their corresponding probabilities.

$$x(k) = \begin{cases} n(k), & H_0 \\ h(k)s(k) + n(k), & H_1 \end{cases} \tag{2.1}$$

where, $x(k)$ represents the sample to be analyzed at instant k, $h(k)$ denotes the channel gain at each instant k, $s(k)$ represents the signal to be detected and $n(k)$ is noise (of variance σ^2) in the channel. H_0 is the null hypothesis; representing a sensed state with an absence of the licensed user signal. H_1 denotes the existence of a licensed user signal within the spectrum under consideration. From Figure 2.2, four possible cases can be defined for the detected signal;

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

Case 2 is known as a correct detection, whereas cases 3 and 4 are termed a missed detection and false alarm respectively.

The goal of the signal detector is to achieve correct detection all the time. However, this cannot be accomplished absolutely in practice because of the statistical nature of the problem. Therefore, signal detectors are designed to function within minimum error levels. A prominent issue for spectrum sensing is missed detection; as it implies interfering with the primary system. Also, the false alarm rate has to be kept as low as possible, to enable the system exploit possible transmission opportunities.

The performance of the spectrum sensing technique is influenced by the probability of false alarm, $P_{FA} = P(H_1|H_0)$, an important metric forspectrum sensing. Equation (2.1) shows that a reliable method to differentiate a signal form noise is required. Transmitter detection methods under study include the following: energy detection, matched filter and cyclostationary detection [3, 4]

2.2.1 Energy Detection

An appropriate option to ascertain the availability of an active communication link when the transmitted signal structure is unknown consists of using an energy detector [24]. This method is based on the premise that the energy of a signal to be detected is always higher than the energy of the noise. This classic method, referred to as *radiometry* is founded on two assumptions, viz; 1.) that the noise power is known *a priori*; and 2.) the test statistics can be accurately modeled as independent and identically distributed (IID) Gaussian random variables (RVs) [25]. In practice, the ED is suitable when the SU cannot gather sufficient information about the PU signal [21]. This method is more generic (as compared to other methods described later in this section), as receivers do not need prior knowledge of the primary user's signal; by which case it is non-coherent. The ED method is also by far the most versatile means of spectrum sensing because of its low computational and implementation complexities [11].

Originally, this approach was outlined in the classic work by Urkowitz [26], were it is assumed that the signals are deterministic in nature, existing over a flat band-limited Gaussian noise channel and exact noise variance is known *a priori*. By applying the sampling theorem to estimate the received signal energy and from the chi-square statistics of the resulting sum of the squared Gaussian random variables, signal detection in [26] is reduced to a simple identification problem; formalized as a hypothesis test. Based on this assumption, a proposed model for detection of energy in deterministic signals under AWGN in the time domain was presented in [26]; consisting of passing the received signal $y(t)$ through an ideal bandpass filter (BPF) with a center frequency f_o and bandwidth W, with transfer function ;

$$H(f) = \begin{cases} \dfrac{2}{\sqrt{N_0}}, & |f - f_0| \leq W \\ 0, & |f - f_0| > W \end{cases} \tag{2.2}$$

where N is the one-sided noise power spectral density which normalizes if found convenient to compute the false-alarm and detection probabilities using the related transfer function. From these, the signal is then squared and integrated over an interval T, to produce a test statistic, V, compared to a threshold, κ. The receiver makes a decision on the target signal, based on the condition that the threshold is exceeded. The received signal $s(k)$, of the SU is represented by the binary hypotheses, as represented in equation (2.1).

Where $x(k)$ is the transmitted unknown deterministic signal, and $n(k)$ is assumed to be AWGN with zero mean and the variance is known beforehand. H_0 and H_1

correspond to the absence and presence of the primary user respectively. Though the archetype energy detector proposed in [26] addresses detection of unknown deterministic signals buried in Gaussian noise, the analysis carried out therein however concerns the time domain, which makes it difficult to estimate the spectral component.

Since then however, ED analysis has been considered with several modifications in literature. In Shehata et al. [27], the authors propose an adaptive scheme to explore ED based spectrum sensing. This method comprises a side detector applied to monitor the spectrum to improve the detection probability. The system model consists of a PU transmitting a QPSK modulated signal within a $200KHz$ bandwidth. The sampling frequency is set 8 times the bandwidth and a 1024-point FFT is used to compute the received signal energy. Results presented indicate improved execution of spectrum sensing during reemergence of the PU in the wake of the sensing time. Nonetheless, from the choice of bandwidth under consideration, this study is restricted to only frequency modulated (FM) signals. Numerical analysis of the ED method over fading channels is presented by Reisi et al. in [28]. In this work, deviating from exact solutions since there are computationally complex, the authors derive approximate closed form expressions for the probability of detection (P_D) for Nakagami fading channels and also obtain a rule of thumb expression relating the number of samples (sensing time) to the SNRs for a given P_D and P_{FA} regarding Nakagami fading models.

In [14] [26, 29, 30, 31, 32, 33] however, detecting unknown deterministic signals is developed as a binary hypothesis test problem. With this, the detection statistics is based on the Neyman-Pearson criterion, wherein the performance of the system is expressed in terms of false alarm and detection probability. These articles for the most part, deal with the sophistication, while leaving out the reliability and accuracy of these technique. The focus in [34] is shifted towards the sensing latency. The possibility of quickest detection, founded on a statistical test to detect the change of distribution in observations as responsively as possible is applied to reduce the transient time between the two states, while ensuring certain false alarm probability. These methods apply well-known algorithms like the generalized likelihood ratio (GRL) test, parallel cumulative sum (CUSUM) test, windowed GRL e.t.c. In retrospect, the methods of energy detection described in the above studies have no resolution component. Likewise, the sensitivity is critically impeded by the practical restriction from the sampling rate of the analog-to-digital converter (ADC) [14].

With the aim of improving the overall sensing performance while scanning wide frequency bands, [35] proposes another form of this method using rows of filters (filter banks). With this, a collection of N sub-filters is used to divide whole frequency bands of interest into N sub-bands. The i^{th} sub-filter of the bank is used to extract spectral information from the i^{th} subband of interest with a normalized center frequency. It is noteworthy that filters of this nature are not very reliable in implementation since the frequency response of the filter influences the quality of estimated power in the sub-band [21].

In [25], an experimental study of ED based spectrum sensing is realized using a software defined radio testbed. Since the choice of the theoretical threshold relies largely on acquisition of a perfect knowledge of noise power (which is challenging in a real environment), the authors apply a histogram based method to determine an appropriate threshold. The offered method eliminates the need to model the test statistics in energy detection by collecting a sufficiently large number of samples to obtain two histograms of the test statistics under hypothesis H_0 and H_1. Based on these histograms, a threshold, Ph_{th}, is chosen to meet a design criteria of the false-alarm and miss-detection probabilities. The construction of the histogram method however, require large number of samples to ascertain a wide range of noise power in the signal; making selection of these threshold require a considerable amount of time. Added to this, the proposed model functions more like an off-line process; which should be done before energy detection.

Recently, in [36] and [37], detection of signals operating in a band of frequencies is executed by splitting spectrum into multiple channels using a theory of quickest detection. Quickest detection refers to real-time detection of changes as quickly; after they occur. In [36], the authors study a case where single narrowband energy detector node is to sense multiple channels. This detector operates with a predetermined belief factor - based on past primary user action to ascertain which channel to sense in the future. This approach proved to reduce sensing time; ensuring a certain false alarm rate is met. In [37], the authors extend this to a case involving multiple narrowband detectors employed to sense wide band channels, with an assumption that the number of channels are more than the number of detectors. Similar analysis in [36] assumes a *belief factor*, adopted to show more spectrum holes can be harvested, as opposed to concentrating each detector on a particular narrowband at all times. An underlying premise from these studies so far is the dynamic range of detector spanning entire bandwidths, while sensing a narrowband per time. Moreover, this assumptions will involve fast changes in the frequency of the local oscillator which imposes its own limitation to the viability of this approach. More so, the analysis so far relies heavily on accurate knowledge of the distribution of primary user activities to reach an optimum detection.

In as much as several techniques have been propounded in literature for detecting the availability of a signal using a single node, it is apparent that not much work has been done in assessing the performance of the energy detection scheme as a *de facto* standard of spectrum sensing employed for opportunistic access.

2.2.2 Matched-Filter Detection

Unlike energy detection, a matched filter (MF) is a linear filter designed to maximize the output signal-to-noise ratio for a given input signal [38]. With this scheme, secondary users (SU) require complete knowledge of the PU transmitted signal. These information includes modulation format, carrier frequency, order, pulse shape, and packet format, are to be known to the secondary user beforehand [39]. These features are used to detect and implement a MF when primary users have pilots, preambles, synchronization words or spreading codes, leading to coherent detection. A matched-filtering process is equivalent to a correlation scheme; wherein a signal is convolved with a filter whose impulse response is a mirror and time shifted version of the reference signal [40]. In operation, a MF convolves the received signal $r(t)$ with a time-reversed version of the known signal as;

$$r(t) \otimes s(T - t + \tau)$$

where T refers to a symbol time duration and τ is a shift in the known signal. The output of a MF, M is compared with a threshold factor κ , to decide the presence or absence of a PU. [38]. Typically, an MF is implemented digitally, and

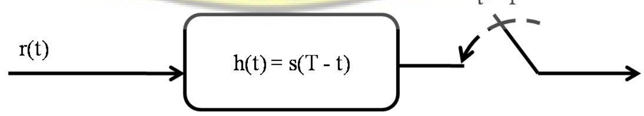

Figure 2.3: Realization of a Matched-filter detector for sensing a PU

its realization is illustrated in Figure 2.3 [41].

An advantage of the MF is that it requires less time to achieve detection; however, false detection occurs when incorrect information concerning the transmitted signal is available at the SU end. A significant drawback of this technique is that an SU would require dedicated receivers for every primary user class. Another demerit of this scheme is the large amount of power consumed as several receiver algorithms relating to the various technology schemes are executed for detection [3].

So far, research work involved with this method is based to a large extent on tackling the disadvantages posed by the conventional design of an MF. In [42] a reconfigurable matched-filter based spectrum is proposed to tackle the flaws associated with the traditional MF design. The generic filter method is the option adopted. In this set up, the coefficient set of the generic filter is changed periodically to scan spectrum of the wireless channel associated with each standard. The effectiveness of this technique relies on reconfiguring the filter to implement the numerous communication standards available. In contrast, weighing the variability of the filtering requirements for different standards, the generic filter will have to be designed for the worst case to accommodate all standards. Aside this, the features of generic designs are slow and large with some degree of power consumption, making a generic implementation of the filtering block less attractive. The second option implemented is a design of optimized individual filters for each wireless standard; termed "space-multiplexing". Nonetheless, this would increase the size of the circuitry, not scalable with a number of standards; while power consumed is not featured in the final analysis. The authors in [43] apply MF spectrum sensing approach to sense the presence of a digital television (DTV) signal. First, the pilot tone is detected by passing the DTV signal through a delay-and-multiply circuit. A decision is reached if the squared magnitude of the output signal is larger than a threshold; by which case presence of a DTV signal is established. But in the generalized SS scenario however, use of a MF can be severely limited since complete information of the tranmitted PU signal is hardly available. In [44], a MF is adapted to sense unused spectrum in a WLAN (IEEE802.11a) by exploring the signals presence in minimum time. This is executed by incorporating an optimal threshold selection that increases sensing accuracy and interference reduction produced by the secondary network.

From the foregoing, it is apparent that [3] this method is only applicable to systems with known signal patterns, such as wireless metropolitan area network (WMAN) signals, thus this method is often referred to as a waveform-based type of sensing; since it works on the signals characteristics. A challenge for this type of detector occurs often when it does not have information about the PU signal, making it suboptimal for efficient spectrum sensing for opportunistic access.

2.2.3 Cyclostationary Feature Detection

When signals exhibit statisitical attributes (like mean, autocorrelation e.t.c.) that change periodically with time, there are termed *Cyclostationary Features* (CF) [45]. Usually, [20] wireless transmissions present cyclostationarity features depending on their data rate, modulation type, and carrier frequency. Most communication signals can be modelled as cyclostationary, since there exhibit underlying periodicities in their signal structures. Cyclostationary feature detection (CFD) is a method that applies cyclostationary features to detect a signal. The identification of a unique set of characteristics particular to a radio signal for a wireless access system can be used to detect the system based on its cyclostationarity features. These features have periodic statistics and spectral correlation not obtained with interference signals or stationary noise. Thus exploiting this periodicity in the received primary signal to identify the presence of primary users makes this method possess a high noise immunity compared to other spectrum sensing methods [46]. This theory conceptualises the fact that man-made signals possess hidden periodicities such as the carrier frequency, symbol rate or chip rate, which can be regenerated by a sine-wave extraction operation, thus producing features at frequencies that depend on the built-in periodicities [47]. A basic analysis of this theory will suffice to help understand its application.

A signal $x(t)$ is said to be cyclostationary, if its mean and autocorrelation function $E_x(t)$, $R_x(t,\tau)$ are periodic [20, 48], expressed respectively by,:

$$E(x) = \mu(t + mT_o) \tag{2.3}$$

and

$$R_x(t,\tau) = \pi(t + mT_o, \tau) \tag{2.4}$$

where, t is the time index, τ is the lag associated with the autocorrelation function and m is an integer. The periodic autocorrelation function is expanded by Fourier series, as,

$$R_x(t,\tau) = \sum_{\alpha=-\infty}^{\infty} R_x^{\alpha}(\tau)\exp(2\pi j\alpha t) \tag{2.5}$$

where,

$$R_x^{\alpha}(\tau) = \lim_{T_0\to\infty}\frac{1}{T_0}\int_T x(t-\frac{\tau}{2})x(t+\frac{\tau}{2})\exp(-2\pi j\alpha t)dt \tag{2.6}$$

The term in (2.6) is the *cycle autocorrelation*, and for a cyclostationary process with period T_0, the function $R_x^{\alpha}(\tau)$ possesses a component at $\alpha = \frac{1}{T_0}$. But, for a stationary process such as noise, (2.6) will be zero-valued. Employing the Wiener relationship (i.e taking the Fourier series representation with respect to τ), results in the cyclostationary spectrum density (CSD), or the spectral correlation function (SCF), which when evaluated leads to,

$$S_x^\alpha(f) = \lim_{\tau\to\infty} \int_{-\tau}^{\tau} R_x^\alpha(\tau)\exp(-j2\pi f\tau)d\tau \tag{2.7}$$

The SCF in (2.7) is a function of frequency, f, and the cycle frequency α, which makes it possible for cyclostionarity feature to be detected in the cycle frequency domain. Since different types of signals have different non-zero cyclic frequencies, they can be identified from their signature. To ease computing of the SCF, (2.7) is expressed alternatively as,

$$S_x^\alpha(f) = \lim_{T\to\infty}\lim_{T_0\to\infty} \frac{1}{T_0 T}\int_{-T/2}^{T/2} X_{T_0}(t, f+\frac{1}{\alpha})X'_{T_0}(t, f-\frac{1}{\alpha})dt \tag{2.8}$$

The term $X_{T_0}(t, f)$ represents the short time Fourier transform of $x(t)$ with bandwidth $\frac{1}{T}$, where $X'_{T_0}(t, f)$ is the complex conjugate of $X_{T_0}(t, f)$ given by ;

$$X_{T_0}(t, u) = \int_{t-T_0/2}^{t+T_0/2} x(v)\exp(-2j\pi fv)dv \tag{2.9}$$

The expression (2.8) is known also as the time smoothed SCF which theoretically achieves true SCF for $T >> T_0$. The CSD is a two dimensional transform that consists of two variables: the cyclic frequency and the spectral frequency, f, [20]. It is clear from the foregoing that the cyclic spectral correlation function (or SCF) is the parameter employed for detecting primary user signals with this method. When SCF is plotted, the occupancy status of the spectrum can be determined. If a primary user signal is present in the operating frequency range, the SCF presents a peak at the center. The peak will be absent in a case where there is no primary user signal present in the frequency range of interest [46]. Also, the SCF can be used to ascertain the type of modulation scheme applied to the primary user signal. This is accomplished by considering the number of secondary peaks at the double frequencies. If the modulation scheme employed is BPSK, there will be single secondary peaks when the operating frequency is doubled.

Unlike the matched filtering approach that involves close synchronization with the signal of interest, cyclostationary analysis does not require frequency or phase synchronization, making it an attractive approach to detection of signals whose carrier frequencies and symbol timing are unknown [49]. Comparatively, the strength of this method lies in its strong performance under low SNR, since noise is totally random and does not present a form of periodic behavior [50, 51].

Using cyclostationary analysis as a technique to accomplish signal detection was described in [45]. In [52], the authors study spectrum detection in a low SNR environment applying the noise rejection property of the cyclostationary spectrum. This is computed by measuring the cyclic spectrum of the received signal. Statistics concerning the spectrum of the stationary white Gaussian process were fully analyzed. An application to the IEEE 802.22 WRAN[1], alongside analytic derivation of the probability of false alarm is also presented. Since the stationary Gaussian process has a zero-valued spectral correlation density function (SCD) at nonzero frequencies, the desired signal is detected by computing the SCD - provided the signal is cyclostationary - such that its cyclic spectrum is not identically zero at some nonzero cyclic frequency. The authors in [48] present a theoretic and hardware implementation of this method, which involves spectral estimation of the cyclostationary spectrum density (CSD) . This is executed by selecting an appropriate size of the FFT; since from (2.8), the number of correlations is largely determined by the size of the FFT. In this paper, CSD estimation is performed

[1]The IEEE802.22 is a standard for Wireless Regional Area Network (WRAN) using whitespaces in the TV frequency spectrum.

along the axis of zero cyclic frequencies and the axis of zero spectral frequency i.e. (2.8) is evaluated at a set of discrete frequency pairs $(\{\alpha_k, f_j\})$. Since practical estimation can only be performed within a limited time duration, CSD is estimated by performing a sliding N point FFT, and correlating the appropriate spectral components. For the hardware implementation, use is made of field programmable logic arrays (FPGA).

With this type of analysis however, a tradeoff exists between the size of FFT and hardware cost. Usually, an FFT with a large data size provides more accuracy, more averaging time for CSD estimation, but with an increase in cost of hardware. It is also noteworthy that CSD estimation is a two dimensional transform, making it computationally complex.

Sutton et al. in [49] propose an alternative approach to feature detection using *signatures* embedded in a signal to solve a number of challenges associated with dynamic spectrum access applications; especially receiver complexity. Using a flexible cognitive radio platform, implementation of a full OFDM-based transceiver using cyclostationary signatures is presented and the system performance is examined from experimental results. Although, methods presented therein are OFDM specific, similar techniques can be developed for any type of signal. A hardware implementation of the CFD technique is presented in [50]. A detector for OFDM signals based on cyclostationary features is presented in [53]; this exploits the inherent correlation of OFDM signals obtained by data repetition in the cyclic prefix; i.e. using knowledge of the length of the cyclic prefix and length of the OFDM symbol. The authors demonstrate that detection performance improves by $5dB$ in applicable cases.

In [54], the problem existent in many systems, where for particular applications, statistical features may not be the same for two adjacent periods, but change smoothly is considered. The periodicity that appears in the aforementioned process does not necessarily extend to a pure cyclostationary process, but leads to an almost cyclostationarity which presents a limitation using cyclostationary feature detection approach. The authors propose a novel estimator for *almost* cyclostationary signals. Even as the CFD has advantages that include reduced sensitivity to noise and interfering signals, as well as the ability to extract key signal parameters - including carrier frequencies and symbol rates; on the flip side, an analysis of cyclostationarity is computationally intensive, requires significantly longer observation time and processing resources of the SU may be limited for the needed signal processing tasks [20, 46]. Added to this,when an insufficient number of samples are utilized, the detection performance will degrade due to the poor estimate of the cyclic spectral density.

From the review of the transmitter detection methods so far presented, it is apparent that though the energy detection method is “crude” [21]; but based on the evaluation criteria mentioned earlier (i.e. latency, complexity etc.), it possesses an edge over the more complex methods like cyctostationary feature and matched filter detectors, that require absolute knowledge of the PU transmitted signal.

Also, from a practical implementation perspective [11], both matched-filter and cyclostaionary feature detection techniques are primarily for narrowband sensing, whereas energy detection can be applied to wideband sensing.

2.3 Interference Based Detection

This theoretical method employs an interference temperature model; which is a measure of how well a radio operating within a particular modulation scheme and protocol can tolerate interference in its spectrum space [55]. This follows the fact that signal power received at a primary receiver reduces exponentially with distance; continuously till it reaches a level of the noise floor [23]. Though a primary transmitter still operates at this point, the receiver handles this process as noise and not transmission. This makes it possible for a secondary user to utilize the channel, since no interference is introduced to the primary users' communication (as the primary receiver is not in receiving mode). Above the maximum

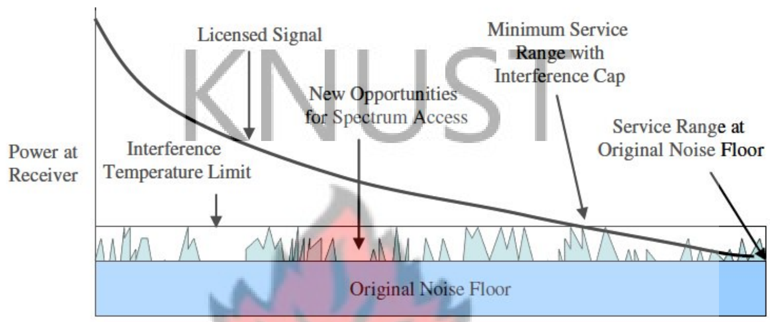

Figure 2.4: Interference temperature model [4].

noise level, an interference cap is introduced, beneath this threshold, the primary receiver will treat this transmission as noise. An illustration of the interference temperature model is shown in Figure 2.4 above. The SU may exploit the channel if the detected primary signal level is below the interference temperature limit. More so, if the power of transmission of an SU stays below the interference gap, it may utilize any frequency parameter of its choice. With this approach, it is hypothesized that the SUs will be allowed to transmit concurrently with the PUs under stringent interference avoidance constraints; wherein it is categorized as a spectrum underlay scheme.

It is noteworthy nonetheless, that this method is far more challenging; since the prime problem faced with an implementation of this technique will be in determining specific receiver interference temperature levels for the various communication standards.

Recently however, in [21], this approach to spectrum sensing was reportedly analysed and declared to be non-implementable, thus no further survey on this method will be conducted in this work.

2.4 Cooperative Detection

In cooperative detection, multiple SUs collaborate in a centralized or decentralized manner to ascertain spectrum holes for opportunistic access. Each cooperating node within this context employs locally, any of the sensing methods previously described, while sharing the raw/refined sensing information with other node(s); dependent on a selected cooperation strategy [21] . This concept of collaboration is considered since effects of shadowing, multipath fading and receiver uncertainty pose severe challenges to single user transmitter detection approach in SS [11]. A depiction of these phenomenon is depicted below and described in detail afterwards.

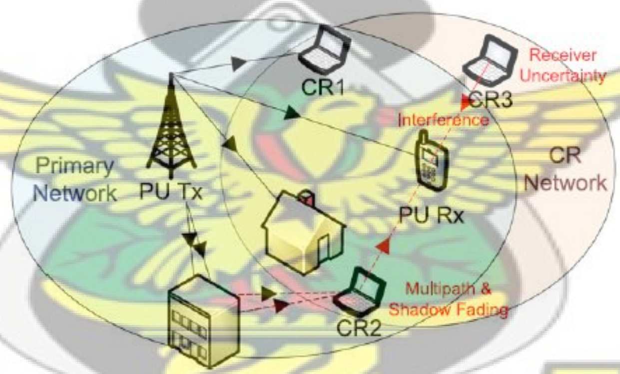

Figure 2.5: Receiver uncertainty and multipath/shadow fading [11].

From the figure 2.5 above, CR1 and CR2 are within range of the primary transmitter (PU TX1) while CR3 is not. As a result of the obstruction from the house and due to multiple copies of the attenuated signal being sent, CR2 suffers multipath and shadowing problems, such that signals from the PU Tx may not be detected correctly. CR3 on the other hand is unaware of the transmission fom PU Tx and the existence of primary receiver (PU Rx), consequently, transmission from CR3 may interfere with reception at the PU Rx; this phenomenon is known as the *receiver uncertainty problem.*

However, owing to spatial diversity, it is unlikely that all SUs spread in space within a network will simultaneously experience receiver uncertainty or fading problems. Since, secondary users that observe a strong signal from the PU Tx, like CR1 in the figure, can sense and communicate sensed result to other users. This collaborative paradigm should tackle flaws in observation at the other users considerably. By this technique of cooperation amongst users, robustness is achieved without severe demands on individual radios; thus enhancing effective primary detection [56].

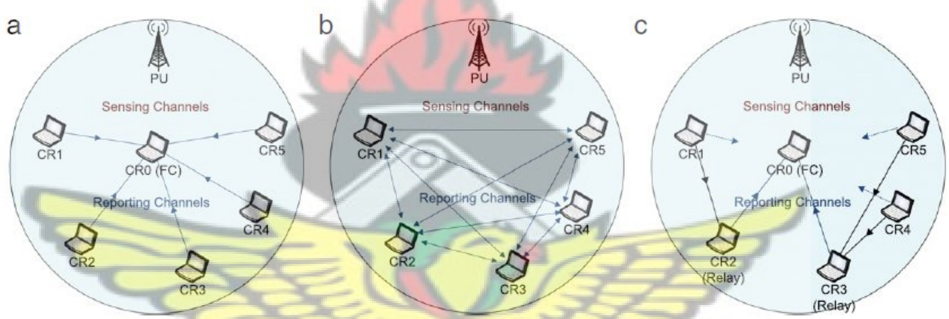

Figure 2.6: Cooperative sensing techniques: (a) Centralized, (b) Distributed (decentralized), and (c) relay assisted [11].

For CSS, SUs require two channels for local sensing to arrive at a decision. Initially, SUs establish a link with the primary transmitter to carryout local sensing; this link between primary transmitter and the various cooperating SUs is known as the *sensing channel.* To share local spectrum sensing data with each other or the fusion center (FC) requires a *control* or *reporting channel.* So far, a medium access protocol coordinates the shift between these two channels [21].

Considering the mode of collaboration between sensing nodes in a detection scheme,CSS is broadly categorized as; centralized, distributed and relay assisted; based on how collaborating SUs convey sensing data within the network [11]. These three cases of cooperative sensing are depicted in Figure 2.6 above. Essentially CSS consists of a series of actions requiring *local sensing, reporting* and *information fusion*. The following subsections highlight the distinguishing features of the various collaborative strategies.

2.4.1 Centralized Cooperative Detection

In a centralized structure, a central unit, designated the *fusion center* (FC) or basestation (BS), determines eventual availability of spectrum holes after collating local SS information from cooperating SUs [56]. This opportunity is either broadcast to all SUs or the FC itself controls traffic by managing detected spectrum usage opportunity in an optimum fashion. The central node (FC) could be an access point (AP) in a wireless local area network (WLAN) or a base station (BS) in a cellular network; while in ad hoc networks, any node - once identified - can act as a master to coordinate CSS. In operation, the FC selects a control channel for the transmitter and tasks the various SUs to send their local sensing results via a reporting channel. It is envisaged, cooperating SUs would send collected data to the FC, allowing it perform a *data fusion* to decide the presence of a primary signal; or they could each send individual decisions and the FC conducts *decision fusion* to assume a decision. For the scenario where the SU sends complete local sensing data, the fusion process is termed soft combining. When the SU quantizes the local sensing information before sending to the FC, this fusion process is termed quantized soft combining. For hard combining fusion, an SU makes decision after sensing and sends one bit as its decision to the FC [57].

2.4.2 Research work on Centralized Detection

In [43], employing CSS to reliably detect primary users is considered by exploiting multiuser diversity; with a criteria of an SU possessing the highest SNR value being selected as the cluster head. Due to the varying distances from the PU, the value of the SNR changes among the SUs; this forms the underlying criteria adopted in this scheme. The authors also present a two-layer model in implementing this technique so as to combat fading in the channels. Though results show a low bandwidth control channel for all spectrum sensing techniques, this method presents a challenge in practical implementation since the time involved in sensing will be prolonged, as it involves traversing two separate layers.

In [58], cyclostationary feature detection is proposed for CSS by applying the generalized likelihood ratio test (GLRT) (which is a complex hypothesis test involving the use of assumed parameters selected by the maximum likelihood estimates [11]). This scheme enables detection of cyclostationary signals for multiple cyclic frequencies. A censoring technique employed for each cooperating user conveys locally sensed results to the FC. Empirical results presented indicate improved energy efficiency from this approach. In this paper also, the test statistic for data fusion at the FC is developed for cooperative sensing. Regrettably however, the consequence of cyclostationarity resurfaces; prior information of signals to be sensed is required, while the issue of complexity is unresolved.

Cooperative processing trade-off is addressed in [59] for energy detectors, wherein, trade-off is formulated as an optimization problem to minimize the total sensing time, subject to constraints of false alarm and detection probabilities. Total sensing time to be minimized include integration time of an energy detector for local processing and reporting time; proportional to the number of cooperating SUs. The results from this work show that, for higher detection sensitivity, a longer integration time is required. This is unlike the general notion of cooperation, wherein an increase in the number of cooperating nodes reduce the required sensing time to achieve the same level of detection sensitivity.

A general weakness of the centralized approach however, is that a FC becomes very critical; making its failure rue the whole concept of cooperation.

2.4.3 Distributed Cooperative Detection

In a distributed cooperation, SUs would not rely on an FC to make a cooperative decision; rather, it is conceived that the SUs communicate within nodes, then converge to a joint (global) decision on the presence or absence of PU in an iterative manner [21]. This is accomplished in three steps defined by a distributed algorithm as follows. First, each cooperating user sends its local sensing data to other users in its neighbourhood (defined by the transmission range of the users). Next, cooperating users combine data with the received sensing information from other users to decide on the presence or absence of a PU based on the local criterion. The shared spectrum observations are usually in the form of soft sensing results or quantized (binary/hard) version of local decisions about spectrum hole availability. In a case where the spectrum hole is not identified, SUs send combined sensing information to other users in the next iteration. These process continues until the scheme converges and a final unanimous decision on spectrum availability is achieved. In this manner, each SU in a distributed scheme partially plays the role of an FC [57]. Figure 2.6(b) depicts cooperation in a distributed mode.

2.4.4 Research work on Distributed Detection

In [60] a distributed CSS scheme for wideband sensing in cognitive radio ad-hoc networks (CRAHNs) is proposed. With this scheme, each SU conducts compressed sensing locally, determines the local spectral estimates, then conveys the spectrum state vectors to its one-hop neighbours. The authors propose a distributed average consensus method, wherein each SU iteratively updates its spectrum state with a weighted sum of the difference values between the SU and its neighbors. From this process, the spectrum state vectors converge to the average statistic at each SU for PU detection. In the same vein, the spectral estimates can be obtained cooperatively by consensus averaging.

In [61], the study in [60] is extended to include spectrum occupied by the SUs, termed *spectral innovation*; in addition to that of the PUs within wideband scenario. The accuracy of estimation is improved by utilizing a spectral orthogonality scheme between PUs and SUs. Based on the work in [60] and [61] a distributed consensus optimization scheme is proposed in [62] for sensing signals in a wideband. After sensed results are compressed, each SU determines an estimate of the instantaneous spectrum by performing an optimized consensus, resulting in enhanced results, which would be broadcast to the various one-hop neighbours. This process is repeated until convergence is reached. The average consensus technique incorporated in the above technique ensures fast convergence; though improvement in time resulting from this approach, is however not considered in the final analysis.

Since sensing signals in multiple bands presents a challenge, [63] introduce an algorithm to tackle detection in a wideband via cooperative spectrum sensing. The proposed technique involves dividing a typical wideband of interest into various sub bands, while a group of SUs are assigned the task of sensing particular narrow subbands. A base station (or FC) is employed in collating results and making final decisions over the full spectrum. Results indicate that the proposed algorithm minimizes time and amount of energy spent for wideband spectrum scanning and effectively detects primary users occupancy status in a wideband spectrum. The algorithmic program presented in this work is purely theoretic, hence ambiguous; since it does not specify a method for local sensing for the various subbands.

The various methods proposed for the application of distributed detection consist of numerous iterations in accomplishing unanimous cooperative decisions, with substantial network information overhead and bandwidth consumption, while increasingly being too complex to implement, thus not aligning with the opportunistic access to spectrum bottom line.

2.4.5 Relay- assisted Cooperative Detection

It is envisaged that under realistic conditions, the sensing and reporting channels in the schemes outlined previously may not function properly. For instance, a particular SU reporting channel may be weak, while its sensing channel strong - arising from shadowing or multipath consequences; yet another SU may possess a strong reporting channel and a weak sensing channel [11, 21] as depicted in Fig. 2.6(c). The relay-assisted detection paradigm provides a scheme where an SU serves as a relay, forwarding sensed information. In [57], the centralized and distributed schema is considered a one-hop cooperation, while the realy-assisted approach is thought of as a multi-hop cooperative scheme.

2.4.6 Research work on Relay- assisted Cooperative Detection

In [64], a theoretic detection performance of an energy detector is considered for channels encountering both multipath fading and shadowing. An analytical framework using data and decision fusion is used to investigate performance; not considering SNR statistics of received primary signals. Under the analysis for data fusion, upper bounds of average detection probabilities were derived for four scenarios: 1) single relay; 2) multiple relays; 3) multiple relays with direct link; and 4) multi-hop relays. The analysis contained in this work is an analytical framework focused on the Rayleigh multipath fading and lognormal shadowing; leaving out other fading models.

Although data and decision fusion models have been employed in earlier works (e.g. in [65]-[64]) to improve the performance and reliability of energy detection with distributed cooperative spectrum sensing, the analysis so far is still limited to a range of known bandwidth. This in itself presents a research gap to be explored.

2.4.7 Conclusion

So far, it is apparent that for transmitter based detection, energy detection method is the most viable approach to sensing spectrum for oppurtunistic access; since, not only does the pair of matched filter and cyclostationarity feature detection methods present some degree of complexity, both of this techniques require prior information on the signal type to be detected. In the same vein, for CSS, techniques available in literature have not sufficiently assessed the capability of the traditional energy detector.

Consequently, in this study, ED for detecting signals in a licensed band is described and its performance evaluated for both fading and non-fading environments.

In the end, this method will prove to be an executable option for the detection of narrow and heterogeneous wideband signals traversing spectrum spread over multiple adjacent narrow bands.

Chapter 3

Methodology

This chapter presents the system model of energy detection and explains the performance metrics. Also presented in this chapter are mathematical derivations to support the analysis adopted for both the case of a single detector and the case of a network of cooperating nodes.

3.1 System Model

In implementing an energy detector, the received signal $x(t)$ is filtered by a band pass filter (BPF), followed by a square law device. The band pass filter serves to reduce the noise bandwidth. Hence, noise at the input to the squaring device has a band-limited, flat spectral density. The output of the integrator is the energy of the input to the squaring device over the time interval T. Next, the output signal from the integrator (the decision statistic), Y, is compared with a threshold, κ, to decide whether a primary (licensed) user is present or not. Decision regarding the usage of the band is made by comparing the detection statistic to a threshold value κ.

Figure 3.1 overleaf shows a block diagram of an energy detector.

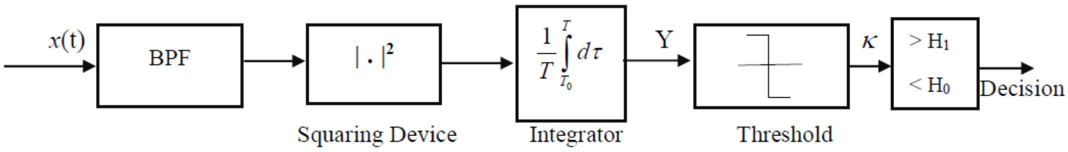

Figure 3.1: Block diagram of an energy detector

Analytically, determining the sample signal $x(t)$ is reduced to an identification problem, formalized as an hypothesis test; H_0 and H_1.

H_0 implies an absence of the signal, whereas H_1 denotes presence of the signal. This is represented by;

$$x(t) = \begin{cases} n(t), & H_0 \\ h \ * s(t) + n(t), & H_1 \end{cases} \tag{3.1}$$

where,

$x(t)$ is the sample to be analysed at each instant t,

$n(t)$- is additive noise; assumed to be white Gaussian noise (AWGN)(with samples having zero-mean and variance σ^2),

h - is the complex channel gain between the primary signal transmitter and the detector.

$s(t)$ - is the transmitted signal to be detected.

The goal is to observe the sample signal $x(t)$, then have some rule decide the correct hypothesis based on the test statistic being either greater or less than the threshold.

Characterising the performance of such a decision rule is realised using some metrics.

3.2 Performance Metrics

The correctness of the spectral availability information is defined using sensing quality parameters. This feature make up the performance metrics. Sensing the performance of the energy detector is specified by the following general metrics:

1. The *probability of detection*, (P_D).

2. The *probability of false alarm* , (P_{FA}),

3. The *probability of missed detection* , (P_M).

In opportunistic spectrum sensing, the **probability of detection** specifies that a detector makes a correct decision that a channel is occupied (H_1). The (P_D) is an indicator of the level of interference protection provided to the primary user. Hence, a large P_D denotes exact sensing; which translate to small chance(s) of interference.

A false alarm event occurs when the detector assumes H_1; when the right decision is H_0. The probability of this occurrence is specified as a **probability of false alarm**. When a false alarm event occurs, the SU would not exploit the free spectrum, thus missing a chance to utilize the free channel. P_{FA} should be kept as small as possible in order to prevent underutilization of transmission opportunities. The performance of the spectrum sensing technique is usually influenced by the probability of false alarm , since this is the most influential metric [15].

The probability of declaring the spectrum space vacant H_0, when it is indeed occupied H_1, is referred to as the **probability of missed detection** (P_M). A high P_M implies an increase in the chance of interference between the PU and the SU. If the detection fails, or a "miss detection" occurs, the SU initiates a transmission , resulting in interference with the PU signal; contravening the opportunistic access concept.

In essence, the spectrum sensing method should record a high probability of detection (low miss detection probability) and low probability of false alarm.

3.3 Performance Measurement

The receiver performance is quantified by depicting the receiver operating characteristics (ROC) curves. This curves serve as a tool to select and study the performance of a sensing scheme. ROC graphs are preferred as a performance measure, since simple classification accuracy do not contain much detail, hence is a poor metric for measuring performance [66]. ROC graphs are employed to show trade-offs between detection probability and false alarm rates, (i.e. P_D versus P_{FA}), thus allowing the determination of an optimal threshold. Complementary ROC curves depict plots of probability of miss-detection ($P_M = 1 - P_D$) versus the probability of false-alarm (P_{FA}).

These curves enable exploration of the relationship between sensitivity (probability of detection) and specificity (false alarm rate) [3]. To plot ROC curves, one parameter is varied while the other is fixed. This enables the study of various scenarios of interest.

3.4 Derivation of P_D and P_{FA}

The noise $n(t)$ (from (3.1)) is considered a bandpass process consisting of two (2) components; the in-phase noise component, $n_i(t)$ and quadrature phase component, $n_q(t)$, whose sample function is written as [68];

$$n(t) = n_i(t)\cos n_c t - n_q(t)\sin n_c t \tag{3.2}$$

where n_c is the angular frequency. If $n(t)$ is restricted to bandwidth B_w, with power spectral density N_0, then $n_i(t)$ and $n_q(t)$ are considered to be two low pass processes with bandwidth less than $B_{w/2}$. The power spectral density of each is equal to $2N_0$. When a sample function has bandwidth B, duration T, it is described approximately by a set of values $2BT$ or its degree of freedom is equal to $2BT$. Therefore, $n_i(t)$ and $n_q(t)$ each possess degrees of freedom d, equal to $2B_wT$ [69]. Applying the approximation in [70], that;

$$\int_0^T n^2(t)dt = \frac{1}{2}\int_0^T [n_i^2(t) + n_q^2(t)]dt \tag{3.3}$$

(since $n_i(t)$ and $n_q(t)$ are considered low-pass processes), and from the sampling theorem, the noise process is expressed as [71];

$$n_i(t) = \sum_{j=-\infty}^{\infty} c_{jk} \sin c(B_w t - j) \tag{3.4}$$

where $\sin cx = \frac{\sin \pi x}{\pi x}$ and $c_{jk} = n_i(\frac{k}{B_w})$ are Gaussian random variables with zero-mean and variance $\sigma_j^2 = 2N_0B_w, \nabla\ j$. And using the fact that [26];

$$\int_{-\infty}^{\infty} \sin c(B_w t - j) \sin c(B_w t - m)dt = \begin{cases} \frac{1}{B_w}, & j = m \\ 0, & j \neq m \end{cases} \tag{3.5}$$

Thus, from (3.4) and (3.5) we obtain,

$$\int_{-\infty}^{\infty} n_i^2(t)dt = \frac{1}{B_w}\sum_{j=-\infty}^{\infty} c_{ij}^2 \tag{3.6}$$

Since $n_i(t)$ has B_wT degrees of freedom over the interval $(0, T)$,

$$n_i(t) = \sum_{j=1}^{B_wT} c_{ij} \sin c(B_w t - j) \qquad 0 < t < T \tag{3.7}$$

Also, the integral $\int_{-\infty}^{\infty} n_i^2(t)dt$ over the interval $0, T$ can be written as;

$$\int_0^T n_i^2(t)dt = \frac{1}{B_w} \sum_{j=1}^{B_wT} c_{ij}^2 \tag{3.8}$$

likewise,

$$\int_0^T n_q^2(t)dt = \frac{1}{B_w} \sum_{j=1}^{B_wT} c_{qj}^2 \tag{3.9}$$

substituting $\frac{c_{ij}}{\sqrt{2B_wN_0}} = d_{ij}$ and $\frac{c_{qj}}{\sqrt{2B_wN_0}} = d_{qj}$ in (3.8) and (3.9), and using (3.3), produces [26];

$$\int_0^T n^2(t)dt = \left[\sum_{j=1}^{B_wT} d_{ij}^2 + \sum_{j=1}^{B_wT} d_{qj}^2\right] \cdot N_0 \tag{3.10}$$

In the same vein, considering the transmitted signal $s(t)$, as a band-pass process, we have that:

$$\int_0^T s^2(t)dt = \left[\sum_{j=1}^{B_wT} b_{ij}^2 + \sum_{j=1}^{B_wT} b_{qj}^2\right] \cdot N_0 \tag{3.11}$$

or,

$$\sum_{j=1}^{B_wT} (b_{ij}^2 + b_{qj}^2) = \frac{E_s}{N_0} \tag{3.12}$$

where $b_{ij} = \frac{s_i(\frac{j}{B_w})}{\sqrt{2B_wN_0}}$, $b_{qj} = \frac{s_q(\frac{j}{B_w})}{\sqrt{2B_wN_0}}$ and $E_s = \int_0^T s^2(t)dt$ is the energy of the signal. The output of this filter is then squared and integrated over a time interval T to yield a measure of the energy of the received waveform (i.e. $X = \frac{1}{T}\int_0^T x^2(t)dt$). The output of the integrator, denoted Y, is the test statistic (testing the hypotheses H_0 and H_1) [24, 26];

$$Y = \frac{1}{N_0} \int_0^T x^2(t) dt \tag{3.13}$$

Under Hypothesis H_0 (with the primary signal absent), the received signal is only noise, i.e. $x(t) = n(t)$. Applying (3.10), the test statistic Y, is written as:

$$Y = \sum_{j=1}^{B_w T} (d_{ij}^2 + d_{qj}^2) \tag{3.14}$$

The test statistic under H_0 is said to be chi-square distributed with $2B_wT$ degrees of freedom, i.e. $Y \sim \chi^2_{2d}$ [24]. The chi-squared distribution is used to test for significant difference between the expected and observed result under the null hypothesis.

Under Hypothesis H_1, the received signal is a sum of the signal and noise, i.e. $x(t) = s(t) + n(t)$. Therefore, using equations (3.3) - (3.11) we get;

$$\int_0^T x(t) dt = \left[\sum_{j=1}^{B_w T} (d_{ij} + b_{ij})^2 + \sum_{j=1}^{B_w T} (d_{qj} + b_{qj})^2 \right] \cdot N_0 \tag{3.15}$$

Applying the same approach as above (i.e. using equation (3.13) and (3.15) , the test statistic is written as;

$$Y = \left[\sum_{j=1}^{B_w T} (d_{ij} + b_{ij})^2 + \sum_{j=1}^{B_w T} (d_{qj} + b_{qj})^2 \right] \tag{3.16}$$

The test or decision statistic (output of the detector) under the case of H_1 is said to have a non-central chi-square distribution with $2B_wT$ degrees of freedom. Non-central chi-squared distribution offers a statistical test the chance to estimate departures from the null hypothesis. This presents an admissible hypothesis alternative to H_0.

The non-centrality parameter ψ, is given as $\frac{E_s}{N_0}$ [26]. Defining the SNR γ, in terms of the non-centrality parameter, gives [71];

$$\gamma = \frac{E_s}{N} = \frac{E_s}{2N_0} = \frac{\psi}{2} \tag{3.17}$$

which is $\psi = 2\gamma$.

Therefore, the decision statistic for the hypothesis H_1 (i.e. when the primary signal is present) is $Y \sim \chi^2_{2d}(\psi)$; also $Y \sim \chi^2_{2d}(2\gamma)$.

Following the notations so far, the decision statistic for the energy of a signal is;

$$Y \sim \begin{cases} \chi^2_{2d}, & H_0 \\ \chi^2_{2d}(2\gamma), & H_1 \end{cases} \tag{3.18}$$

The probability density function (PDF) for a chi-squared distribution; for this case Y is (from [24]);

$$f_Y(y) = \begin{cases} \frac{1}{2^d\Gamma(d)} y^{d-1} e^{-\frac{y}{2}}, & H_0, \\ \frac{1}{2}\left(\frac{y}{\psi}\right)^{\frac{d-1}{2}} e^{-\frac{\psi+y}{2}} I_{d-1}(\sqrt{\psi y}), & H_1, \end{cases} \tag{3.19}$$

where $\Gamma(.)$ is the gamma function (its definition is given in Appendix A) and $I_v(.)$ is the vth-order modified Bessel function of the first kind.

3.4.1 Probability of Detection for AWGN Channel

The additive white Gaussian noise (AWGN) is a channel model where the only impairment to communication is noise; with a constant spectral density. With this model, noise possesses zero mean, and is assumed to be *white* over the bandwidth of consideration; i.e. samples of the noise process are uncorrelated. These model does not account for channel impairments (hence it is considered a non-fading model). It produces insight to the behaviour of a system before any other phenomenon is conceived.

The probability of detection is the probability that H_1 is selected when a signal is present. Probability of detection, P_D and false alarm P_{FA} for a given threshold (κ), are represented respectively by [24]:

$$P_D = P(Y > \kappa | H_1) \tag{3.20}$$

$$P_{FA} = P(Y > \kappa | H_0) \tag{3.21}$$

where κ is the decision threshold. Expressing the P_D and P_{FA} in terms of the probability density function yields;

$$P_{FA} = \int_{\kappa}^{\infty} f_Y(y)dy \tag{3.22}$$

applying (3.19);

$$P_{FA} = \frac{1}{2^d \Gamma(d)} \int_{\kappa}^{\infty} (\frac{y}{2})^{d-1} e^{-\frac{y}{2}} dy \tag{3.23}$$

also, substituting $\frac{y}{2} = t$, $\frac{dy}{2} = dt$ and changing the limits of (3.23);

$$P_{FA} = \frac{1}{\Gamma(d)} \int_{\frac{\kappa}{2}}^{\infty} (t)^{d-1} e^{-(t)} dt \tag{3.24}$$

or

$$P_{FA} = \frac{\Gamma(d, \frac{\kappa}{2})}{\Gamma(d)} \tag{3.25}$$

where $\Gamma(d, x)$ is the incomplete gamma function, defined by $\Gamma(d, x) = \int_{x}^{\infty} t^{d-1} e^{-t} dt$ [72]. Since the signal power is unknown, the false alarm probability P_{FA} is set to a constant; applying (3.25), the detection threshold Y can be determined.

The value of κ in real communication systems is influenced by the system requirements. Research efforts like [73] choose a threshold κ in a way the P_{FA} is bounded by a target value. From (3.25), P_{FA} depends on two parameters: time-bandwidth product d and the threshold κ. Thus the value of κ is not related to SNR (γ).

Typically, P_{FA} is given a value between $10^{-1} - 10^{-2}$. The IEEE 802.22 standard recommends $P_{FA} < 0.1$ for spectrum sensing [74]. Time-bandwidth product ($d = B_w T$) is between the range $1 - 25$ [26]. For example, $P_{FA} < 10^{-2}$ is attained with $d = 25$ at $\kappa \geq 76$. Since κ varies from 0 to ∞, P_{FA} is easily computed using (3.25) for a given d.

From (3.19), the probability of detection is obtained by the cumulative distribution function (CDF);

$$P_D = 1 - F_Y(y) \tag{3.26}$$

The CDF of Y is obtained (for an even number of degrees of freedom- $2d$ in this case) as;

$$F_Y(y) = 1 - Q_d(\sqrt{\psi}, \sqrt{y}) \tag{3.27}$$

Thus, from (3.27), the probability of detection, P_D for an AWGN channel is ;

$$P_D = Q_d(\sqrt{\psi}, \sqrt{\kappa}) \tag{3.28}$$

equivalent to;

$$P_D = Q_d(\sqrt{2\gamma}, \sqrt{\kappa}) \tag{3.29}$$

where $Q_d(.,.)$ is the generalized Marcum-Q function. Using eqns. (3.25) and (3.29); which are expressions for the P_{FA} and P_D respectively, Receiver Operating Characteristics curves describing the performance of an energy detector in an

AWGN can be drawn.

3.4.2 Probability of Detection for Fading Channels

Since signals take more than a path between a transmitter and receiver, they are generally modelled by fading distributions that account for uncertainties encountered in the channel. Among these are Rayleigh, Nakagami and Rician fading models. These channel models serve as tools for studying both multipath and path loss features of a typical environment where spectrum sensing is to be employed.

For *Rayleigh fading*, the signal is not received on a line-of-sight path; directly from the transmitting antenna [75]. This fading model considers urban multipath features, including effects of the ionosphere and troposphere. More so, it describes the statistical time varying nature of the received envelope of a flat fading signal or the envelope of an individual multipath component [76]. When this model is employed, attenuation of the signal is Rayleigh distributed, making the SNR at every node exponentially distributed [77].

By averaging the conditional P_D in the AWGN case, (as given in (3.29)) over the SNR fading distribution, closed form expression for the P_D in Rayleigh fading channels is expressed [24]. It is noteworthy that the P_{FA} of (3.25) will remain unchanged under any fading channel, since the P_{FA} is independent of SNR.

If the signal amplitude follows a Rayleigh distribution, the SNR γ, follows an exponential PDF [24];

$$f(\gamma) = \frac{1}{\bar{\gamma}} \exp(-\frac{\gamma}{\bar{\gamma}}) \qquad \gamma \geq 0 \tag{3.30}$$

To obtain the Probability of Detection for Rayleigh channels, (3.29) is averaged over (3.30) i.e.;

$$P_{D_{Ray}} = \int_{0}^{\infty} P_D f(\gamma) d\gamma \tag{3.31}$$

from (3.29),

$$P_{D_{Ray}} = \frac{1}{\gamma} \int_{0}^{\infty} Q_D(\sqrt{2\gamma}, \sqrt{\kappa}) \exp(\frac{-\gamma}{\bar{\gamma}}) d\gamma \tag{3.32}$$

Substituting $\sqrt{\gamma} = x$; $\Rightarrow d\gamma = 2xdx$ above, yields;

$$P_{D_{Ray}} = \frac{2}{\gamma} \int_{0}^{\infty} x.Q_D(\sqrt{2x}, \sqrt{\kappa}) \exp(\frac{-x^2}{\bar{\gamma}}) dx \tag{3.33}$$

From the solution in Appendix A.1 [78], substituting $p^2 = \frac{2}{\bar{\gamma}}$, $a = \sqrt{2}$, $b = \sqrt{\kappa}$ and $M = d$, yields the Probability of detection in Rayleigh channel as:

$$P_{D_{Ray}} = e^{-\frac{\kappa}{2}} \sum_{n=0}^{d-2} \frac{1}{n!} \Big(\frac{\kappa}{2}\Big)^n + \Big(\frac{1+\overline{\gamma}}{\overline{\gamma}}\Big)^{d-1} \left[e^{\left(-\frac{\kappa}{2(1+\overline{\gamma})}\right)} - e^{\left(-\frac{\kappa}{2}\right)} \sum_{n=0}^{d-2} \frac{1}{n!} \left(\frac{\kappa\overline{\gamma}}{2(1+\overline{\gamma})} \right) \right] \tag{3.34}$$

The Nakagami fading distribution is a convenient model for analysing the performance of digital communication systems over generalized fading channels. This fading distribution is assumed in the analysis of many terrestrial wireless communication systems, since it is flexible and embraces scattered, reflected and direct components of the original transmitted signal. For urban multipath environments, the Nakagami-m fading model has been shown to be very suitable [77]. The probability of detection over Nakagami channel is determined by averaging the detection probability for a given SNR over the Nakagami distribution. If the signal amplitude follows a Nakagami distribution, then PDF of SNR γ, follows a gamma PDF given by [24];

$$f(\gamma) = \frac{1}{\Gamma(m)}\left(\frac{m}{\gamma}\right)^{m}\gamma^{m-1}\exp\left(-\frac{m}{\overline{\gamma}}\gamma\right), \qquad \gamma \geq 0 \tag{3.35}$$

The average P_D in the case of Nakagami channels is obtained by averaging (3.35) over (3.29)

$$P_{D_{Nak}} = \int_{0}^{\infty} P_D(\gamma) f(\gamma) d\gamma \tag{3.36}$$

where $f(\gamma)$ is the probability density function of the instantaneous SNR at the receiver node, and modifying the variable $x = \sqrt{2\gamma}$ results in

$$P_{D_{Nak}} = \alpha \int_{0}^{\infty} x^{2m-1}\exp\left(-\frac{mx^2}{2\overline{\gamma}}\right) Q_u\left(x, \sqrt{\kappa}\right) dx \tag{3.37}$$

where

$$\alpha = \frac{1}{\Gamma(m)2^{m-1}}\left(\frac{m}{\overline{\gamma}}\right)^{m} \tag{3.38}$$

m is the Nakagami-m fading parameter, which describes the severity of fading; $m < 1$ suggests severe fading, while $m > 1$ indicates less severe fading [79]. Solving the integral in (3.37) as identified in [24] gives a closed form expression of the Probability of detection in Nakagami channels as:

$$P_{D_{Nak}} = \alpha\left[G_1 + \beta\sum_{n=1}^{d-1}\frac{(\kappa/2)}{2(n!)}F_1\left(m; n+1; \frac{\kappa}{2}\frac{\overline{\gamma}}{m+\overline{\gamma}}\right)\right] \tag{3.39}$$

where $F_1(:, :, .)$ is the confluent hypergeometric function, and the representations of β and solution of G_1 are provided in Appendix A.

For the special case of $m = 1$ in (3.39) we get an alternative relationship for $P_{D_{Ray}}$; numerically equivalent to (3.34).

3.4.3 Cooperative Spectrum Sensing over Fading Channels using Energy Detection

So far, we have considered the task of spectrum sensing with a single receiver, using the energy detection method. With cooperative spectrum sensing (CSS), sensed information collected at various locations of the SUs are used for jointly ascertaining spectrum availability. CSS is intended to provide diversity gains against channel fading effects, since the odds of multiple receivers undergoing adverse fading conditions at the same time is less likely; compared to a situation where only a single detector is employed.

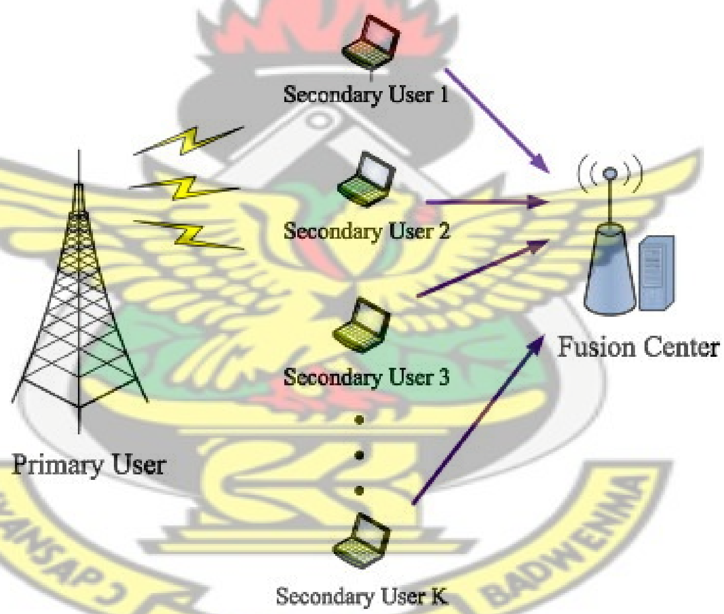

Figure 3.2: A network of cooperative secondary users employing energy detection [80].

The receivers either execute detection individually, based on the measured energy and transmit their individual hard decisions to a base station or fusion centre (FC) for decision combining (as shown in Figure 3.2 above), or they forward soft information to be combined at the FC to make the final decision as to the presence or absence of a primary user [80].

Detection of existence of an unknown signal $s_i(t)$ within a bandwidth B_w was considered earlier in Section 3.1, wherein it was thought of as a binary hypothesis test; that still holds for the case of CSS. Closed form expressions were derived to represent the probability of detection P_D, and the probability of false alarm P_{FA} for the case of a single receiver.

With CSS, we consider M samples of the received signal collected by N energy detectors in the system, (i.e. the various (SUs) detect the PU separately) and send their sensing data in the form of 1-bit binary decisions (1 or 0) to the base station (BS) or Fusion centre (FC). The hard decision combining rule (OR, AND, and MAJORITY rule) is executed at the FC to make the final decision regarding whether the primary user is present or not [81]. It is noteworthy that the choice of N relies on the resolution required, with higher N resulting in more detection of white spaces. However, a large number of N energy detectors will increase the complexity of the detection circuitry. Under this analysis, we assume that all SUs receive the primary signal with the same local mean power; the distance between any two sensing nodes are negligible, more so, the noise and average SNR are the same for all the SUs.

The process of combining the reported sensed results, for arriving at a cooperative decision is termed *Data fusion* [11]; wherein, each SU (i.e. energy detector node) sends its detection to be combined at the FC or basically amplifies the received signal from the primary user and forwards same to the fusion centre [64]. After the combination of sensed information from the various detector nodes, existing receiver diversity techniques such as equal gain combining (EGC), maximal ratio combining (MRC) and square law combining (SLC) are employed for soft combining of local observations or test statistics. Although a majority of these diversity techniques can be applied to the energy detection scheme, we restrict our anal-

ysis to the MRC and SLC techniques. With the MRC scheme, signals from L autonomous diversity branches are combined before sampling; consequently, the output SNR is a sum of the instantaneous SNRs from all diversity branches [14], i.e. $\gamma_{MRC} = \sum_{l=1}^{L} \gamma_L$. The output decision is combined after sampling with the SLC receiver. The decision statistics under this scheme, Y_{SLC}, is the sum of L (IID) χ^2_{2d} under H_0 and the sum of L $\chi^2_{2d}(\varepsilon)$ under H_1; where $\varepsilon = 2\gamma_{SLC}$ [82].
The known statistics using data fusion or soft combining include minimum, maximum and average. The performance of each of these case is considered next.

Case I: Minimum Selection

With this, detection decision is reached only if the detector with minimum decision variable exceeds the detection threshold [83], i.e. $Y = \min(Y_1, Y_2, ...Y_N)$. The detection probability is expressed by;

$$\begin{aligned} P_D^T &= P_R\left[\min\left(Y_1, Y_2, ...Y_N\right) > \kappa | H_1\right] \\ &= \prod_{i=1}^{N} \left\{P_R\left[Y_i > \kappa | H_1\right]\right\} \\ &= \prod_{i=1}^{N} \left[Q_{d_i}(\sqrt{2\gamma_i}, \sqrt{\kappa})\right] \end{aligned} \tag{3.40}$$

and the probability of false alarm,

$$\begin{aligned} P_{FA}^T &= P_R\left[\min\left(Y_1, Y_2, ...Y_N\right) > \kappa | H_0\right] \\ &= \prod_{i=1}^{N} \left\{P_R\left[Y_i > \kappa | H_0\right]\right\} \\ &= \prod_{i=1}^{N} \left[\Gamma\left(d_i, \tfrac{\kappa}{2}\right) \Big/ \Gamma\left(d_i\right)\right] \end{aligned} \tag{3.41}$$

Case II: Averaging

In this instance, a decision is arrived at by considering the average of the whole local decision, i.e. $Y = {(Y_1 + Y_2 + ... + Y_N)}/{N}$. Remarkably, averaging does not have an effect on the mean of a statistic; instead, it raises the degree of freedom by some order n and reduces the variance by the same factor n.
The detection and false alarm probabilities are given respectively by;

$$P_D^T = P_R\left[\left(Y_1 + Y_2 + ... + Y_N/_N > \kappa/_{H_1}\right)\right]$$

$$= Q_d\left(\sqrt{2\gamma_t}, \sqrt{\kappa}\right) \tag{3.42}$$

and

$$P_{FA}^T = P_R\left[\left(Y_1 + Y_2 + ... + Y_N/_N > \kappa/_{H_0}\right)\right]$$

$$= \Gamma\left(d, \tfrac{\kappa}{2}\right)\Big/\Gamma\left(d\right) \tag{3.43}$$

where $d = \sum_{i=1}^{N} d_i$ and $\gamma_t = \sum_{i=1}^{N} \gamma_i$ is the received SNR of the signal over the bandwidth B_w.

Case III: Maximum Selection

With this case, the detector with the maximum or peak detection decision variable is used to make the global decision, i.e. $Y = \max(Y_1, Y_2, ...Y_N)$. The detection and false alarm probabilities are given by;

$$P_D^T = P_R\left[\max(Y_1, Y_2, ...Y_N) > \kappa/_{H_1}\right]$$

$$= 1 - \prod_{i=1}^{N}\left\{1 - P_R\left[Y_i > \kappa/_{H_1}\right]\right\} \tag{3.44}$$

$$= 1 - \prod_{i=1}^{N} \left[1 - Q_{d_i}\left(\sqrt{2\gamma_i}, \sqrt{\kappa}\right)\right]$$

and

$$P_{FA}^{T} = P_R\left[\max\left(Y_1, Y_2, ...Y_N\right) > {}^{\kappa}\!/_{H_0}\right]$$

$$= 1 - \prod_{i=1}^{N} \left\{1 - P_R\left[Y_i > {}^{\kappa}\!/_{H_0}\right]\right\} \tag{3.45}$$

An alternate method for making collaborative decision is for each SU to conduct energy detection of the signal, after which the result is fused with others to form a global decision. This process is termed *Decision fusion*. Assuming uncorrelated decisions for N detectors, applying the k-out-of-N decision fusion rule where a decision is reached once k out of N detectors agree, the effective detection and false alarm probabilities at the fusion centre is given by;

$$P_{\chi}^{T} = \sum_{i=k...N} \prod_{j=1}^{i} P_{\chi}^{(j)} \prod_{j=i+1}^{N} \left(1 - P_{\chi}^{(j)}\right) \tag{3.46}$$

Where (χ = "*f*") represents the probability of false alarm and (χ = "*d*") corresponds to the probability of detection.

For the special case of $k = 1$, this corresponds to the "OR" decision rule, which specifies that if any one of the local decisions sent to the FC is a logical one, the final decision is one (i.e. when at least 1 out of k SUs detect a PU, it is adjudged that a PU signal is present) [84]. (3.46) becomes;

$$P_{\chi}^{T}(k = 1) = 1 - \prod_{i=1}^{N} (1 - P_{\chi}^{(i)}) \tag{3.47}$$

which is numerically equivalent to (3.44) and (3.45).

The case where $k = N$, is termed the "AND" rule; which is when *all* the local decisions sent to the FC is one, resulting in the final decision being one. i.e.

$$P_\chi^T(k = N) = \prod_{i=1}^{N} P_\chi^{(i)} \tag{3.48}$$

setting $k = N/2$ corresponds to the MAJORITY decision rule ; when half or more of the local decisions sent to the FC is one - resulting in the terminal decision of one. i.e. putting $k = N/2$ in (3.47)

$$P_\chi^T\left(k = {}^N\!/_2\right) = \sum_{i=\frac{N}{2}\ldots N} \prod_{j=1}^{i} (P_\chi^{(i)}) \prod_{j=i+1}^{N} (1 - P_\chi^{(i)}) \tag{3.49}$$

It is noteworthy that for independent and identical fading, both OR and AND decision fusion rules yield similar outcome as the minimum and maximum statistics of data fusion respectively [14].

In the next chapter, an analysis of the case scenarios is presented, including interpretation of results obtained from the analysis, which is based on the approach hitherto described.

Chapter 4

Results and Discussion

4.1 Introduction

In the previous chapter, the system model was introduced with mathematical deductions to present a theoretical description of detecting the energy of a signal in a spectrum. In this section, simulations are performed alongside description of scenarios involved with the sensing of primary user signals embedded in various forms of noise, applying the energy detection scheme. Results of the analysis performed are also presented here, where deductions and interpretations are also discussed.

4.2 Simulation Result and Discussion

In this section, through simulations, the capability of an energy detector applied to a secondary user for spectrum sensing is evaluated. All simulations in this work is executed using MATLAB[2] version R2012a. MATLAB is an application with tools for numerical computation and a fourth-generation programming lan-

[2] MATLAB is a product of The Mathworks, Inc.

guage. MATLAB contains tools for data visualization; serving as a convenient "laboratory" for computations and analysis.

Monte Carlo (MC) method, which is a stochastic technique (based on the use of random numbers) forms the basis of these simulations.

The receiver performance is quantified by depicting the receiver operating characteristics (ROC) curves, (P_D versus P_{FA}). Or equivalently, the complementary ROC curves (which is the probability of a missed detection ($P_M = 1 - P_D$) versus P_{FA}).

ROC curves show plot of probability of miss-detection (P_M) (the probability that the SU fails to detect the presence of the PU) versus the probability of false-alarm (P_{FA}) (the probability that the SU decides the PU is in operation whereas it is absent) [67]. These curves enable exploration of the relationship between sensitivity (probability of detection) and specificity (false alarm rate), for a variety of thresholds, thus allowing the determination of an optimal threshold [3]. To plot ROC curves, one parameter is varied while the other is fixed. This enables the study of various scenarios of interest.

Applying a single energy detector node for sensing is explored next.

4.2.1 Single User Detection

The effect of SNR on detection performance using an energy detector operating over a non-fading (AWGN) channel is carried out next.

Figure 4.1 depicts detection performance for a single energy detector operating over an AWGN channel. Here, the probability of false alarm P_{FA}, is set at 0.01, the time bandwidth factor $d = 1$, number of Monte Carlo sample points, $N = 1000$.

From the figure, it is deduced that detection performance improves with an increase in SNR values. Marginally before 15dB and prominently thereafter. This is consistent with the overall concept of energy detection, since this method offers optimal performance as signal power levels increase (high SNR).

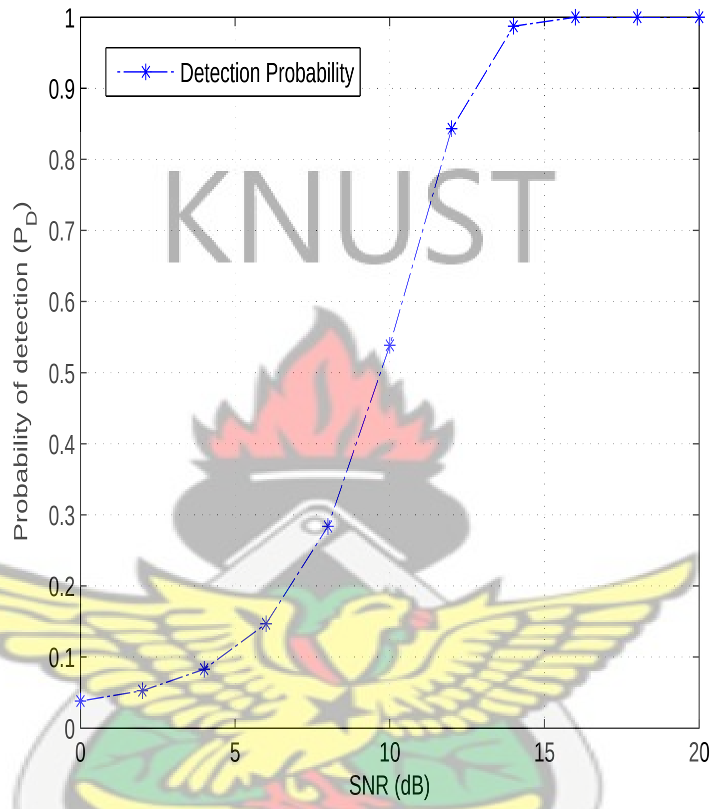

Figure 4.1: Effect of SNR on probability of detection P_D, in AWGN.

Next, the effect of increased probability of false alarm (P_{FA}) on detection performance is explored. For this case, P_{FA} is increased from 0.01 to 0.05 and 0.1 respectively, as shown in Figure 4.2. From this plot, it is inferred that a 5% increase in the false alarm rate (i.e. from 0.01 to 0.05) increases the detection probability up to 1.7 times for a certain values of SNR.

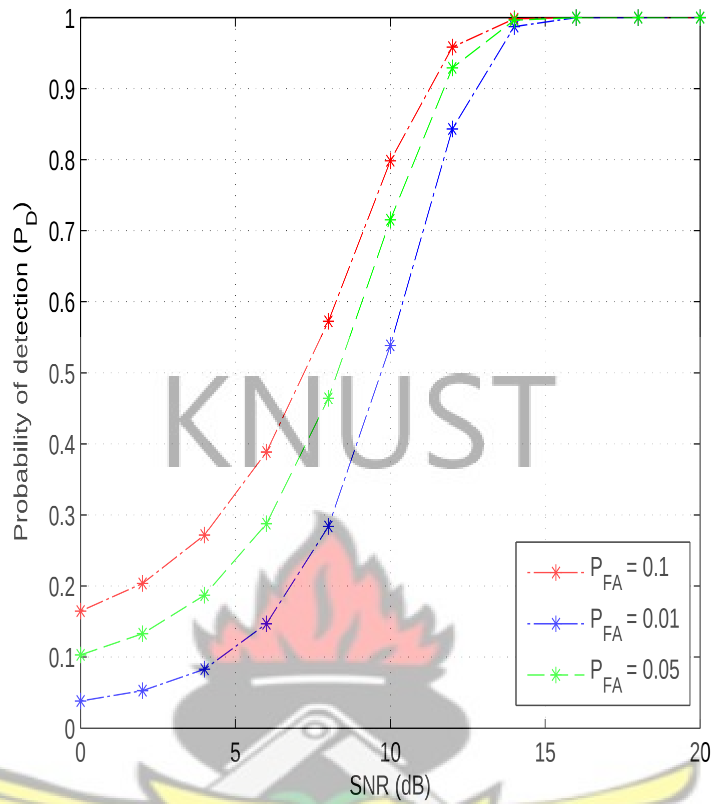

Figure 4.2: Probability of detection Vs SNR with varying values of false alarm probability in AWGN.

Figure 4.3 shows the complementary ROC curve for energy detection over a non-fading (AWGN) channel (a case where the form of interference is only noise). This shows the relationship between the probability of missed detection P_M, and false alarm probability P_{FA}, for 0 -15 dB average SNR, time bandwidth product $d = 4$, sample size $N = 1000$ respectively.

The probability of missed detection is a complement of detection probability. Related by the expression $P_M = 1 - P_D$), and is used in this case for clarity.

Numerical results shown in the plot are based on equation (3.29) and are represented by curves. While the simulation are represented by discreet marks. From this plot, the probability of miss improves rapidly with increasing $\overline{\gamma}$; roughly a gain of one order of magnitude is achieved when $\overline{\gamma}$ increases from 10 dB to 15 dB, when a node experiences no channel fading effects. This buttresses the point made earlier that an increase in SNR produces greater detection performance for a non-fading channel.

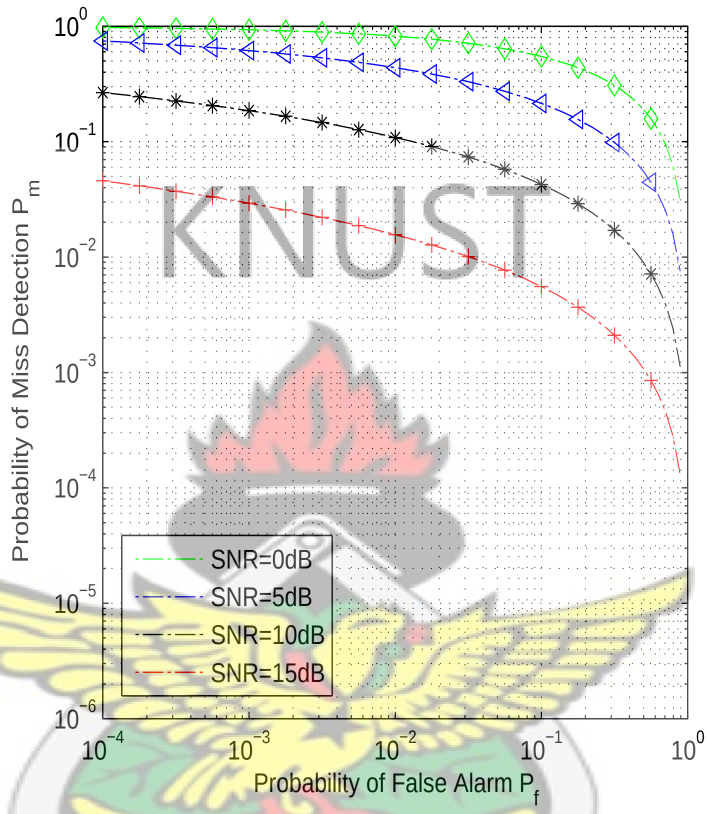

Figure 4.3: Complementary ROC curves for Energy Detection over AWGN.

The complementary ROC curves over Rayleigh channel for average SNR ($\overline{\gamma}$) values of $0-15$dB; time bandwidth product $d = 4$, sample size $N = 1000$ is as shown in Figure 4.4. From this $P_M - P_{FA}$ plot, it is observed that the slopes are low for P_F< 0.1, and a 5 dB increase in SNR (from 10dB to 15dB), has an increase in missed detection probability (reduced P_D) of up to 0.6 times; compared to probability of detection over AWGN.

It is apparent that energy detection executed over a Rayleigh channel exhibits a tough detection performance, compared to that of AWGN. This is not far-fetched, since the fading severity is more in a Rayleigh channel compared to that of AWGN, (which is a case of no fading, shown previously).

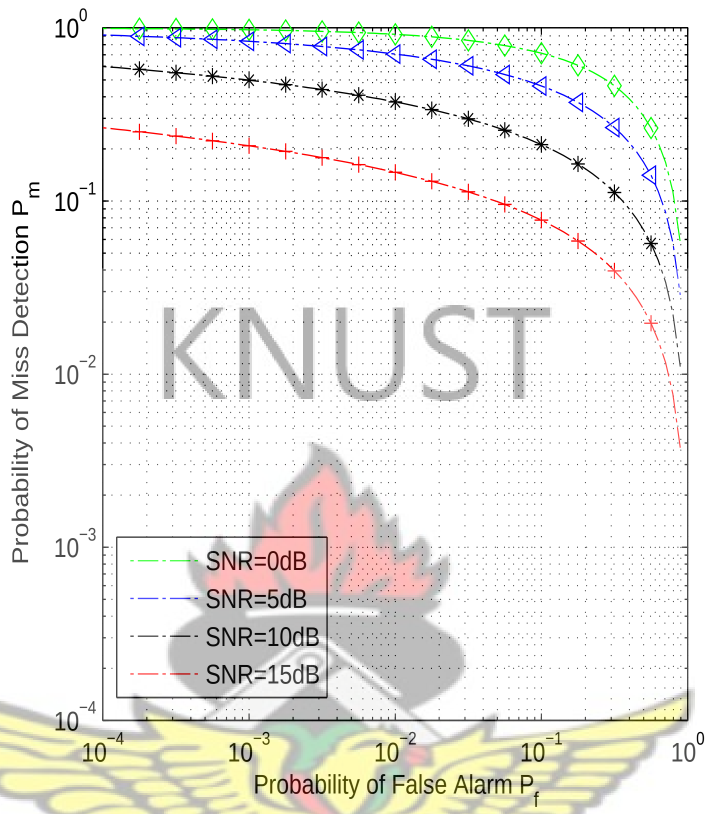

Figure 4.4: Complementary ROC curves for Energy Detection over Rayleigh fading channel.

Figure 4.5 below substantiates the concept (from equation (3.17)) that for similar signal energy, improved performance is achieved by employing less number of samples; as obtained when the energy of the signal E_s, increases for a given number of samples N. This is observed when less number of samples are used for 10dB and 15dB respectively in the figure.

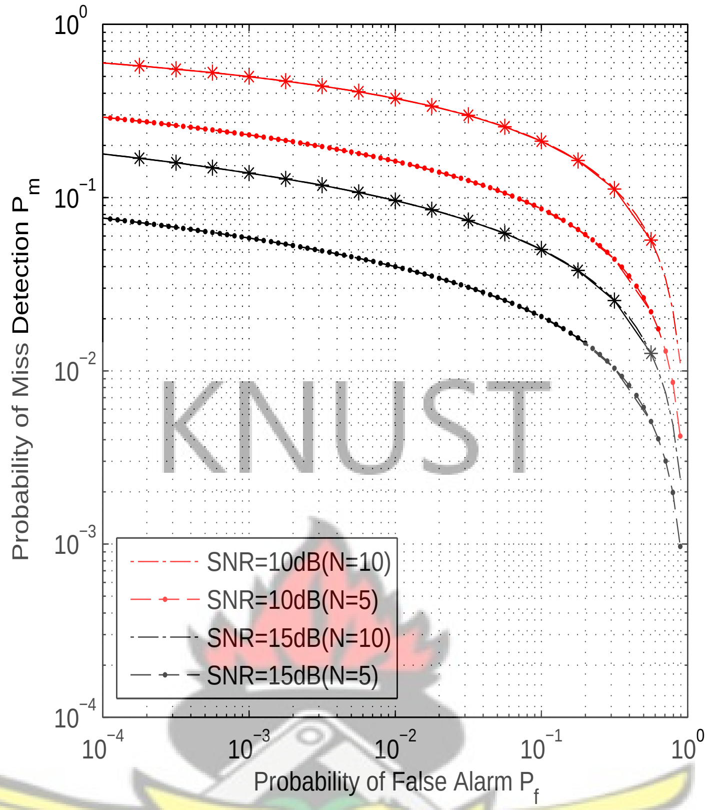

Figure 4.5: Variation of received signal E_s with sample size N.

Next, the performance of an energy detector in a Nakagami channel is explored. This is as depicted in Figure 4.6.

From this figure, we observe that the probability of miss detection (increased detection performance) rapidly improves with increasing average SNR ($\overline{\gamma}$). A gain of roughly one order of magnitude is observed for SNR values of 10dB and 15dB respectively; from the position of the P_M for $m = 2$, compared to the Rayleigh case of $m = 1$ in Fig. 4.4.

Where m is the Nakagami parameter, expressed in equation (3.38)).

It is deduced that greater performance is achieved in a Nakagami fading model than a Rayleigh model, since fading severity is less (from $m = 2$ to $m = 1$). This is adduced to the fact that the sample signals face less obstructions, as they travel along the transmitter line-of-sight route to the receiver.

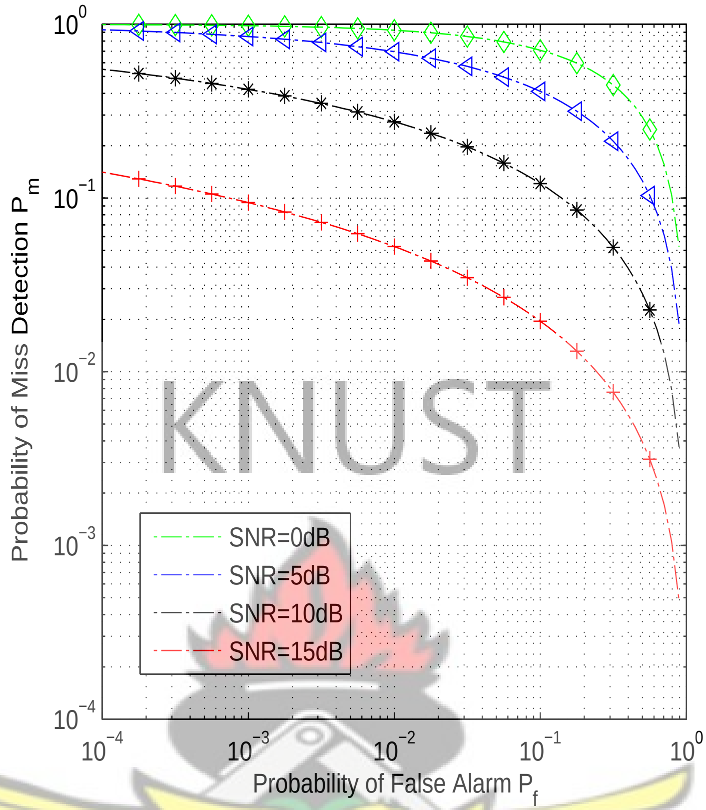

Figure 4.6: Complementary ROC curves over Nakagami-m fading channel.

The performance gain as the Nakagami order (m) increases for a specific SNR is quantified next.

Fig. 4.7 depicts a case for SNR ($\overline{\gamma} = 20dB$). From this plot, there is approximately an increase of roughly one order of magnitude from the P_M perspective for $m = 2$, compared with the Rayleigh case ($m = 1$).

Consequently, we conclude that the receiver performance improves using the energy detection method of spectrum sensing, when the Nakagami order increases. i.e. just as the severity of fading reduces, better detection performance is achieved.

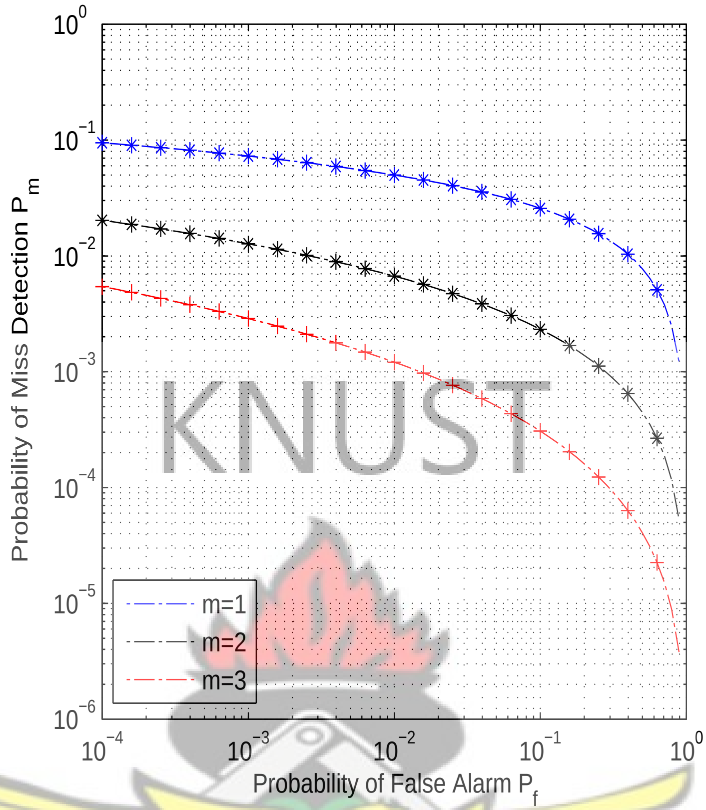

Figure 4.7: Complementary ROC curves for Nakagami fading at different m values ($\overline{\gamma} = 20dB$, $d = 1.5$ and $N = 10$)

4.2.2 Cooperative Detection

Next, networks of cooperative energy detectors in the various fading channels are considered.

In Fig. 4.8, using 10 energy detectors, the performance comparison of the various data fusion methods involved in cooperative spectrum sensing(CSS), described in section 3.4.3, above is considered.

From this figure, the OR fusion rule shows a better performance compared to the MAJORITY and AND fusion rules. This is attributed to the fact that OR decision fusion rule involves result of a minimum of a single user out of K energy detector nodes to declare the availability or presence of a PU. Though AND fusion rule indicates a slightly better performance at low P_{FA}, as compared to the OR rule, as seen from the figure.

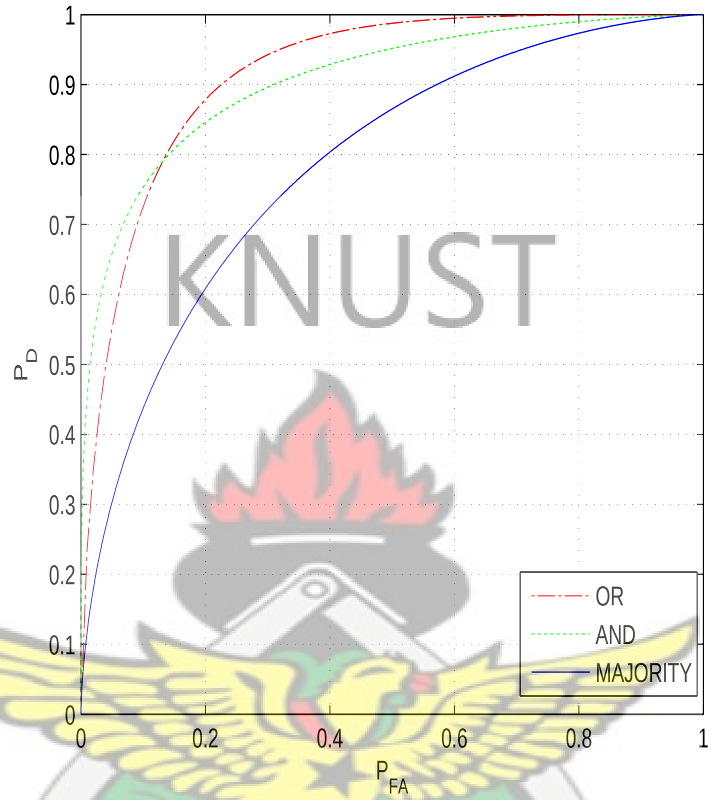

Figure 4.8: ROC curves for OR, AND and MAJORITY fusion rules for $M = 10$ energy detectors at mean SNR $\overline{\gamma} = 15dB$.

Since the OR combining rule minimizes communication overhead - attributed to its property of sending a minimum of a single decision to the FC, this fusion rule will be adopted in the rest of the analysis for cooperative users in the various channel models under consideration.

How does cooperative reception improve the performance of the energy detector? This question is investigated in Figure 4.9 and 4.10 respectively below.

Figure 4.9 shows the complementary ROC performance curves of the energy detector over Rayleigh fading. The number of cooperating nodes (M) are 10, with average SNR ($\overline{\gamma}$) values of $0, 5, 10, 15dB$, and time bandwidth product, $d = 5$.

The same parameters are applied to the case of Nakagami fading of Figure 4.10. From both Figures, there is a gain of one order of magnitude improvement in the missed detection probability P_M, (ie. an increased detection probability) using the energy detection method applied to a network of cooperating nodes; compared to the single user detection case.

Observe that the slopes of the curves in Figure 4.10 are steeper than those of Figure 4.9. Thus, the highest performance gain is observed from the Nakagami fading case, compared to the Rayleigh fading, with the same parameters considered.

It is interesting to note that energy detection using a single user over an AWGN performs nearly identical with employing a network of cooperative energy detectors over a Nakagami fading channel.

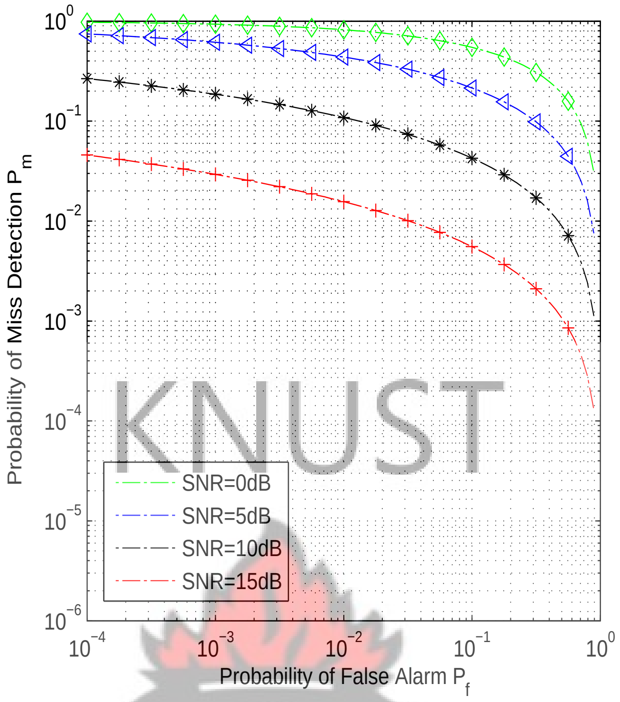

Figure 4.9: Complementary ROC curves over Rayleigh channel for $M = 10$ cooperating detectors at SNR ($\overline{\gamma}$) =0, 5, 10, 15 dB.

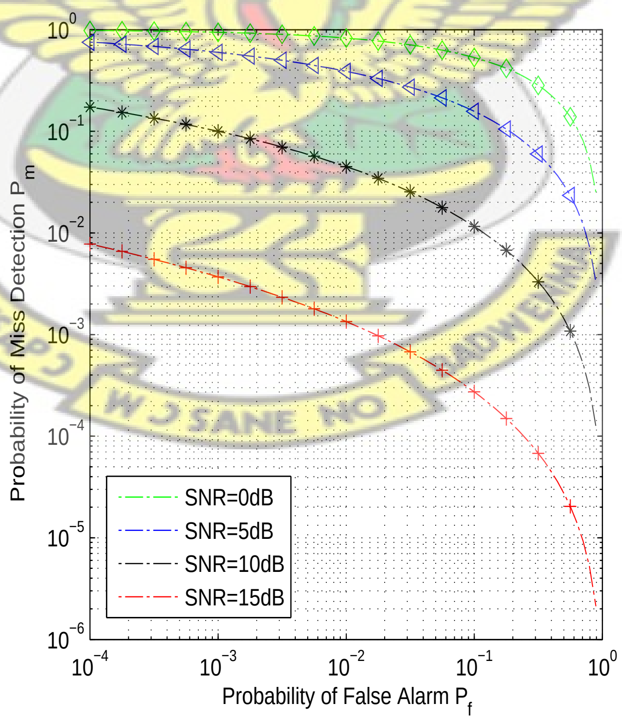

Figure 4.10: Complementary ROC curves over Nakagami channel for $M = 10$ cooperating detectors at SNR ($\overline{\gamma}$) =0, 5, 10, 15 dB.

From the foregoing, it is apparent that cooperative sensing is a promising method of combating the inherent performance deterioration of the energy detector at severe fading and shadowing environments.

Chapter 5

Conclusion and Recommendation

5.1 Conclusion

The electromagnetic spectrum is an essential, but scarce resource to the birth of high data rate wireless communication technology. To utilize the available spectrum optimally, use of an intelligent radio platform (known as Cognitive Radios) was conceived. An important prerequisite for this technology however, is the ability of unlicensed (secondary) users to detect unused (vacant) spectrum - a process known as *Spectrum Sensing*. This process also has to be devoid of complexity. Of the methods so far explored, detecting the energy of a signal within a band (energy detection method) has proved to be less complex, most feasible; though sub-optimal.

This study provides useful insight to the behaviour of the energy detection technique, as it relates to detecting signals in a band for opportunistic access. In this work, the performance of an energy detector in detecting unused (vacant) spectrum was evaluated. The study includes a theoretical background; wherein closed form expressions for the detection probability and false alarm probabilities for a sensing node over both a non-fading (AWGN) and fading (i.e. Rayleigh and Nakagami-m) channels were derived. Using the various fading and non-fading models, different tests was carried out to assess the performance of the energy detection technique. Employing complementary Receiver Operating Characteristics (ROC) curves, receiver performance is quantified for both single user detection and a network of cooperative detector nodes.

Simulation results indicate that depending on the threshold of a single user energy detector, performance improves over a non-fading channel (AWGN), compared to a fading channel (Rayleigh and Nakagami), for various average values of SNR. Comparing AWGN curves with those representing fading, spectrum sensing presents a challenge for a single node over Rayleigh and Nakagami fading channels. More so, as SNR increases, detection probability increases for a single user detector node in a channel with no fading. Interestingly, fewer samples produce better performance for non-fading channels for the case of a single secondary user. For a single energy detector node also, reducing fading severity (i.e. increasing Nakagami parameter m values) enhances detection probability for signals over fading channels, as result show.

A simulation comparison of AND, OR and MAJORITY cooperative decision fusion rules was undertaken and results show that OR rule (corresponding to considering the decision of at least one detector out of k available detectors) outperforms the AND and MAJORITY combining rules.

The effect of cooperating nodes using ED technique over various fading channels is examined using complementary ROC curves. Results signifying an increased probability of detection is observed. This asserts the expectation of higher detection probability to overcome effects of multipath and hidden node challenges, encountered by signals in practical wireless scenarios. In general, our cooperation study identified a robust detection performance; which relate to optimum detection of primary signals in the presence of radio uncertainties, compared to the case of single user detection.

5.1.1 Recommendation

From the foregoing, it is apparent that the range of SNR studied is high, for both the single and cooperative user cases. Further works in the study of spectrum sensing using the energy detection method should consider the performance limits of this method with regard to the SNR.

Though various techniques have been proposed in literature, practical implementation has remained elusive. In this regard, small scale experiments (away from simulations) need to be conducted to ascertain the reliability of this approach in real world scenarios. Test beds like the Universal Software Radio Peripheral (USRP) will assist in both experimental and qualitative analysis; to reduce as much as possible, simulation of novel techniques involved with identifying unused spectrum and the whole concept of opportunistic spectrum access.

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Appendix A

Definition of Functions

$$\int_0^\infty dx.x.\exp\left(\frac{-p^2x^2}{2}\right)Q_M(ax,b) =$$

$$\frac{1}{p^2}.\exp\left(-\frac{b^2}{2}\right).\left\{\left(\frac{p^2+a^2}{a^2}\right)^{M-1}\left[\exp\left(\frac{b^2}{2}.\frac{a^2}{p^2+a^2}\right)-\sum_{n=0}^{M-2}\frac{1}{n!}\left(\frac{b^2}{2}.\frac{a^2}{p^2+a^2}\right)^n\right]\right.$$
$$\left.+\sum_{n=0}^{M-2}\frac{1}{n!}\left(\frac{b^2}{2}\right)^n\right\} \quad (A.1)$$

$$\beta = \Gamma(m)\left(\frac{2\overline{\gamma}}{m+\overline{\gamma}}\right)^m e^{-\kappa/2} \quad (A.2)$$

The equation

$$G_1 = \int_0^\infty x^{2m-1}\exp\left(-\frac{mx^2}{2\overline{\gamma}}\right)Q\left(x,\sqrt{\kappa}\right)dx, \quad (A.3)$$

can be evaluated for interger m, by making use of [78] to yield;

$$G_1 = \frac{2^{m-1}(m-1)!}{\left(\frac{m}{\overline{\gamma}}\right)^m}\frac{\overline{\gamma}}{m+\overline{\gamma}}e^{-\frac{\kappa}{2}\frac{m}{m+\overline{\gamma}}}\left[\left(1+\frac{m}{\overline{\gamma}}\right)\left(\frac{m}{m+\overline{\gamma}}\right)^{m-1}\right.$$
$$\left.\times L_{m-1}\left(-\frac{\kappa}{2}\frac{\overline{\gamma}}{m+\overline{\gamma}}\right)+\sum_{n=0}^{m-2}\left(\frac{m}{m+\overline{\gamma}}\right)^n L_n\left(-\frac{\kappa}{2}\frac{\overline{\gamma}}{m+\overline{\gamma}}\right)\right] \quad (A.4)$$

$$\overline{P_{d_0}^{(k)}}_{Gen} = 1 - \sum_{k=0}^{\infty} \frac{(-1)^z}{z!} \frac{G(u_k + z, \frac{\kappa}{2})}{\Gamma(u_k + z)} \int_0^{\infty} \tau_k^z f_\tau(\tau_k) d\tau_k \tag{A.5}$$

$$\overline{P_{dRIC}} = 1 - \sum_{z=0}^{\infty} \frac{1}{z!} \frac{G(u_k + z, \frac{\kappa}{2})}{\Gamma(u_k + z)} \frac{\Omega^z (z!)^2 (1+Z)}{(1+Z+\Omega)^{1+z}} \exp\left(\frac{-ZQ}{1+Z+\Omega}\right) \sum_{y=0}^{z} \frac{1}{(j!)^2 (z-1)!} \left(\frac{Z(1+Z)}{1+Z+\Omega}\right)^j \tag{A.6}$$

A.1 MATLAB SOURCE CODES

Single user Energy Detection Spectrum Sensing for Rayleigh and Nakagami fading channels;

```
%Complementary ROC curve for energy detection over Rayleigh
%and Nakagami fading channels
function[SNR]=gamma
clear all
l=1; % Number of diversity brabches
s=1;m=1;% m= Nakagami fading index (m=1 is Rayleihh) and s=1,
%is a constant parameter
color = 'rgbmy';
tick1='−−−: ';
tick2=' −. o';
i=1;
y=5; % Average Receieved SNR value in dB
omg=10^(0/10);
t=1;
for pf=10.^(−4:0.05:0) %False alrm probability
    mu=10; %mu is half degree of freedom (Number of imput samples)
```

```
lab = gammaincinv(1-pf,mu);
k=0:30;
P=((gammainc(lab,mu+k)).*(omg.^k)*(m^(m*l)).*gamma(m*l+k)).
/(((m+s*omg).^(m*l+k))*gamma(m*l).*gamma(k+1));

Pd(t)=1-sum(P); %Detection Probability
Pm(t)=1-Pd(t); %False alarm probability
Pf(t)=pf;
t=t+1;
end

loglog(Pf,Pm,[color(i) tick1(i) tick2(i)]);
hold on
loglog(Pf (1:4:81),Pm(1:4:81),'*');

axis([1e-3 1 1e-3 1]);axis square

xlabel('Probability of False Alarm P_f')
ylabel('Probability of Miss Detection P_m')
```

Comparison of the AND, OR and MAJORITY hard decision fusion rules for energy detetion;

```
% Complementary ROC curves for OR, AND and MAJORITY fusion rules
funtion[zetta]=epsilon
clear all
 pfa=0:0.001:1;
 lamda=norminv(1-pfa,1,sqrt(2e-4));
  %snr=15; %-22,-18,-15  %(original!)
  snr=15;
 for i=1:length(lamda)
```

```
    A=lamda(i)-(1+10^(0.1*snr));
B=2^0.5*(1+10^(snr*0.1))*0.01;
pd(i)=0.5.*erfc(A./B/sqrt(2));
 end

  pfaand=pfa.^10; % where the exponent denotes the number of users
 pdand=pd.^10;
 %PmAND=1-pdand;
 pfaor=1-(1-pfa).^10;
 pdor=1-(1-pd).^10;
 %PmAND=1-pdor;
 plot(pfaor,pdor,'-.r',pfaand,pdand,':g',pfa,pd,'b');
legend('OR','AND','MAJORITY')
%plot(pfa,pd);
 grid;
 xlabel('P_{FA}');
 ylabel('P_D');
 hold on
```

Cooperative Energy detection for AWGN;

```
funtion[alpha]=beta
 clear all
i=1;u=15;    %originally u=4 (so set it to this to get the original value)
snr=10^(0/10);      %0dB SNR
t=1;
for pf=10.^(-4:0.05:0)      %(-4:0.05:0)
lab = 2*gammaincinv(1-pf,u);
Pd(t)=marcumq(sqrt(2*snr),sqrt(lab),u);
Pm(t)=1-Pd(t);
Pf(t)=pf;
t=t+1;
```

```
end
b1=loglog(Pf,Pm,'g-.');
hold on
k1=loglog(Pf (1:5:81),Pm(1:5:81),'gd');
hold on
axis([1e-4 1 1e-6 1]);axis square
grid off
xlabel('Probability of False Alarm P_f')
ylabel('Probability of Miss-detection P_m')

%legend('SNR=0dB','','SNR=5dB','','SNR=10dB','','SNR=15dB', '')
snr=10^(5/10);      %5dB SNR
t=1;
for pf=10.^(-4:0.05:0)
lab = 2*gammaincinv(1-pf,u);
Pd(t)=marcumq(sqrt(2*snr),sqrt(lab),u);
Pm(t)=1-Pd(t);
Pf(t)=pf;
t=t+1;
end
b2=loglog(Pf,Pm,'b-.');
hold on
k2=loglog(Pf (1:5:81),Pm(1:5:81),'ob');
hold on

snr=10^(10/10);      %10dB SNR
t=1;
for pf=10.^(-4:0.05:0)
lab = 2*gammaincinv(1-pf,u);
Pd(t)=marcumq(sqrt(2*snr),sqrt(lab),u);
Pm(t)=1-Pd(t);
Pf(t)=pf;
```

```
t=t+1;
end
b3=loglog(Pf,Pm,'k-.');
hold on
k3=loglog(Pf (1:5:81),Pm(1:5:81),'*k');
hold on

snr=10^(15/10);      %15dB SNR
t=1;
for pf=10.^(-4:0.05:0)
lab = 2*gammaincinv(1-pf,u);
Pd(t)=marcumq(sqrt(2*snr),sqrt(lab),u);
Pm(t)=1-Pd(t);
Pf(t)=pf;
t=t+1;
end
b4=loglog(Pf,Pm,'r-.');
hold on
k4=loglog(Pf (1:5:81),Pm(1:5:81),'r+');
hold on
grid on
%legend([k1 k2 k3 k4], 'SNR=0dB','SNR=5dB', 'SNR=10dB', 'SNR=15dB')
legend([b1 b2 b3 b4], 'SNR=0dB','SNR=5dB', 'SNR=10dB', 'SNR=15dB')
```