UNIVERSITY OF ALBERTA

MINT 709 Capstone Project

Spectrum Sensing with Improved Energy Detectors in Impulsive Noise Environment

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Abstract

Cognitive radio (CR) is a technology that can alleviate the problem of radio frequency (RF) spectrum scarcity by opportunistically accessing the unused RF slots called spectrum holes. The detection of spectrum holes, called spectrum sensing, is the foremost task for utilization of the unused RF spectrum. Of the several spectrum sensing techniques available, the energy detector (ED) is recognized for its simple structure and non-coherent nature. However, the performance of the ED is known to degrade in multipath fading, an inherent phenomenon in wireless propagation. Moreover, the ED is known to be optimal only in Gaussian noise environments and thus its performance degrades in non-Gaussian environments. Motivated by these facts, we investigate the performance of an improved energy detector (IED), which is a more generalized version of the energy detector, in channels suffering from Rayleigh fading and Laplacian noise, first, for a single CR. Our results show a significant performance gain compared to the performance of the traditional energy detector. To further enhance the performance, a number of collaborating CRs is considered for joint detection of the spectrum holes. As expected, cooperation among different CRs yields encouraging performance benefits, which we quantify in this paper.

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List of Acronyms

ARQ	Automatic repeat request
BHT	Binary hypothesis testing
CR	Cognitive radio
CDF	Cumulative distribution function
dB	Decibel
ED	Energy detector
FC	Fusion center
FCC	Federal communication commission
GGN	Generalized Gaussian noise
GMN	Gaussian mixture noise
GPS	Generalized positioning system
GHz	Giga Hertz
HF	High frequency
IED	Improved energy detector
LoS	Line of sight
MGF	Moment-generation function
MHz	Mega Hertz
NP	Neyman-Pearson
PDF	Probability density function
PU	Primary user
RF	Radio frequency
RV	Random variable
ROC	Receiver operating characteristic
SU	Secondary user
SNR	Signal to noise ratio

List of Symbols

μ	Average value of Laplacian noise
$\bar{\gamma}$	Average SNR per symbol
T	Decision variable
b	Variance in Laplacian noise
n	Noise
K	Number of cognitive radios
p	Power operation in improved energy detector
P_d	Probability of detection in spectrum sensing
P_f	Probability of false alarm in spectrum sensing
P_e	Probability of error in spectrum sensing
Q_d	Probability of detection in cooperative spectrum sensing
Q_f	Probability of false alarm in cooperative spectrum sensing
Q_e	Probability of error in cooperative spectrum sensing
h	Rayleigh fading channel
y	Received signal
γ	SNR per symbol
s	Signal
H_1	Signal present
H_0	Signal absent
b_0	Scaling parameter
σ	Variance
E_s	Energy of signal
σ_ω	Variance of noise

Chapter 1

1.1 Introduction and Motivation

Wireless communication has become the largest sector of communication used worldwide and has an exceptional growth rate in day-to-day usage. Many more users are routinely utilizing the wireless services for social interactions due to increase in the user-friendliness of various wireless devices on top of the ongoing advancement in the state of art attributes in wireless communication. Recent studies have demonstrated that global mobile data traffic grew alarmingly by as much as 70 percent in the year 2012, and it is anticipated to grow in the next five years at a compound annual growth rate of 66 percent [1].

The enormous increase in the number of users translates into a demand for an equivalent bandwidth to accommodate them. The available bandwidth, in turn, is directly determined by the available radio frequency (RF) spectrum. However, the RF spectrum used for wireless services is not infinite. Moreover, major portions of the RF spectrum are already allocated for providing a specific wireless service to the targeted user group. For example, the North American broadcast television channels 2 through 69 are exclusively designated approximately between 54 and 806 MHz. Such fixed spectrum allocation policy became a well-accepted norm worldwide, where specific users were assigned to operate on a specific RF band. The users that are explicitly licensed to operate on a specific range of frequency are called the licensed users or primary users (PUs) of the spectrum.

However, recent studies have shown that the licensed users do not always occupy the spectrum allocated to them and that there is a huge underutilization of the band of frequencies across time as well as across space [2]. These unused spectrum bands or slots are called *spectrum holes* [3]. Due to such vast underutilization, the introduction and expansion of new wireless services has become difficult due to scarcity of the RF spectrum, which rather than being a physical scarcity, is a perceived scarcity due to inefficient usage of the licensed spectrum. If by some means, the presence of spectrum holes can be detected, then it may be possible to utilize them opportunistically and accommodate more users which do not have an exclusive license to operate in that particular frequency band but are always looking for possibilities to communicate. Such unlicensed users are called secondary users (SUs) of the spectrum, and the task of detection of the spectrum holes is termed as *spectrum sensing*. This task demands for the SUs to be more intelligent and spectrum aware. The smart devices, which came into existence for addressing the fundamental need to identify the spectrum holes and communicate over them, are called cognitive radios (CRs) [3]. The emergence of CRs thus lead to the birth of a new notion called dynamic spectrum utilization, as opposed to the traditional static spectrum utilization policy.

The foremost task in promoting the aforementioned concept of dynamic spectrum utilization is the detection of spectrum holes. Several popular techniques are available in the literature for spectrum sensing such as matched filter detection, cyclostationary feature detection, wavelet-based detection and energy detection [2]. Among these techniques, the energy detector (ED) is one of the most popular and widely used techniques due to its simple structure. A traditional ED consists of a noise pre-filter, followed by a squaring operation and a finite-time integrator, whose output is compared to a preset detection threshold to result in a decision on the presence or absence of the PU signal. Moreover, an ED does not require any prior information about the PU signals and thus may be more suitable for spectrum sensing across a wide range of RF spectrum which may contain a variety of PU signals operating with different modulation types and thus any *a-priori* PU signal information may not be available at the detector.

Due to such characteristics, the ED has attracted extensive attention in the literature. Its performance has been analyzed extensively in multipath fading, an inherent phenomenon in wireless propagation channels [2], [3], [5]-[7]. However, a recent work [6], [8], [9] has shown that the energy detector does not necessarily maximize the detection performance or minimize the probability of error in making a correct decision on the presence or absence of the PU signal. This situation may arise in fading channels and /or in non-Gaussian noise environments where the use of an energy detector may not be the optimal choice [7]. Motivated by these facts, a more generalized version of the ED, termed the improved energy detector (IED), in which the squaring operation of the energy detector is replaced by an arbitrary $p > 0$ power operation such that the energy detector is a special case(p=2), came into existence. However, achievable performance gains obtained by using an IED in multipath fading and non-Gaussian noise environments are still unknown and require further investigation which is one of the primary objectives of this study.

Next, the main objectives of the project are outlined briefly.

1.2 Objectives

1. To investigate the spectrum sensing performance of the IED in wireless multipath fading and non-Gaussian noise environments.
2. To extend the scenario 1 to cooperative detection to investigate any further possible improvement in performance.

Objectives 1 and 2 are briefly elaborated as problems 1 and 2, respectively, in the following section.

1.3 Problem statements

1.3.1. Problem 1

To investigate the spectrum sensing performance of an improved energy detector in multipath fading and in non-Gaussian noise. The classical energy detector is recognized as an optimal detector in Gaussian noise environments [7]. However, its performance is likely to degrade in non-Gaussian noise environments. In some scenarios, the received signal may become impaired due to non-Gaussian noise; for example, man-made signals may produce an impulsive behavior, [10] due to the emission from microwave ovens [11] and the co-channel interference in cellular networks [12]. The performance of the improved energy detector in such non-Gaussian noise environments in addition to the omnipresent wireless multipath fading needs investigation.

1.3.1. Problem 2

To investigate the cooperative spectrum sensing performance of an improved energy detector in multipath fading and in non-Gaussian noise. In some instances, the SU or the CR may be shadowed [3] from the PU such that it cannot detect the PU transmission and may start to transmit, thus harmfully interfering with the PU transmission. To mitigate this problem, the notion of cooperative spectrum sensing where a number of CRs collaborate with each other to jointly detect the PU presence has evolved [3]. However, the investigation of cooperative spectrum sensing with an IED-equipped CR in multipath fading and non-Gaussian environments is unexplored and thus is another focus of this study.

Chapter 2

Literature review

2.1 Cognitive Radio

Because of the ever-expanding demand for additional bandwidth, spectrum policy providers and communication technologists are pursuing a solution before the probable spectrum shortfall occurs. Meanwhile, recent studies [13] show that the allotted spectrum is largely underutilized by many frequency slots and times. In order to provide a solution for an insufficient spectrum and its underutilization, CR technology is highly regarded due to its ability to promptly and separately adapt operating parameters to changing demands and conditions in wireless communications. The design principle of the CR networks regards the CR users as visitors in the spectrum they occupy. This principle necessitates efficient spectrum management functions in order to allow SUs to occupy vacant channels without causing interference while the PUs are not active, and then to remove the SUs from these channels when PU activity is detected. The successful operation of this principle is accomplished through spectrum sensing solutions [13]. The primary objective of spectrum sensing is to administer more spectrum access opportunities to CR users without any obstruction within the primary networks. CR hardware should be capable of identifying the fractions of the spectrum in which the activity of the licensed users is diminished and used mainly for communication. Licensed channels, also defined as primary bands, should be immediately vacated if legitimate or PU's are detected. Thus, accurate sensing must be performed on the wireless spectrum, and such sensing is a key challenge in CR technology. So, that CR networks are responsible for ascertaining the transmission and preventing interference with the primary networks. Thus, the CR networks should be able to sense the primary band intelligently, to avoid any possible interference with the transmission of the PUs. This requirement necessitates crucial support from the physical layer of the cognitive radios' architecture, along with the intelligent algorithms that are implemented within the software [13]. In the next section, the RF spectrum is described briefly.

2.1.1 Radio frequency spectrum

The RF spectrum is assigned to the portion of the continuum that is allotted to some form of coordinated use. At the lower end, this range includes the ultra-low frequencies (a few kilohertz). These frequencies are used for communication which measures the distance between two extremities around the globe and penetrates the watery surface of the earth. The spectrum's higher end reaches into the sub millimeter waves that correspond to frequencies of 300 GHz and above. The customary usage of the spectrum has been shaped by practical factors: with lower frequencies, the operating range and antenna size increase while making range of frequency to decrease. However, these decreases in range of frequencies make the wide channels difficult to justify. With higher frequencies, the operating ranges of frequencies that can be obtained drops, but wider bandwidths become effortless, partially because the spectrum becomes more plentiful [14]. Historically lower frequencies were preferred and were popular because new technologies became available at the end of nineteenth century. Then with the emergence of the tube amplifier, higher frequencies became easily accessible, and the size of the radio devices and antennas could shrink to the point where even a few millimeters became sufficient for an advanced precision GPS receiver. The highest frequencies, which are covered by national and international frequency management, extend up to 2,400 GHz, which has become the most sought-after RF spectrum due to a range that spans 10 octaves between ~30 MHz and ~30 GHz [14]. The different types of usage of RF spectrum span a wide range: at the lower end, long-range communications and radio/TV broadcasting predominate; at the higher end, uses of high-speed data transmission and location determination predominate. The main differences in the RF spectrum allocation are in the mobile services, for example, broadcasting, telephone services, and safety-of-life services. Other differences are in radio navigation, radiolocation and, last but not least scientific uses [14]. In the next section spectrum underutilization is discussed.

2.1.2 Spectrum underutilization

The radio spectrum is a finite resource, systematized by government bureaus such as the United States, Federal Communications Commission (FCC). Internally, the current spectrum regulatory framework, and all of the frequency bands are exclusively allocated to distinguishable services, and no violations by unlicensed users are permitted. It is believed that there is spectrum scarcity at frequencies that can be economically used for wireless communication and this spectrum scarcity problem is worsening due to the development of many new wireless services. However, the FCC has indicated that the actual licensed spectrum is essentially under-utilized in many temporal and geographical dimensions [15]. A remedy for spectrum scarcity is to increase the spectrum's utilization by allowing SUs to dynamically access under-utilized licensed bands, in which licensed users are absent [15]. CR improves the spectrum utilization by allowing the secondary networks to obtain unused radio spectrum from primary licensed networks or to contribute to the spectrum with the primary networks. As a comprehending wireless communication system, CR is conscious of the RF environment. The parameters are then selected (such as the carriers frequency and transmission power) to optimize spectrum usage and accommodate its transmission and reception accordingly [15].

2.1.3 Spectrum holes

Due to the underutilization of the spectrum by PUs, the unlicensed users have an opportunity to analyze and use the spectrum slots that are not being used. These slots are commonly known as spectrum holes, the vacant slots in frequency across time, and are a basic resource for most CR systems. Most existing systems distinguish the spectrum holes by determining whether or not a PU's signal is idle or active within the spectrum and then begin to access these spectrum holes accordingly; therefore, the CR and PUs may use the spectrum band at different time niches or in different geographic regions [16]. The complexity of the decision model for spectrum access depends on the parameter considered during a spectrum analysis. As well, the utility of the cognitive user is then obtained through the access to the spectrum holes. After a decision is made on spectrum access based on a spectrum analysis, the spectrum holes are then accessed by unlicensed users. The CR transmitter will also be required to perform a negotiation with the CR receiver to then synchronize the transmission; therefore, the transmitted data can then be admitted successfully [17].

2.2 Spectrum sensing

CR co-exists with many other radio systems, using the same spectrum without interfering with one another and while sensing the spectrum's availability. Cognitive radio is still unable to make a variety of deliberations within spectrum sensing [2]. Continuous spectrum sensing is crucial for a cognitive radio system to be able to continuously sense the spectrum's occupancy.

Typically, a CR system will utilize the spectrum without interfering with the PU; however, the CR system must infinitely sense the spectrum in case the PU returns. This process is known as continuous spectrum sensing. If the PU returns to a spectrum in use, the cognitive radio system will have an alternative spectrum to which it can switch should the need arise. For the reason, sensing monitors are important for allocating the necessary alternative empty spectrum. This process is also necessary for the CR to detect the type of transmissions being received. The CR system should be able to determine the type of transmission that the PU is using so that any spurious transmission and interference then can be ignored, as well as the transmission that is being made by the CR system itself [20]. However, it is sometimes tough for the CR to have the exact measurements of the signal between the primary transmitter and the receiver; therefore existing spectrum sensing algorithms focuses on detection of the primary transmitted signal based on the local observations of the CR.

There are many spectrum sensing techniques to enhance the detection probability and some of the well-known spectrum sensing techniques is described as follows:

- *Matched filter detection*: When the prior knowledge of the PU is known by the SU, then the optimal signal detection is known as matched filter, detection which drastically escalates the signal–to–noise (SNR) ratio of the signal being acquired. One of the assets of the matched filter is that it requires less time to reach high processing gain but its requirement for a dedicated sensing receiver for all PU signal types is a significant downfall [3].
- *Cyclostationary detection*: This technique is more robust for noise unpredictability than other detection techniques. If the PU signal shows strong cyclostationary properties, it can be detected at exceedingly low SNR values, by exploiting the information embedded within the obtained signal. A signal is known as cyclostationary if the autocorrelation is a recurring function of function time t with some period [18]. The main advantage of cyclostationary detection is that it has superior detection performance even in low SNR region but is more complex to implement than other detection techniques [3].
- *Wavelet detection*: This is a multi-resolution analysis mechanism, where an input signal is disintegrated into various frequency components; at that moment, each component is carefully considered with a resolution suited to its scales. The wavelet then alters its irregularly shaped wavelets as a basic function to offer an exceptional apparatus with

sharp developments and local features [19]. For signal detection over wide-band channels, the wavelet approach shows superiority for both implementation cost and flexibility in adapting to the dynamic spectrum, as opposed to the conventional use of multiple narrow-band band-pass filters but it faces a critical challenge while implementing this process in practice is its high sampling rate for characterizing the large bandwidth [3].

- *Energy detection*: This technique is used when the primary user's prior knowledge is unknown. The method of energy detection is known for its optimal performance in detecting any zero mean on constellation signals. In this method, the RF in the channel or the indicator to which the strength of the obtained signal is then measured to further judge whether the channel is idle or not. Although the energy-detection process can be implemented without any prior knowledge of the PU signal but it still has some drawbacks, first one is it performs poorly in low SNR, and second is its inability to differentiate the interference from other SUs sharing the same channel and the PU [3].

2.2.1 Cognitive radio spectrum sensing methodologies

Number of attributes must be fused into any CR spectrum sensing schemes, which ensures that spectrum sensing is undertaken to meet the requirements of particular applications. The methods and attributes of the spectrum sensors ensure that the CR system is able to prevent any interference that may impede the performance of any alternative users while carefully maintaining its own function [20]. The different sensing methodologies are described below:

- *Spectrum sensing bandwidth*: This method has a number of problems, including whether or not will effectively sense the number of channels and whether or not they are being used. By sensing these channels separately from the channels that are currently occupied, the system is capable of identifying which alternative channels can be used should the current channel become occupied. Secondly, the definite reception of the bandwidth needs to be determined. A slender bandwidth reduces the system's noise floor and, thereby improves the sensitivity, but must acquire an adequately broadband width to properly detect transmissions in the channel.
- *Transmission type sensing*: The system must be able to identify transmissions from the PU for a specific channel. And also to analyze transmissions from other units in the same

system as itself. This system should also be capable of identifying various types of transmissions that could possibly be spurious signals.

- *Spectrum sensing accuracy*: A cognitive radio spectrum sensing mechanism must be able to recognize alternative signal levels accurately; therefore, the number of false alarms that may be received is significantly reduced.
- *Spectrum sensing timing windows*: The cognitive radio spectrum sensing technique must allow for different time niches when it is not transmitting properly, In order to enable the system to detect any other signals. This technique must be able to adapt to the frame format for the overall system [20].

2.3 Binary hypothesis testing (BHT)

As spectrum sensing problem requires a binary decision to be made on the presence/absence of the PU signal, statistical hypothesis testing is typically performed. The received signal $y(t)$ can be expressed in the form of a classical binary hypothesis testing model of the form [5]

$$y(t) = \begin{cases} n(t) & : H_0 \\ hs(t) + n(t) & : H_1 \end{cases} \qquad (2.1)$$

where H_0 denotes the hypotheses that the signal is absent, H_1 denotes that the signal is present, $n(t)$ is the additive noise, h is the wireless fading channel coefficient, $s(t)$ is the PU signal with energy E_s. This received signal is fed as an input to the ED for making a decision whether a PU signal is present or absent.

An ED is one of the most widely used detection technique due to its simple structure and non-coherent nature, as discussed earlier this technique can be used when the PU prior knowledge is unknown, it structure and functionality are described in next section.

2.4 Energy detector

The structure of ED is shown in Fig.1, where a received signal is fed to the noise pre-filter to choose the bandwidth of concern. The output signal is then squared and integrated over the observation interval, and the integrator's output is then compared to a predetermined threshold to decide on the presence or absence of the PU signal [6].

The ED is known to be an optimal in detecting signals in Gaussian noise environments, but this technique operates poorly under low SNR conditions perhaps because the noise variance is not precisely established at a low SNR, and the noise unpredictability may render the energy detection useless. ED's performance is likely to degrade in non-Gaussian noise environments as it likely to have low SNR, and consists of different noises like man-made noises which make ED perform poorly. Another problematic issue is the ED's inefficiency in differentiating the interference from secondary users utilizing the same channel as the PU. Furthermore, the threshold used in energy selection depends on the noise variance, and small noise power estimation miscalculations can result in a significant performance loss [22].

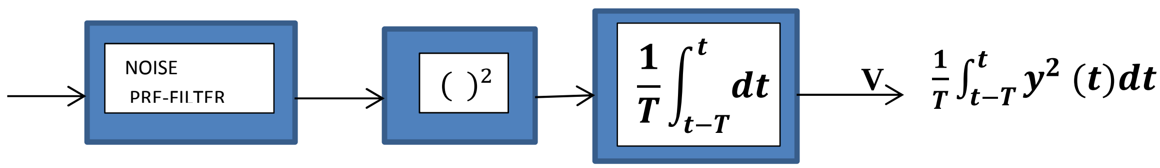

Fig. 1: Structure of an energy detector

In order to achieve a better performance in non-Gaussian noise environment an IED was proposed, which has a slightly different structure than ED. Its structure and functionality is explained in the next section.

2.5 Improved energy detector

. In various communication applications, the probability of an erroneous detection or of a precise detection is of great interest. A detector that expands the generalized possibility function may not be as reliable as a detector that maximizes the possibility of erroneous detection [22]. These considerations have motivated us to use the proposed IED in [3] which is likely to be more efficient than those presently used.

As the traditional ED is not an optimal tool in non-Gaussian noise environments, an IED is suggested which is based on a simple modification to the traditional energy detector. This modification simply replaces the traditional ED squaring operation of the signal's amplitude with an arbitrary positive power operation. The numerical results show that the desired power operation of the signal amplitude depends only on the feasibility of the detection, the average signal-to-noise ratio, or the sample size; however, it generally does not equal two as in the traditional ED [3]. Fig. 2 represents the structure of IED.

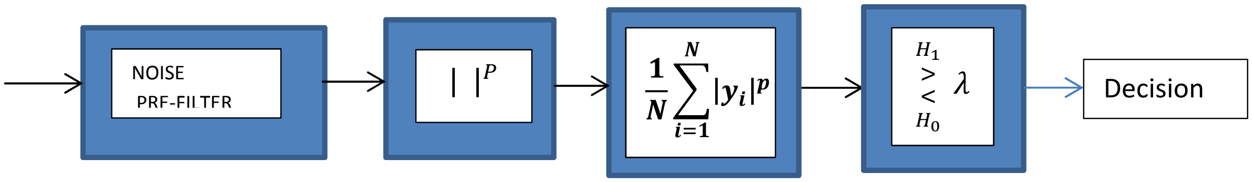

Fig. 2: Structure of an improved energy detector

The IED's digital implementation receives the signal and pass it through noise pre-filter (to limit the noise bandwidth), and then the output is sampled at a sufficient rate (According to sampling theorem) later achieved output is passed through an inconsistent power operation followed by an average over time (samples), when the signal output is generated after completing these phases, it is compared to the predetermined threshold to verify whether the signal is present or not, and resulting in a decision variable as given by

$$T = \frac{1}{N}\sum_{i=1}^{N}|y_i|^p \tag{2.2}$$

where T is the decision variable, N is the number of samples and y_i for all $i = \{1, 2, \dots, N\}$ are the received signal samples and p is the arbitrary positive power operation.

2.6 Performance metrics

For the better detection of signals in spectrum sensing there are many performance metrics which plays an important role as they will be crucial in making a decision on presence or absence of the PU signal. These performance metrics are as described below:

- *Probability of detection*(P_d): The P_d, is the probability of detecting the presence of a signal in a cognitive radio network. A lower threshold will increase the P_d.

$$P_d = \Pr\{H_1 \text{ true} \mid H_0\} = \Pr\{T > \lambda \mid H_1\} \tag{2.3}$$

where P_d is the probability of detection, and λ is the threshold [3].

- *The probability of false alarm*(P_f): The P_f is described as the ratio of the time when the envelope is above the threshold of the total time. A lower threshold will increase the P_f.

$$P_f = \Pr\{H_1 \text{true} \mid H_0\} = \Pr\{T > \lambda \mid H_0\} \tag{2.4}$$

where P_f is the probability of false detection [3].

- *Probability of error in decision making*(P_e): The P_e is described as the signal transmission in reporting channels between the cognitive radio and common receiver.

$$P_e = \Pr\{H_0\}.P_f + (1 - P_d)\Pr\{H_1\} \tag{2.5}$$

where P_e is probability of error [3].

- *SNR*: The SNR is defined as a ratio of the signal power to the noise power, which is expressed mainly in decibels. A ratio higher than 1:1 indicates more signal than noise. The SNR for Rayleigh fading is given as $\gamma = |h|^2 \frac{E_{s^2}}{\sigma_{\omega^2}}$

  where h = number of channels and σ_ω = variance of noise.
- *Detection threshold*(λ): the detection threshold is also called a sensory threshold, which is the level of strength that a stimulus must reach to be detected.

2.7 Fading channel models

When a signal is sent over a large distance, and the signal quality appears to be degraded even without the presence of large quantities of additive noise this degradation of signal quality is known as fading, and the channels that display these properties are known as fading channels. Fading channel models are often used to model the effect of electromagnetic transmission of information over the air and in cellular networks and broadcast communications The radio signals in cellular systems generally propagates on three mechanism; reflection, diffraction, and scattering. As a result of these mechanism cellular radio propagation can be roughly characterized by three independent phenomenon; path loss with distance, shadowing and multipath fading. Multipath fading produces rapid variation in the received signals envelope and is caused plain waves comes from multiple directions with random phases and combines them at a receiver antenna. Multipath-fading channels can be modeled as randomly time-variant linear filters, whose inputs and outputs can be described in both the time and frequency domain [35]. The different fading channel models are as described below:

- **Rayleigh fading** Rayleigh fading is a statistical model of or the effect of a propagation environment on a radio signal, such as that used by wireless devices. Rayleigh fading models assume that the magnitude of a signal that has passed through such a transmission medium (a communication channels) will either vary randomly, or fade, according to a Rayleigh distribution – the radial component of the sum of two uncorrelated Gaussian random variables.

Rayleigh fading is normally used as a suitable approach to take when analyzing and predicting radio wave propagation performance in areas such as cellular communications in a well built-up urban environment, which has many reflections from buildings. High frequency (HF) ionosphere radio wave propagation, where reflections (or more exactly, refractions) occur at many points within the ionosphere, is also another area where the Rayleigh fading model can be used effectively. This model can also be used for tropospheric radio propagation because it has many reflection points and the signal may follow a variety of different paths.

There is a Rayleigh propagation model most applicable in situation involving many different signal paths, none of which is dominant. In these situations, all the signal paths vary and can impact on the overall signal at the receiver [23].

This model is particularly useful in scenarios where the signal may be considered to be scattered between the transmitter and receiver. In this scenario, no single signal path dominates, and a statistical approach is required for analyzing the overall nature of the radio communications channel. This model can be used to describe the form of fading that occurs when multipath propagation exists. In any terrestrial environment, a radio signal will travel via a number of different paths from the transmitter to the receiver. The most obvious path is the direct, or line of sight path (LoS).

However many objects will be present around the direct path. These objects may either reflect or refract the signal. As a result, the signal may reach the receiver by following many other paths.

When the signals reach the receiver, the overall signal is a combination of all the signals that have reached the receiver by the many of different available paths. These signals will all sum together, the phase of each signal being important. Depending on how these signals sum together, the overall signal will vary in strength. If they were all in phase with each other, they will all add together; however, this case does not normally occur, as some signal will be in phase and others out of phase, depending upon the various path lengths, and therefore some will tend to add to the overall signal, whereas others will subtract from it [23].

For Rayleigh fading channel, the probability density function (PDF) of the envelope $\alpha = |h|$ is of the form

$$p_\alpha(\alpha) = \frac{\alpha}{b_0} \exp\left\{-\frac{\alpha^2}{2b_0}\right\}, \quad \alpha \geq 0, \tag{2.6}$$

where $2b_0$ is equivalent to the average envelope power.

The other fading models are briefly described as follows:

- **Rician fading** is a stochastic model for radio propagation abnormalities caused by partial cancellation of a radio signal solely caused by its own errors – the signal then arrives at the receiver through several different paths, with at least one of the paths changing. Rician fading occurs when one of the paths, typically a line-of-sight signal, becomes much more powerful than the rest. The amplitude gain within Rician fading is characterized by Rician distribution [24].
- **Nakagami$-\boldsymbol{m}$ fading** is a generic distribution, referred to as Nakagami$-m$, constructed as the product of N statistically independent, but not necessarily identically allotted. The Nakagami distribution can model fading conditions that are either more or less severe than Rayleigh fading which are introduced and then analyzed. This proposed distribution has turned out to be an exceptionally convenient tool for analyzing the operations of digital communication systems over a large number of generalized fading channels. The main results of the improved model are two-fold. Primarily, the moments-generating function (MGF), probability density function, cumulative distribution function (CDF), and moments of the Nakagami$-m$ distribution are imitated in a closed-form. Utilizing these formulae, the commonly used closed-form interpretations for the amount of fading, outage probability, and the average symbol error probability for several binary and multilevel modulation signals of digital communication systems functioning over Nakagami$-m$ fading channel models are presented [25], [26].

2.8 Cooperative Diversity

In wireless communication the cooperation between the pair of user's has been recommended as a mean to provide diversity in the wireless system. Diversity can be achieved by partnering users through a signaling scheme, allowing the information to transmit using both the antennas. The previously proposed schemes involve the users repeating the detected symbol or analog symbols of their partners [37]. Both of these schemes, despite of a noisy channel between the users shows improvement in the system capacity and outage probability [38].

In cooperative diversity, cooperative communication exploits the nature of the broadcast in wireless mediums that allow transmission of a radio's information jointly through relaying. As explained [27], along with other potential benefits, cooperative communications allow for spatial diversity when it is available during the time frame in which multiple transmissions experience fading and/or shadowing that is essentially independent. For example, if a source of the signal experiences a deep fade at the destination, then the signal can be effectively communicated to the destination via one of the relays. Due to coordinated communications, a network problem can inherently create issues of protocol because layering and cross-layer architectures will naturally arise. Starting as low as the physical layer, encoding and signal processing algorithms are required from the commencement(s) followed by relay(s), and signal processing and decoding algorithms are also required at the destination(s). However, these issues can easily be addressed simply as a part of the link layer, coding and retransmissions, essentially as an automatic repeat request (ARQ). Establishing the schedule for these adequate transmissions in time and frequency needs to be adequately addressed by protocols within the link layer and medium-access control sub-layer in coordination with the physical layer. Proper synchronization of these signals in terms of the carrier, symbols, and frame synchronization is particularly important in the physical and link layers. Collecting an array of radios into cooperative groups is a cross-layer issue that can involve medium-access control, physical, link, and even network layers. Designing an effective cooperative communication system requires an understanding of these various issues.

Some of the different cooperative strategies in cooperative communication are described below with respect to relays transmission:

- **Amplify and forward** relays simply amplify the received subject to their given power constraint and amplifying a linear transformation corresponding to the relay. When a collective number of relays become active, they check each relay in their own block of channel users so that the transmissions they permit do not interfere at the given destination, or they can simultaneously relay; therefore, the transmission interfere at the destination. The former approach offers better diversity benefits, but decreases the bandwidth's efficiency [28].
- **Decode and forward** relays administer a form of detection and/or decoding algorithms, receive signals, and re-encode information into transmitting signals. This decoding and re-encoding operation often responds to a non-linear transformation of the received

signals. Although relays decoding has the advantage of reducing the impact of the receiver's noise, it can drastically limit performance because of the incoming effects of fading [28].

2.8.1 Cooperative spectrum sensing

Within a cooperative cognitive radio spectrum sensing system [20], sensing can be initiated by using more than one radio within the cognitive radio network. Generally, a dominant station may obtain reports of many signals from a diverse range of radios within the network and then help the cognitive radio network to carry out its function. The interference can be reduced with cognitive radio cooperation in situation where a single cognitive radio cannot detect a PU due to a series of issues. A complication can arise such as simple shading from a primary user; however, if a SU is delegated as a recipient, the secondary user can be permitted to detect both the PU and the signal from the cognitive radio system [20].

To show the diversity gain of coefficient spectrum sensing, we continue to use the simplest energy detection scheme, keeping in mind that similar gain will also be achieved with more sophisticated detection schemes. We assume that cooperation is done in a centralized way where each secondary user sends its measurement output Y to a Fusion center (FC), which then makes a final decision after combining all the received $Y's$ and broadcasts the decision to the secondary users. We consider two combining schemes [28].

- **Soft-decision combining** in cooperative spectrum sensing means that information on the reliability of the sensing information is included by sharing more information on the observed signal energy between cooperating radios than just a decision about, whether the channel is free or occupied [28]. If no quantization is used, the cooperating radios send their full observation of the signal energy to the cognitive radio requesting sensing information. This radio then sums up the observations from the cooperating users and compares the sum to a threshold. Soft decisions can also be made with less precision than by sending the full observation of the signal energy.
- **Hard-decision combining** in cooperative spectrum sensing, means that each user observes the signal energy in the spectrum band compares this energy to a threshold, and makes a decision about the presence of a PU according to each other user's observations. Each cooperative node then shares its decision with the other cooperating radios by using

zero or one to indicate whether the node has observed a free channel or an occupied channel, respectively.

These decision made by all the cooperating radios can be combined using several different fusion rules, OR-rule or AND-rule [29], an OR-rule is being used in our case as it outperforms other rules and gives better performance.

- **OR-rule:** Using an OR-rule, the decision is made that a PU is present if even one of the cooperative radios detect it. The joint probability for detection Q_d and false alarm Q_f can therefore be expressed as [29].

$$Q_d = 1 - (1 - P_d)^k \quad (2.7)$$

$$Q_f = 1 - \left(1 - P_f\right)^k \quad (2.8)$$

where Q_d is the probability for detection in cooperative sensing, Q_f is the probability for false alarm in cooperative sensing, P_d is the probability of detection, P_f is the probability of false alarm and K is the number of CRs.

- **AND-rule:** Using an AND-rule, the decision is only made if all the cooperative radios detect the presence of the PU, this process leads to a low-joint probability of false alarm. Therefore, theoretical probabilities of detection Q_d and false alarm Q_f for K cooperative users using an AND-rule can be calculated as follows [29]

$$Q_d = {P_d}^K \quad (2.9)$$

$$Q_f = {P_f}^K \quad (2.10)$$

2.9 Noise models

Noise refers to the unwanted disturbance which degrades the quality of signals and images. Noise can be characterized as altering the acquired signal; But is not a part of the initial signal. Noise may be modeled by a histogram or a PDF, which is based upon the PDF of the signals [30].

In spectrum sensing, signal modeling is done by Gaussian modeling of the noise, as this method has been effective for a long time; normally the central limit theorem is used to justify the above assumption. The Gaussian assumption also allows analytical traceability for thermal noise in a Gaussian noise. The non-Gaussian noise arises quite often while practicing sensing.

Some examples of non-Gaussian noise are radar clutter noise, low-frequency atmospheric noise, and urban and man-made noises [31].

The Gaussian and non-Gaussian noise models are discussed in detail below.

2.9.1 Gaussian noise

It enacts statistical noise having a PDF equivalent to that of the normal dispersal, which is also known as Gaussian distribution. Gaussian noise is routinely not reliant on time, so that its actions are unpredictable and not in any way systematically planned. The amplitude of the frequency can fluctuate, simply by creating a crackling notation or sound. Gaussian noise can be caused by splashing in a tank or an unplanned interruption within a sensing device, for example.

A special case is known as white Gaussian noise, which contains a flat power spectral density, signifying that it carries a consistent amount of power at any given frequency. β equals to zero for white noise, white noise and white light share some of the same properties. White light consists of all the visible colors within the spectrum just as white noise is created by combining the tones of all the different frequencies.

Pure white noise beyond all the frequencies cannot physically exist. Such noise would require an infinite quantity of energy, and all established energy is a finite source. White noise is also created within a specific and distinguishable range of frequencies. Similarly, for a miniscule band of frequencies, visible white light contains a flat frequency spectrum. White noise is not always Gaussian noise. For Gaussian noise, the PDF of the noise has a Gaussian distribution, which basically defines the probability of the signal having a certain value [22].

2.9.2 Non-Gaussian noise

It is used to test the performance of detection techniques, and can be classified as class A noise and class B noise. Class A represents the noises like electromagnetic interference, which occurred mainly in telecommunications and class B noises are usually man-made noises or naturally occurring noises. The model can be sequenced to be modeled and is transformed to Gaussian by using non-linear transformations. Some of the popular non-Gaussian noise models applicable in communication systems are now briefly explained below:

- **Gaussian Mixture Noise (GMN)** is frequently used to depict man-made noise, impulsive phenomena, and certain types of ultra-wide-band interference.

- **Generalized Gaussian Noise (GGN)** is another popular model for non-Gaussian noise. GGN contains Laplacian($\beta = 1$) and Gaussian ($\beta = 2$) noise as special cases.
- **Co-channel interference** from other CRs may also impair spectral sensing. [33]
- **Laplacian Noise** is drawn from Laplacian distribution and is also known as bi-exponential noise. Its PDF, $p_n(x)$ is given as follows [34].

$$p_n(x) = \frac{1}{2b} exp\left(-\frac{|x-\mu|}{b}\right) \tag{2.11}$$

where b is the variance, and μ is the mean of the Laplacian noise.

Chapter 3

Spectrum sensing with an improved energy detector in Laplacian noise

3.1 Introduction

In this chapter, the performance of spectrum sensing using an IED in multipath fading and non-Gaussian noise environments is discussed. The wireless multipath fading is modeled as the Rayleigh faded and the non-Gaussian noise is modeled as Laplacian which popularly models an impulsive noise environment. First, single CR-based spectrum sensing is considered and the effect of various severity levels of the Laplacian noise on the detection reliability of the IED is characterized. Further, the effect of SNR, detection threshold and various values of the IED parameter p is illustrated.

However, a single CR may suffer from hidden terminal problem if the CR is shadowed by large obstacles such as buildings, hills, etc. such that it is cannot correctly identify the presence of PU in the band of interest and starts to transmit thus harmfully interfering with the PU transmission. To mitigate the problem and to increase the reliability of PU signal detection, a number of collaborating CRs for jointly identifying the PU signal is considered by deploying the OR-based suboptimal fusion rule. The interplay among the parameters such as SNR, noise severity levels, IED parameter p in collaborative spectrum sensing is investigated.

In this project, Rayleigh fading is used mainly because of its ease of analysis. It provides sufficient insights in an IED and the performance analysis in non-Gaussian noise and fading and achieves our desire to investigate the problem in a multipath fading and impulsive noise environment.

The rest of the chapter is organized as follows. The system model is described in Section 3.2. The simulation model is briefly discussed in Section 3.3. Numerical results and discussions for single CR as well as multiple CRs based spectrum sensing are presented in section 3.4. Finally, the chapter is concluded in Section 3.5.

3.2 System model

The received signal at the CR under the two hypotheses can be expressed as

$$y(t) = \begin{cases} n(t) & : H_0 \\ hs(t) + n(t) & : H_1 \end{cases} \tag{3.1}$$

where $s(t)$ is the PU signal, $n(t)$ is the additive noise modeled as Laplacian noise with mean with mean h and variance $2b^2$ whose PDF is given by

$$p_n(x) = \frac{1}{2b} exp\left(-\frac{|x-\mu|}{b}\right) \tag{3.2}$$

where and h is the Rayleigh fading channel, whose PDF of the envelope$\alpha = |h|$is given by

$$p_\alpha(\alpha) = \frac{\alpha}{b_0} \exp\left\{-\frac{\alpha^2}{2b_0}\right\}, \quad \alpha \geq 0, \tag{3.3}$$

where $2b_0$ is equivalent to the average envelope power. The received signal is fed to the input of the IED which, after processing, yields the decision statistic of the form

$$T = \frac{1}{N} \sum_{i=1}^{N} |y_i|^p \underset{H0}{\overset{H1}{\gtrless}} \lambda \tag{3.4}$$

where y_i for all $i = \{1, 2, \dots, N\}$ are the received signal samples and λ is the detection threshold. Then, the need is to study the detection performance in terms of metrics such as the probability of detection(P_d), the probability of false alarm (P_f), and the probability of error(P_e).

In case of cooperative spectrum sensing, we assume that there are a total of K CRs each independently sensing the presence or absence of the PU signals. Each CR after sensing, comes up with a binary decision on the PU signal activity and forwards its decision to the FC. The FC is responsible for combining the received decision and yielding a final decision on the presence of absence of the PU signal. We assume the FC deploys the OR rule in combining the individual CR decisions. Among several suboptimal decision fusion techniques, the OR rule infers the presence of the PU signal when there exists even a single CR that decides in favor of the PU being present. Since the OR is very conservative in allowing the CR to access the licensed band, it has minimal chances of causing interference to the PU. Since, the overall spectrum sensing performance of the CR network is now of interest, the desired performance metrics for cooperative spectrum sensing are: cooperative detection probability(Q_d), cooperative probability of false alarm (Q_f) and the cooperative probability of error(Q_e). For OR rule, these metrics are related to the metrics for a single CR as [3]

$$Q_d = 1 - (1 - P_d)^{\mathrm{K}} \tag{3.5}$$

$$Q_f = 1 - (1 - P_f)^{\mathrm{K}} \tag{3.6}$$

$$Q_e = (1 - Q_d + Q_f)/2. \tag{3.7}$$

Next, we focus on the numerical and simulation analysis for the aforementioned scenarios.

3.3 Description of simulation model

The system model is implemented in MATLAB and simulated using Monte-Carlo method with iterations up to 10^6.Next, we briefly describe the generation of Rayleigh fading channel coefficient and independent samples of the Laplacian noise.

Rayleigh fading channel generation

When the received signal consists of a large number of reflected, diffracted and scattered waves, the received complex envelope can be treated as a complex Gaussian random process [33] such that

$$h(t) = h_I(t) + jh_Q(t) \tag{3.8}$$

where $h_I(t)$ and $h_Q(t)$ are independent and identically distributed zero-mean Gaussian random variables and $j = \sqrt{-1}$is the imaginary unit.Then, the amplitude of $h(t)$, denoted by $\alpha(t) = |h(t)|$will be Rayleigh distributed with the PDF given in (3.3).

Generation of Laplacian noise

The PDF of the Laplacian noise in (2.7) can be used to find its CDF which is given by [32]

$$F_n(x) = \begin{cases} \frac{1}{2}\exp(-\frac{\mathrm{x}-\mu}{\mathrm{b}}) & \text{if } \mathrm{x} < \mu \\ 1 - \frac{1}{2}\exp(-\frac{\mathrm{x}-\mu}{\mathrm{b}}) & \text{if } \mathrm{x} \geq \mu \end{cases} \tag{3.9}$$

where the symbols are consistent with the previous notations. To obtain the Laplacian noise samples, we first generate a uniform random variable (which lies in between 0 and 1). This generated value is utilized as an ordinate and mapped using the inverse CDF of (3.9) to the corresponding abscissa which represents the sample which has the Laplacian distribution. Independent noise samples are generated using independent uniform random variables.

3.4 Numerical results and discussion

In this section, numerical plots are illustrated to gain meaningful insights for understanding the effect of critical parameters of interest and also to characterize the spectrum sensing performance of the IED under various values of the parameters. Several graphical plots are obtained to gain physical insights into the behavior of the IED. Specific numerical examples are discussed wherever applicable to further explain the physical insights. Note that one of the most important detector parameters of interest, the probability of error in decision making P_e, for equally likely hypotheses $\Pr\{H_0\} = \Pr\{H_1\} = 1/2$ can be written as

$$P_e = (1 - P_d + P_f)/2, \tag{3.10}$$

which is considered in the numerical plots. Similarly, the cooperative probability of detection Q_d and the cooperative probability of error Q_e for collaborative spectrum sensing are considered.

3.4.1 Single cognitive radio spectrum sensing

In this section, we illustrate the numerical analysis on spectrum sensing using a single CR. Next, the numerical results are discussed in details as follows:

Effect of μ on optimal p

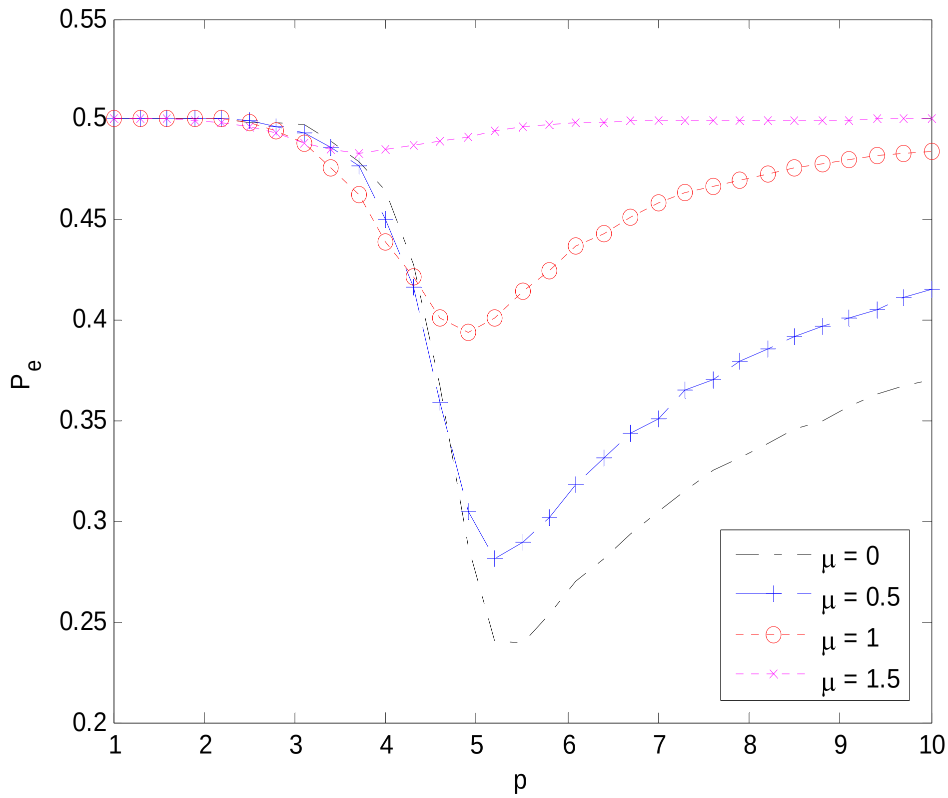

Fig.3. P_e against p for various μ values at $\sigma = 1$ and $\lambda = 5.5$, and $N = 8$

TheP_e vs. $p$plots in Fig. 3 show the effect of average value of Laplacian noiseμon parameter $p$of the IED at various values of μ value. Clearly, the IED performance degrades at higher average noise levels and thus lower levels of noise is desirable. Also, the ED performance is severely affected by non-Gaussian noise environment which is evident from the observation that for all μ values, the error in making a correct decision with an ED is no better than flipping a coin since the error probability is 0.5 for all μ. Thus, it is also clear that the ED is not the optimal choice for the parameter p and other p values yield significant reduction the probability of error in decision making. For instance, at $\mu = 0.5$, the $p = 5.5$ detector has an error probability of about 0.24 while the ED has an error probability of 5.5 which means as much as 52% improvement in detection performance can be attained by tuning the parameter p to 5.5 instead of keeping it constant at 2 as in the traditional ED.

Effect of σ

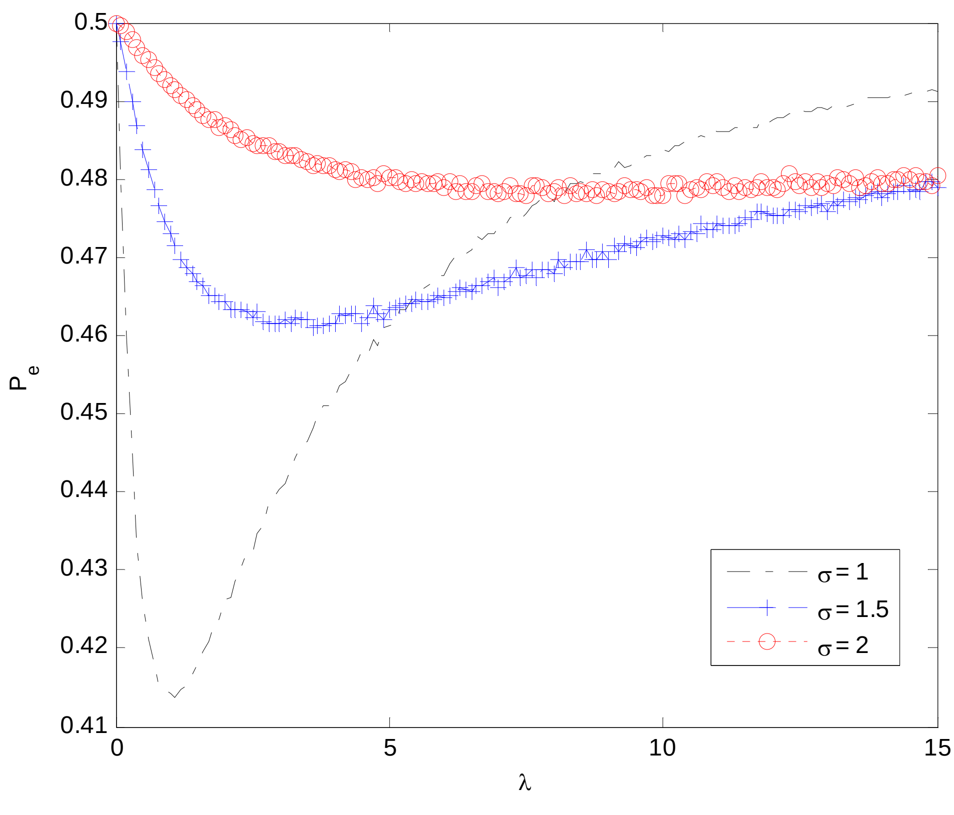

Fig.4. P_e against λ for various σ at an SNR of 0 dB, $\mu = 0$, $p = 3.5$, and $N = 8$.

Next, we study the effect of the noise variance on the IED sensing performance. Several P_e vs. λ plots are obtained at different values ofσ for an IED with $p = 3.5$. Clearly, a larger σ results in a higher error probability and also the threshold value that yields a minimum probability of error, varies with σ. Thus, the optimal choice of λ depends upon the level of noise variance.We can see that a larger noise variance degrades the detection performance and to mitigate the effect of larger noise variance, a higher detection threshold may be selected.

Effect of λ on optimal p with varying SNR

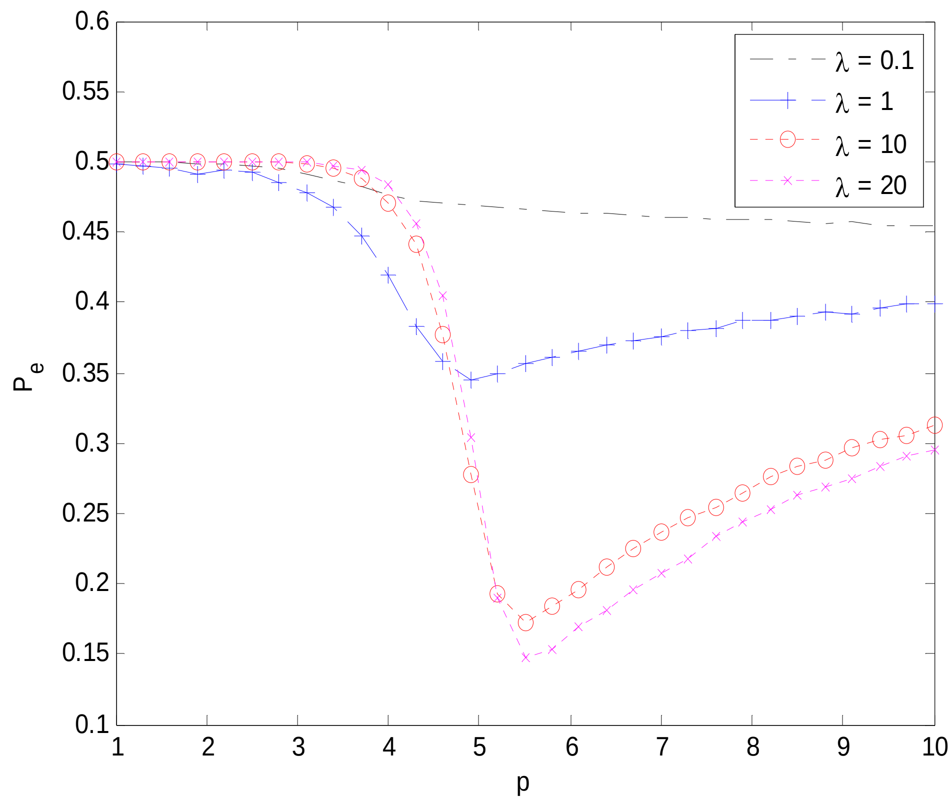

Fig.5. P_e against p varying λ with SNR = $-10{:}\,20$ dB, $\mu = 0, \sigma = 1$, and $N = 8$.

In Fig. 5, the effect of varying levels of SNR and p on the detection performance is studied at different values of the detection threshold. As p varies from 0 to 10, the SNR is varied from -10 dB to 20 dB and the corresponding P_e is computed at each (p, SNR) pair. Interestingly, the choice of different p at different SNRs yields significant performance benefits relative to the traditional ED. For example, with an optimal p of 5.5, the probability of error reduces by as much as 70% compared to the traditional ED observed at $\lambda = 20$. Further, the performance gets better (reduced probability of error) as the detection threshold is increased. For example, for an IED with $p = 5.5$, the probability of error is reduced from 45% to 15% when the detection threshold is increased from $\lambda = 0.1$ to $\lambda = 20$. Thus, a joint selection of an optimal p as well as λ is critical for attaining meaningful performance gains with an IED (compared to the ED) operating in regions with varying levels of SNR.

Effect of λ on optimal p with fixed SNR

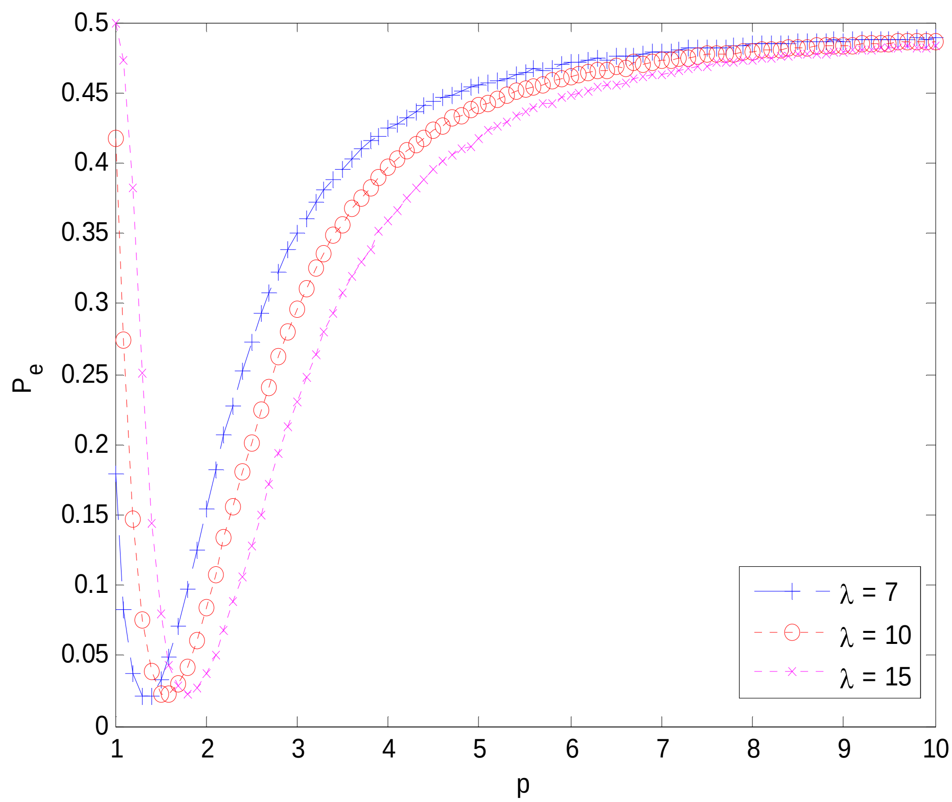

Fig.6. P_e against p varying λ with SNR =10 dB, $\mu = 0$, $\sigma = 1$, and $N = 8$.

In Fig.6, the effect of various λ on P_e vs. p curves is shown for a fixed SNR of 10 dB. In this case, unlike the case in Fig. 5, the SNR remains the same for all values of p. The difference is that the optimal value of p is confined within a smaller range ($1 < p < 2$). In other words, not much change in the optimal p is observed with changes in the detection threshold. Another interesting observation is that even though the optimal p does not change much when the SNR is fixed, the performance gain compared to a traditional ED is still significant. For example, at $\lambda = 10$, the $p = 1.3$ detector has about 80% less probability of error compared to the corresponding ED.

$\boldsymbol{P_e}$ vs. $\boldsymbol{\lambda}$ for various $\boldsymbol{p}$

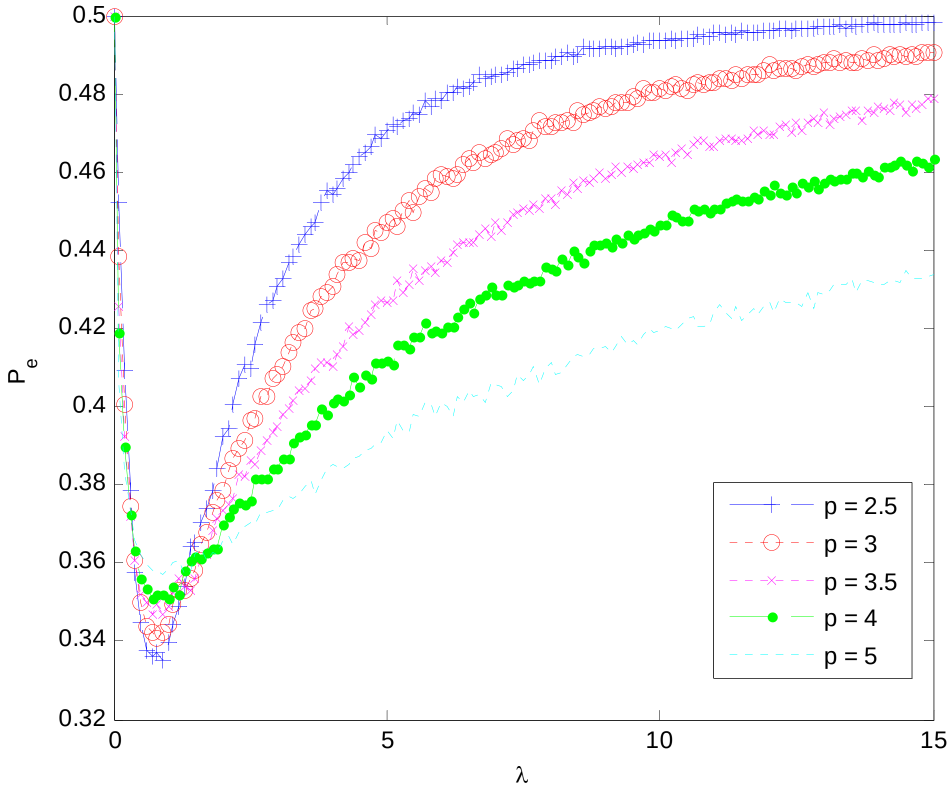

Fig.7. P_e against λ varying p with SNR = 0 dB, $\mu = 0, \sigma = 1$ and $N = 8$.

In Fig. 7, the P_e vs. λ curves are plotted for various values of the IED parameter p. An arbitrary set of p values which may not necessarily be the optimal ones are used to generate the graph. From the graphs, it is observed that for arbitrary p, the optimal threshold values are more or less the same and also the difference in performance of the various IEDs is similar. Thus, from this graph, we deduce that an IED is most useful when a proper p value is selected based on a certain criteria, say, a p that minimizes the probability of error or that which maximizes the probability of detection, etc. and that an arbitrary selection of p does not yield significant performance gains.

3.4.2 Coopeartive cognitive radio based spectrum sensing

In this section, the numerical analysis on spectrum sensing using a single CR is forwarded to cooperative spectrum sensing where mutiple CRs are used. Next the numerical results are discussed in details as follows:

Effect of K at various SNRs

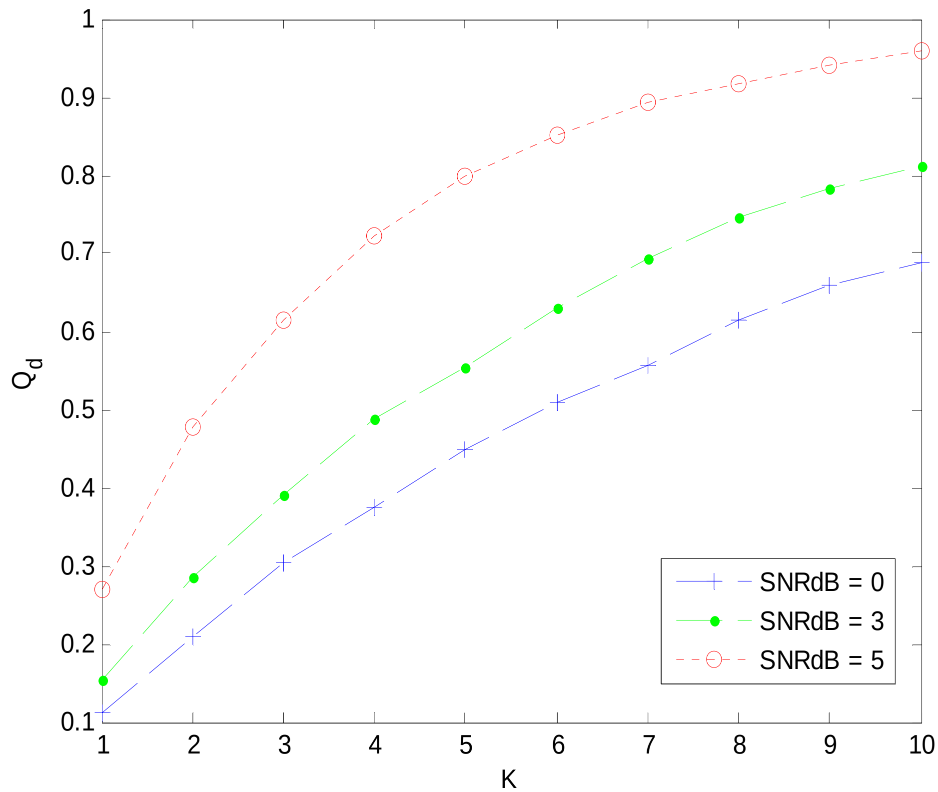

Fig.8. Q_d versus K varying SNR with $\mu = 1.5$, $\sigma = 2.5$, $p = 3.5$, $\lambda = 270$ and $N = 4$.

The effect of the number of cooperating CRs, K for various SNR values on the overall probability of detection is shown in Fig. 8. Interestingly, increasing the number of CRs yields a significant improvement in spectrum sensing performance of the CR network. As much as 70% increase in $Q_d$is observed when the number of CRs is increased from 1 to 10. Also, increase in SNR yields remarkable gain the Q_d. For example, increasing the SNR from 0 dB to 5 dB yields about 54 % increase in Q_d when the number of cooperating CRs is 5. Thus, increase in SNR as well as the number of cooperating CRs is always beneficial in improving the cooperative probability of detection of a CR network.

Effect of μ on K

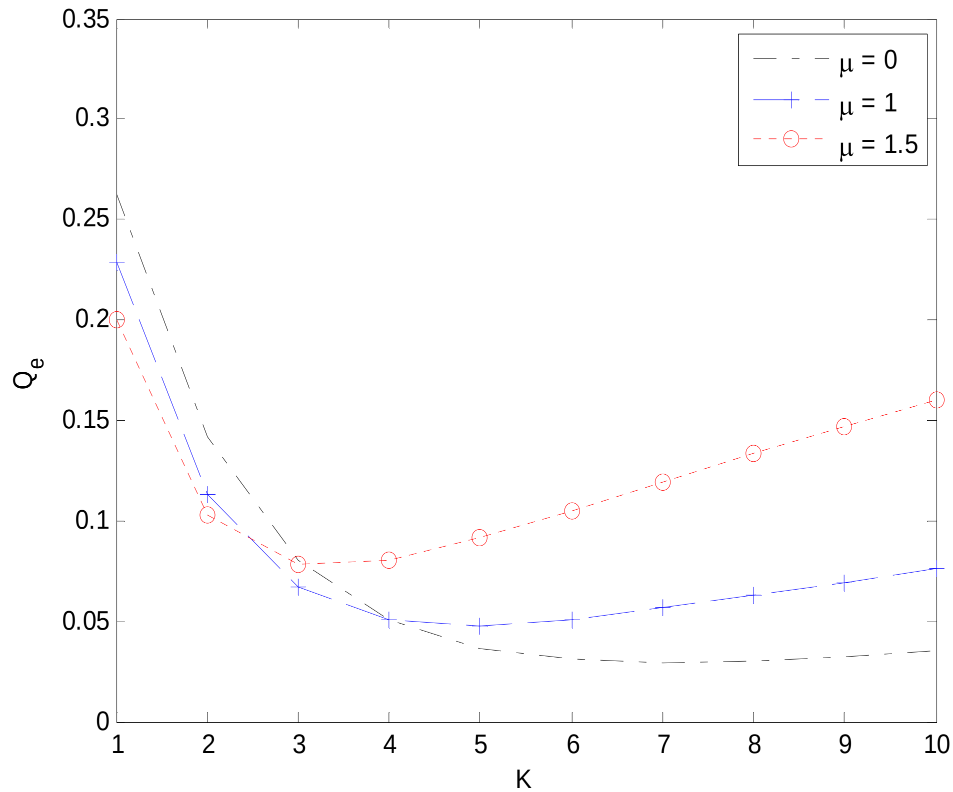

Fig.9. Q_e versus K varying μ with SNR = 5 dB,$\sigma = 2.5$, $p = 3.5$, $\lambda = 270$ and $N = 4$.

The interplay of the number of CRs and the average value of the Laplacian noise on the overall probability of error in making a decision is depicted in Fig. 9. A couple of interesting observations are evident. First, increasing the number of cooperating CRs is not always beneficial in terms of minimizing the cooperative probability of error. The overall probability of error keeps on decreasing with increasing K until it reaches a certain minimal value. Further increasing K beyond that point would start increasing Q_e thus indicating degradation in the overall sensing performance of the CR network. Thus, an optimal number of CRs must be selected to minimize the overall probability of error in making a decision. Second, it can be observed that an increase in the average level of the Laplacian noise tends to increase Q_e for a fixed number of CRs. For example, for a CR network with 10 cooperating CRs, about 70 % increase in the probability of error is observed when μ increases from 0 to 1.5. In such situations, a decrease in the optimal number of cooperating CRs is needed to minimize Q_e. Thus, increasing the number of users does not seem to be beneficial in minimizing Q_e at higher average noise levels.

Effect of σ on K

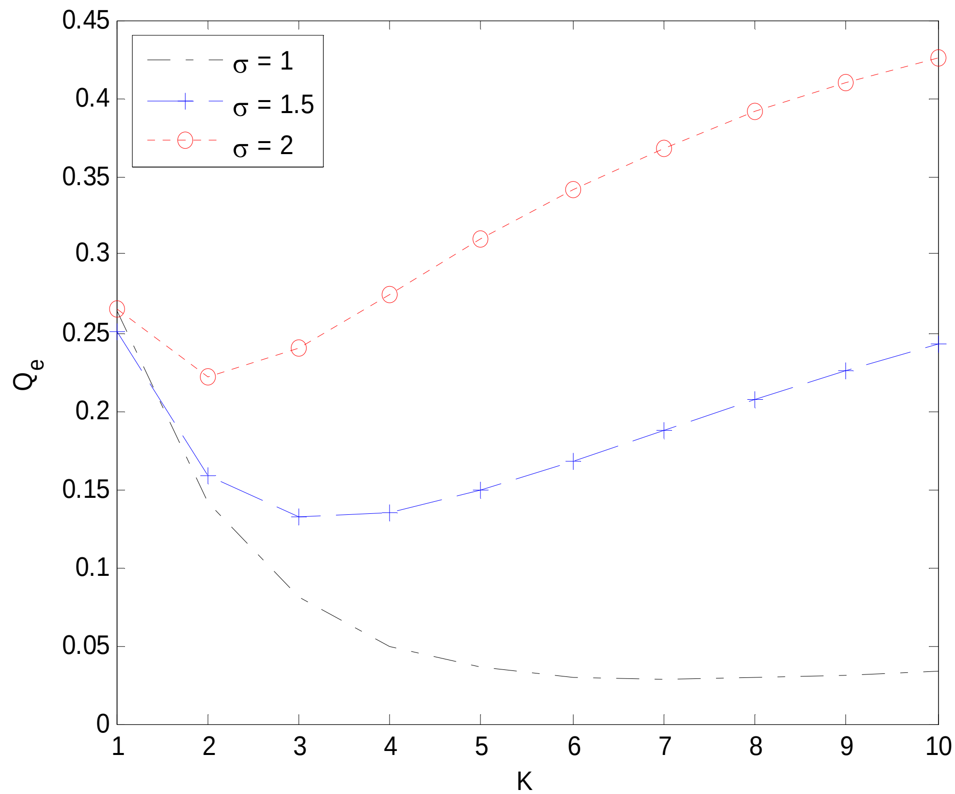

Fig.10. Q_e versus K varying σ with SNR = 5 dB, $\mu = 2.5$, $p = 3.5$, $\lambda = 270$ and $N = 4$.

The scenario for Fig. 10 is almost same but instead, the effect of number of CRs and the variance of Laplacian noise on the overall probability of error in making a decision is depicted in the above plot. First, increasing number of cooperative CRs is not always beneficial in terms of minimizing the cooperative probability of error same as observed in previous plot. The overall probability of error keeps on decreasing with the increasing K until it reaches a certain minimal value. Further increasing K beyond that point would make Q_e to increase resulting in the degradation in overall sensing performance of the CR network. Thus, an optimal number of CRs are required to minimize the overall probability of error in making a decision. Second, it can be noticed that increasing the variance of the Laplacian noise tends to show an increase in Q_e for a fixed number of CRs. For example, for a CR network with 10 cooperative CRs, about 72% increase in the probability of error when σ increases from 1 to 2. In such a situation, a decrease in the optimal number of CRs is needed to minimize the Q_e. Thus, increasing the number of users does not seem to be beneficial in minimizing Q_e at higher variance levels.

Effect of K on p

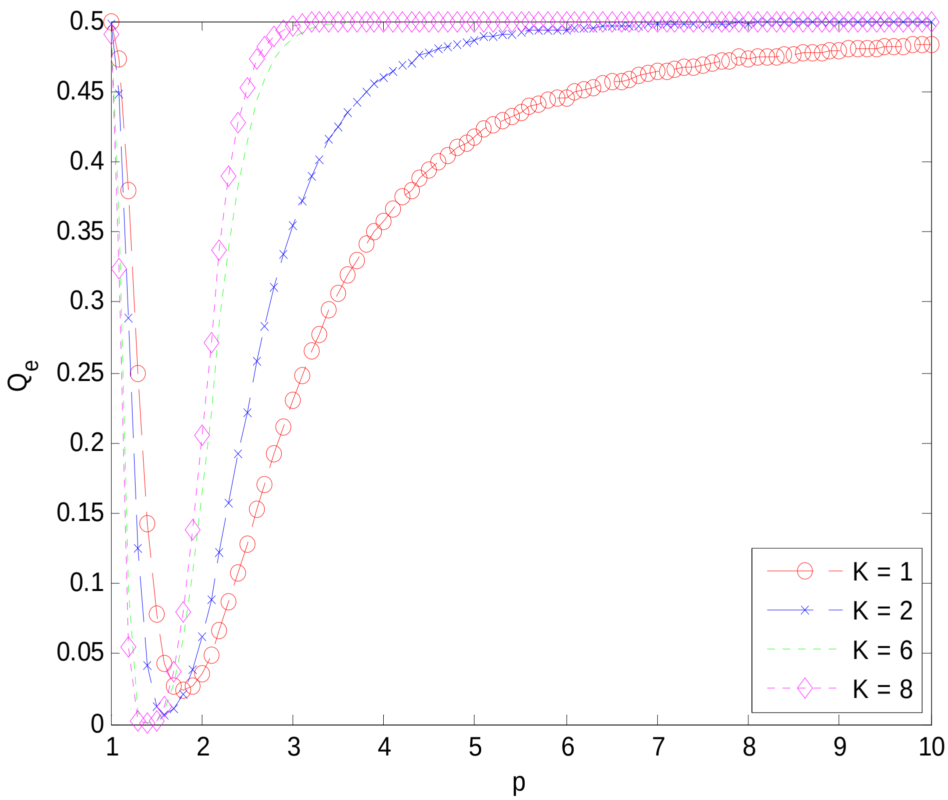

Fig.11. Q_e versus p varying K with SNR = 10 dB, $\mu = 1.5, \sigma = 2$, $\lambda = 15$ and $N = 4$.

The effect of number of CRs, K on p has been depicted in Fig. 11. Increasing number of K shows a minimal difference in Q_e, as the number of CRs increases the optimal p can be achieved which is almost closer to that of the traditional energy detector. For example, when the number of CRs is increased from 1 to 8, it can be observed that the curves start merging after 6

CRs giving the optimal value of p and minimal Q_e. Thus, an optimal number of CRs can be fixed for better performance gain with minimal probability of error.

3.5 Conclusion

In this chapter the sensing performance of an IED in Rayleigh fading and Laplacian noise is characterized. The effect of various levels of severity of the Laplacian noise on the detector performance metrics is studied through numerous simulation examples. Our results quantify the degradation in detection performance with the increase in the average value and variance of the noise. To mitigate the impact of severe noise levels, adaptive tuning of the IED parameter p is required and the optimal p value which maximizes the detection performance (by minimizing the probability of error in decision making) depends upon critical parameters such as the mean and variance of the noise, SNR level, and detection threshold. Also, significant performance gains compared to the traditional ED can be obtained with a proper choice of p. Next, the scenario is extended to cooperative spectrum sensing with K collaborating CRs each deployed with an IED. The central controller or the FC combines the individual decisions made by each CR according to the OR rule and comes up with a final decision on the PU signal. Interestingly, cooperation is proven to be beneficial to improve the reliability of spectrum sensing provided the optimal number of users K as well as IED parameter p is chosen appropriately.

Chapter 4

Conclusion and Future Work

The idea of CR networks came into existence to address the ever increasing demand for ubiquitous wireless services, by promoting the concept of dynamic spectrum utilization where the access to the use of licensed spectrum is not sternly limited to the PUs but can be made opportunistically accessible to the incumbent users called the SUs provided the SUs can successfully sense the presence of vacant bands. Spectrum sensing thus evolved as a fundamental task to promote such opportunistic communication is to identify the RF bands with idle PUs and to communicate over them without causing harmful interference to the PUs when they reappear. Motivated by the need to effectively sense the spectrum in wireless environments with impulsive noise at the receiver, in this project, the spectrum sensing performance of an improved energy detector in multipath fading modeled by Rayleigh distribution, and a non-Gaussian noise environment modeled by the Laplacian distribution is investigated. Compared to the traditional ED, the IED has a potential to yield significant performance gains even in scenarios where the noise has a high average value and/or variance. Also, the interplay among critical parameters such as the SNR, detection threshold, and the tunable parameter p on the sensing performance is quantified. Such quantification is necessary to efficiently design a reliable detection system for CR communication. To further enhance the performance of the IED-based CR network, a cooperative network of CRs operating in Rayleigh fading and Laplacian noise was considered with each CR deploying an IED. Significant increases in detection probability were observed with the increases in the number of collaborating users. However, to minimize the error in decision making, the number of collaborating users K as well as the IED parameter p needs to be chosen appropriately for the given operating conditions.

Further extension of the current work to incorporate the effect of shadowing on the detection performance of a single CR, and the role of collaborative detection in mitigating the impact of shadowing would be interesting. Similarly, consideration of other noise models such as the generalized Gaussian, Gaussian mixture, and Cauchy noise models and the role of the improved energy detector parameter p in mitigating the adverse impact of noise on the detection performance would yield considerable insights on the design of an effective spectrum sensing algorithm in a wider class of non-Gaussian noise environments.

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