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MINIMIZE THE ENERGY CONSUMPTION OF MOBILE SPECTRUM SENSING FOR COGNITIVE RADIO

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Abstract

Cognitive radio is a low-cost communication system, which can choose the available frequencies and waveforms automatically on the premise of avoiding interfering the licensed users. The spectrum sensing is the key enabling technology in cognitive radio networks. It is able to fill voids in the wireless spectrum and can dramatically increase spectral efficiency.

In this book, we will know the techniques to minimize the energy consumption and we will use MATLAB to simulate the received signals from the cognitive radio networks and an energy detector to detect whether the spectrum is being used. The project also compares the theoretical value and the simulated result and then describes the relationship between the signal to noise ratio (SNR) and the detections, and the result will show that with the increasing of the SNR (from 10 dB to 0) the detections we get also increased and within 7 dB and 5 dB, the increasing slope is the largest. So, the SNR influences the detections. It indicates that with the increasing of the SNR, the more spectrums which are occupied we can detect. At last, we will be talking about the future work.

Abbreviations

Chapter one	
PU	Primary Users
SU	Secondary Users
FSA	Fixed Spectrum Access
SDR	Software Defined Radio
CR	Cognitive Radio
SS	Spectrum Sensing
SNR	Signal To Noise Ratio
WSN	Wireless Sensor Network
CRS	Cognitive Radio Spectrum
Chapter two	
ITU	International Telecommunication Union
RAT	Radio Access Technology
SDR	Software Defined Radio
RAN	Radio Access Network
CSS	Cooperative Spectrum Sensing
TSEEOB	Two Stage Energy Efficient One Bit
TSTB	Two Stage Two Bit
DF	Final Decision
Chapter four	
AWGN	Additive White Gaussian Noise
ROC	Receiver Operating Characteristic
PFA	Probability of False Alarm
Chapter five	
CRN	Cognitive Radio Network
EESS	Energy Efficient Spectrum Sensing
RL	Reinforcement Learning

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Chapter One

Introduction

1.1. Overview

Radio spectrum is a vitally important one that we use in our day-to-day life. The applications of the Radio spectrum are vast, some of them are used to transmit information wirelessly through television, radio broadcasting, mobile phones, and Wi-Fi to communications systems for the emergency services, GPS, and radar, etc., Hence many critical services rely on the spectrum and thus it creates an indispensable part of all of our lives and one that is habitually taken for granted. Meanwhile, the increase in demand for the transmission of information, swift communications, and higher definition media may cause scarcity of spectrum usage. This might occur due to the outstrip of the spectrum supply. The key factor for the swift wireless communication which aids the rising tide of data is the availability of more spectrums. Moreover, it is a naturally available limited resource which has been already encumbered heavily.

Therefore, managing the available spectrum is predominantly important as well as a crucial task for the government. Radio waves compromise a specific part of the electromagnetic spectrum, which is the combination of many waves such as X-ray, Infrared waves, and light waves. However, the electromagnetic spectrum is classified into different waves correspondingly with their frequencies, which are estimated in Hertz [1]. However, the radio spectrum bounded from the low-frequency level 10 kHz to high-frequency level 100 GHz. While described in terms of wavelength the low-frequencies are about 30km long and high frequencies are about 3mm.

The Radio spectrum is divided into bands corresponding to their frequencies and exploited for several services. For example, in Europe, Asia, the Middle East, and Africa, the FM radio band is utilized for the radio broadcast and operates over 87.5 MHz-108 MHz Usually, the band is then subdivided into channels and is used for transmitting the services [1]. Thus, the individual channels in the FM band represent the separate radio stations. Furthermore, the increasing demand for higher resolution images and videos can cause scarcity of available spectrum, and hence reconfigurable radio terminal is the best available option for the next generation. By enhancing proper radio management services the terminals can be coercively modified into more effective to aid spectrum resources over intricate diversified networks and limited wireless networks.

Other important parameters to be considered while dumping the information in a wireless communication network is radio frequency allocation. Moreover, most of the RF spectrum is allocated while some of them are either overexploited or underexploited. Besides, these underexploited spectrums are called spectrum holes or vacant spectrum [2]. However, Spectrum Hole is a key term used in Cognitive radio in subjects with the spectral band. The term Cognitive Radio was first utilized by Mitola et al in [3]. Since the Cognitive radio network has the advantage of sensing the spectrum holes without any intricate, it can effortlessly adapt to the surrounding radio environment by applying its intelligence. Hence, it can seamlessly access the licensed spectrum more effectively and efficiently [4]. To enhance energy efficiency in all aspects many works have been implemented by the researchers. Nevertheless, some of them lack efficiency and some attain local optimization instead of global search optimization very easily. So, this paper introduces the

Fractional optimization model which combines the GWO and fractional CS algorithm to enhance the random walk to avert the local optimization problem. Thus, this method effectively provides the best solution that is an optimized solution.

1.2. Cognitive Radio

Wireless devices that communicate with one another using electromagnetic radio spectrum suffer from interference in a way or another. One consequence of this phenomenon is that such devices cannot usually operate on the same frequency band. The traditional approach to alleviate this issue has been to assign specific frequency bands of the radio spectrum to specific licensed users, such as TV broadcasters. The licensed users are often referred as Primary Users (PU) of the network, and the Secondary Users (SU), such as certain mobile devices, are not allowed to transmit on the band allocated to them. This policy is called Fixed Spectrum Access (FSA) [5]. Fast evolution of wireless communication systems has led to a situation in which the radio spectrum is almost fully allocated to PU’s. This is called the spectrum scarcity problem; the radio spectrum is becoming a limited resource and thus cannot support the increasing number of wireless devices infinitely [5, 6]. However, recent studies and measurements in various countries show that significant part of the radio spectrum is inefficiently used, utilization being in the range of 5% to 50% [7–9]. Therefore, it could be concluded that instead of the spectral scarcity, the inefficient utilization of the radio spectrum should be of the main concern in today’s radio communication policy. The emerging radio technologies are intended to allow the utilization of locally unoccupied frequency bands by the secondary users without interfering to the primary users. Therefore, the communication capacity of secondary users is strongly dependent on reliable and efficient detection of primary users and spectral opportunities by the means of spectrum sensing or geolocation-based databases. Software Defined Radios (SDR) that align their communication based on the detection of primary users are commonly referred as Cognitive Radios (CR) [10, 11]. A definition of cognitive radio that is widely referred to in today's literature is presented by Haykin in [7]: Cognitive Radio is defined as an intelligent wireless communication system that is aware of its surrounding environment and uses the methodology of understanding by building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g. transmit power, carrier frequency, and modulation strategy) in real time with two primary objectives in mind: One: highly reliable communication whenever and wherever needed, Second: efficient utilization of the radio spectrum.

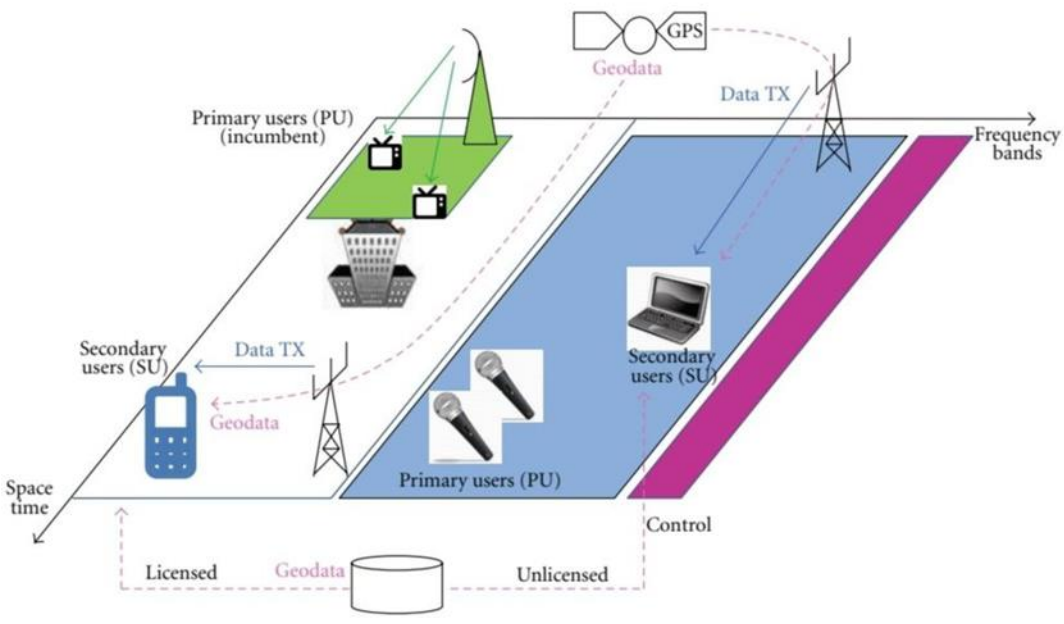

Figure (1.1): Opportunistic spectrum access overview.

1.3. The Advantages of Cognitive Radio

1. Overcome radio spectrum scarcity.

2. Avoid intentional radio jamming scenarios.

3. Switch to power saving protocol.

4. Improve satellite communications.

5. Improves quality of service (QoS).

1.4. Disadvantages of Cognitive Radio

1. Require prior information of the primary user.

2. Poor performance for low SNR cannot differentiate users.

3. Require partial prior information.

4. High sampling rate.

5. High computational cost.

1.5. Energy Efficient Spectrum Sensing

The SS process increases the energy consumption of sensing devices [12]. More often these devices will be energy constrained. Thus excessive SS, although critical for providing accurate information about the radio environment may lead to premature depletion of the sensing devices battery and consequently shorten its lifetime. Energy efficiency is thus a pertinent issue in a CRN. As the number of wireless devices and equipment continue to increase, there will always be a corresponding increase in the demand for more energy supply and a constant pressure in crafting out more energy efficient devices.

The importance in optimizing energy efficiency in cognitive radio networks are numerous but most of them points to the issue of design, green communications policy, savings as regards to monetary cost and end users' gratification and fulfillment. The more the energy being expended a wireless device, the more the heat due to the fact that energy used up in wireless devices gives rise to heat. Environmental issues such as green-house gas problem have also been a major source of concern to various government agencies around the world. The more energy being used, the more green-house gas is being produced. Due to this reason, a lot of compulsory and non-compulsory standards now necessitate wireless devices to be more energy efficient. there are many technologies that contribute to increasing energy efficiency, but most of them are almost not without flaws apart from the cost of a dedicated WSNs, WSN sensing the spectrum for CRNs is the best of all techniques as energy wasted by CRN in SS is almost zero**.**

Any CR device can start searching spectrum holes which are indicated in the database. If database shows some real-time spectrum holes then CR devices can directly start using it otherwise from the historic information it can understand Primary User's usage pattern in that region and start spectrum sensing to find out the spectrum holes. As the CR device knows about primary signal characteristics in a particular time from database, spectrum sensing can be less complex, accurate and less time consuming.

And by combining information from the database, history of primary user's usage patterns and signal characteristics of primary users, CR devices need not search the entire spectrum for availability but can rather zone in on a particular region. This process will save time and battery consumption.

1.6. The Aim of Book

The aim of this book is to comprehend the utilization of spectrum sensing in cognitive radio networks, and investigate the technique of the spectrum sensing. and minimize the energy consumption by different techniques.

We will use mat lab to simulate the signals from the cognitive radio networks and an energy detector to determine the status of the primary users. After getting the result, try to find the relationship between the factor SNR to and the final detections and investigate how the SNR influence the detections. Comparing the theoretical value and the measured value to determine whether the simulation working successfully.

1.7. Book Organization

The project was organized as following:

Chapter one is a simple introduction about the radio spectrum.

Chapter two about cognitive radio system (CRS).

Chapter three about system and mathematical model.

Chapter four about simulation and results.

Chapter five conclusion and future work.

Chapter Two

Cognitive radio system (CRS)

2.1. Definition and High-Level Concept

There are different definitions of cognitive radio system (CRS), from many authors and organizations. The definition giving the common understanding about CRS and now adopted for most is from International Telecommunication Union (ITU) [13]. CRS is a radio system employing technology that allows the system:

(i) to obtain knowledge of its operational and geographical environment, established policies, and its internal state (*cognitive capability*);

(ii) to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives (*reconfigurable capability*);

(iii) to learn from the results obtained (*learning capability*). At high level concept presented in Figure 2, the main components of the CRS are the intelligent management system and reconfigurable radios [14,15]. CRS is also able to take action including obtaining knowledge, the CRS dynamically and autonomously makes reconfiguration decisions according to some predefined objectives, for example, in order to improve efficiency of spectrum usage. Based on the decisions made, the CRS adjusts operational parameters and protocols of its reconfigurable radios. Such parameters include output power, frequency range, modulation type, and radio access technology (RAT) protocols. Software-defined radio (SDR) approach is used to implement the reconfigurations. Also, the CRS can learn from its decisions to improve its future decisions. The results of learning contribute to both obtaining knowledge and decision making. CRS can be classified into two types: heterogeneous

CRS and spectrum sharing CRS. The first type uses the network centric approach where one or several operators operate several radio access networks (RANs) using the same or different RATs. Frequency bands allocated to these RANs are fixed. Cognitive network optimizes radio resources and improves the Qi's. The second type of CRS is sharing CRS, where several RANs using the same or different RATs can share the same frequency band by using the unoccupied subbands in an intelligent and coordinated way. Most of standardization activities are related to this type of CRS

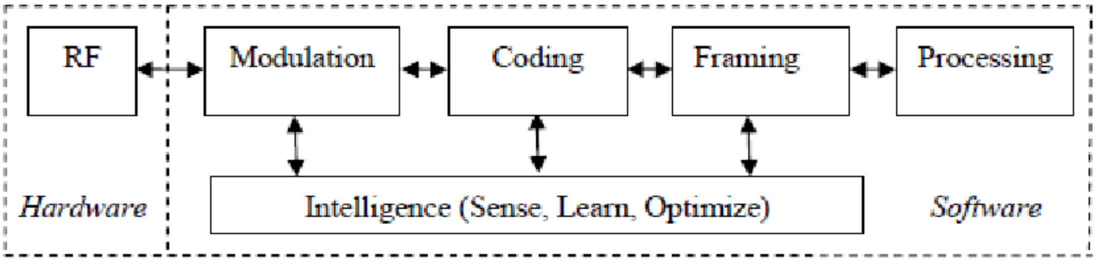

Figure (2.1): Block diagram of cognitive radio.

2.2. System model

We consider CSS in a centralized CR network consisting of a cognitive base station (fusion center) and a number of SUs. In the network, each SU sends its sensing data to the base station, and the base station combines the sensing data from different SUs and makes the final decision on the presence or absence of the PUs. We assume the sensing data are sent from the SUs to the base station free of error throughout this article. In this section, energy detection and CSS are introduced.

2.3. Energy detection

The target of spectrum sensing in CR network is to determine whether a licensed band is currently occupied by any PUs or not. This can be formulated into a binary hypothesis testing problem as. [16]

$$x(n) = \begin{cases} \omega(n), & H0 \\ h(n)s(n) + \omega(n), & H1 \end{cases} \qquad (2.1)$$

where n = 0, 1, ... , N; and N is the number of samples. The PU signal, background noise, and received signal are denoted by s(n), ω(n), and x(n), respectively. h(n) is the impulse response of the channel between the SU and PU. H0 represents the absence of primary signal, while H1 represents the presence of primary signal. The noise ω(n) is assumed to be additive white Gaussian noise with zero mean and unit variance (i.e., ω(n) ~ N(0, 1)). For ease of analysis, we assume that the channel impulse response h(n) is unchanged during the sensing process, i.e., h(n) = h [17]. Mathematically, the problem can be formulated as a binary hypothesis testing as follows:

$$T = \frac{1}{N} \sum_{n=1}^{N} |x\ (n)|2 \quad \begin{cases} > \lambda & H1 \\ < \lambda & H0 \end{cases} \qquad (2.2)$$

where T is the test statistic, and λ is the predetermined threshold. Let σ_s^2 and σ_ω^2 denote the transmitted signal power and noise power, respectively, and assume that $\sigma_\omega^2 = 1$. Define $\gamma = \sigma_s^2 / \sigma_\omega^2$ as the SNR value. The local false alarm and detection probability of the SU can be represented as [18]

$P_f = \Pr\ (T > \lambda | H0)$

$$= Q\ (\ (\lambda - 1) \sqrt{\frac{N}{2}}\ ) \qquad (2.3)$$

$Pd = \Pr\ (T > \lambda | H1)$

$$= Q\left((\lambda - \gamma - 1) \sqrt{\frac{N}{2(\gamma + 1)2}} \right) \quad (2.4)$$

where Q(.) is the Q-function.

2.4. CSS

We consider a CR network composed of K SUs and a base station (fusion center), as shown in Figure (2.2). We assume that each SU performs energy detection independently and then sends the local decision to the base station, which will fuse all available local decision information to infer the absence or presence of the PU.

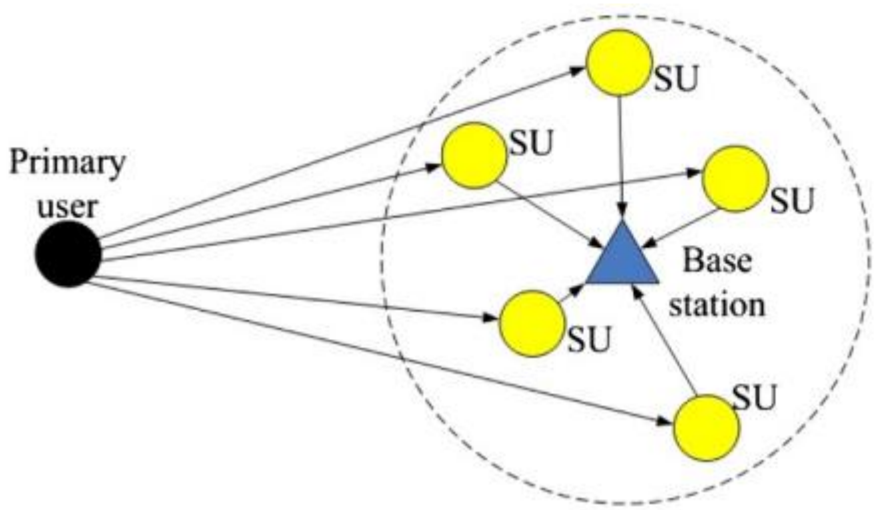

Figure (2.2): cooperative spectrum sensing structure in a CR network.

In the conventional hard combination CSS scheme, each cooperative partner i makes a binary decision based on its local observation and then forwards its one-bit decision Di (Di = 1 stands for the presence of the PU, and Di = 0 stands for the absence of the PU) to the base station. At the base station, all one-bit decisions are fused together according to the logic decision fusion rule [19,20], and the final decision can be obtained as

$$Y = \sum_{i=1}^{K} Di \begin{cases} \geq k & H1 \\ < k & H0 \end{cases} \quad (2.5)$$

where H0 and H1 denote the decision made by the base station that the PU is present or absent, respectively. The threshold k is an integer, representing the "n-out-of-K" rule. It can be seen that the OR rule corresponds to the case of $k = 1$, the AND rule corresponds to the case of $k = K$, and in the VOTING rule k is equal to the minimal integer larger than K/2 [19].

Only one-bit decision information is used in the hard combination CSS, and thus its detection performance is limited. Soft combination CSS scheme uses the accurate sensing results from the SUs, and it can achieve the better performance; however, its overhead is large. Two-bit overhead combination CSS scheme can obtain relatively higher performance than hard combination CSS with lower overhead than soft combination CSS, and it makes a trade-off between hard and soft combination CSS scheme.

2.5. TSEEOB-CSS

The TSTB-CSS algorithm proposed in [21] can improve the performance of the conventional hard combination CSS algorithm; however, its sensing time and energy consumption are the same as those in hard combination CSS. In this article, two TSEEOB-CSS algorithms are presented with almost the same sensing accuracy, and their sensing time and energy consumption are reduced greatly especially when the SNR is high or no PU exists.

In the proposed algorithms, we try to reduce the energy consumption of conventional CSS scheme with Ns samples by designing two TSEEOB-CSS schemes with αNs-sample first stage detection and $(1 - \alpha)$Ns-sample second stage detection. We assume that, in the Ns-sample detection of these three algorithms, the presence/absence status of the PU does not change. In other words, the received signal is stationary with the observation time T (i.e., Ns samples); this assumption is commonly used in the literature [22-25].

2.5.1. The first proposed algorithm

The first proposed two-stage one-bit CSS scheme is shown in Figure (2.3) , and the proposed scheme is represented by the following steps:

Step 1: Perform the first stage coarse energy detection with αNs samples at each SU, where 0 <α< 0.5. The sensing result of the SUi can be calculated as

$$T1_i = \frac{1}{\alpha Ns} \sum_{n=1}^{\alpha Ns} |xi\ (n)|^2 \qquad (2.6)$$

where xi(n) is the nth sample of the signal to be sensed at the SUi. If the detection result of SUi(i = 1, 2, ... , K) T1i > λ1 +Δ, sends the local decision D1i = 1 to the fusion center indicating that PUs exist; if T1i < λ1 −Δ, sends the local decision D1i = 0 to the fusion center indicating that no PU exists; if λ1 − Δ ≤ T1i ≤ λ1 +Δ, nothing will be sent. λ1 and Δ are two positive parameters that define the upper threshold λ1 + Δ and the lower threshold λ1 − Δ in the first stage detection.

Step 2: The first stage local decisions D1i are fused at the fusion center, and the final decision DF can be obtained as

$$DF = \begin{cases} 1, & More\ than\ K/2SUs\ indicate\ presence\ of\ PU \\ 0, & More\ than\ \frac{K}{2SUs}\ indicate\ absence\ of\ PU \\ Final\ decision\ cannot\ be\ obtained, & Otherwise. \end{cases} \qquad (2.7)$$

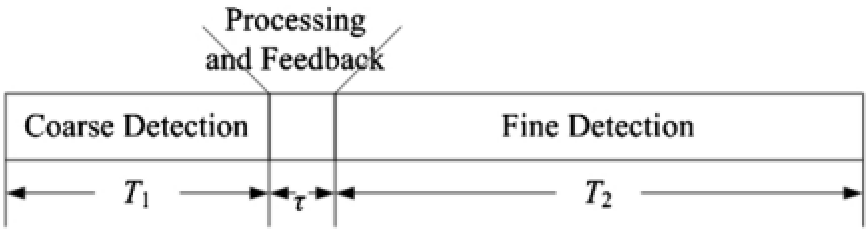

Figure (2.3): The proposed two-stage one-bit cooperative spectrum sensing scheme.

If the final decision DF can be obtained, DF is sent to each SU. If the final decision DF cannot be obtained, nothing will be done Step 3: If the final decision DF is received by the SUs, goes to step 6. If the final decision DF is not received by the SUs after τ period, perform the second stage fine energy detection with (1 − α)Ns samples, and the sensing result of the SUi can be calculated as.

$$T2i = \frac{1}{(1-\alpha)Ns} \sum_{n=1}^{(1-\alpha)Ns} |xi\ (n)|^2 \qquad (2.8)$$

Assume τ << T1 < T2 in Figure (2.3), and thus τ can be ignored compared with T1 and T2. Step 4: Local decision D2i (i = 1, 2, ... , K) is obtained through the second stage fine energy detection as

$$D2_i = \begin{cases} 1 & T2i \geq \lambda 2 \\ 0 & T2i < \lambda 2 \end{cases} \qquad (2.9)$$

where T2i is the second stage local sensing result of SUi using energy detection. Then the local decisions D2i are sent to the fusion center.

Step 5: The second stage local decisions D2i are fused at the fusion center, and the final decision DF can be obtained according to

$$DF = \begin{cases} 1 & \sum_{i=1}^{k} D2i \geq K/2 \\ 0 & Otherwise. \end{cases} \qquad (2.10)$$

DF is sent to each SU, and goes to step 6.

Step 6: Current detection ends.

The first TSEEOB-CSS algorithm described above can achieve almost the same performance as the conventional hard combination CSS algorithm. Its sensing time and energy consumption are reduced obviously when no PU exists or the SNR of PU is high, and therefore the sensing time can be saved and the energy efficiency can be improved effectively.

2.5.2. The second proposed algorithm

The first proposed TSEEOB-CSS algorithm above can achieve better performance with lower energy; however, the sensing results in the first stage coarse detection are not fully utilized, and its energy efficiency can still be improved. Thus, a second TSEEOB-CSS algorithm is proposed based on the first one, and its structure can also be described in Figure (2.3). The second TSEEOB-CSS scheme is represented by the following steps:

Step 1: Perform the first stage coarse energy detection with αNs samples at each SU as in Equation (2.6). If the detection result of SUi (i = 1, 2, ... , K) T1i > λ1 +Δ, sends the local decision D1i = 1 to the fusion center indicating that PUs exist; if T1i < λ1 −Δ, sends the local decision D1i = 0 to the fusion center indicating that no PU exists; if λ1 − Δ ≤ T1i ≤ λ1 +Δ, nothing will be sent.

Step 2: The first stage local decisions D1i are fused at the fusion center, and the final decision DF can be obtained as in Equation (2.7). If the final decision DF can be obtained, DF is sent to each SU. If the final decision DF cannot be obtained, nothing will be done.

Step 3: If the final decision DF is received by the SUs, goes to step 6. If the final decision DF is not received by the SUs after τ period, for the SUs that did not obtain the local decision D1 at the first stage, perform the second stage fine energy detection with (1 − α)Ns samples as in Equation (2.8), and for the SUs that obtained the local decision at the first stage, no more processing is needed. Assume τ << T1 < T2 in Figure (2.3), and thus τ can be ignored compared with T1 and T2.

Step 4: Local decision D2i(i = 1, 2, ... , K) is obtained through the second stage fine energy detection as

$$D2_i = \begin{cases} 1, & T2i \geq \lambda 2, when\ D1i\ was\ not\ obtained \\ 0, & T2i < \lambda 2, when\ D1i\ was\ not\ obtained \\ D1i, when D1i\ was\ obtained. & \end{cases} \quad (2.11)$$

where T2i is the second stage local sensing result of SUi using energy detection, D1i is the local decision of the SUi in the first stage. Then the local decisions D2i are sent to the fusion center.

Step 5: The second stage local decisions D2i are fused at the fusion center, and the final decision DF can be obtained according to

$$DF = \begin{cases} 1 & \sum_{i=1}^{k} D2i \geq K/2 \\ 0 & Otherwise. \end{cases} \quad (2.12)$$

DF is sent to each SU, and goes to step 6.

Step 6: Current detection ends.

The first proposed TSEEOB-CSS algorithm can achieve excellent performance with less energy consumption; however, the local decisions of the coarse detection are not fully used. The local decisions of the coarse detection are obtained through two-threshold sensing scheme, and they are more reliable than those of the conventional sensing with the same number of samples. If the local decisions of the coarse detection are utilized in the algorithm, its energy efficiency can be improved. Thus, the second TSEEOB-CSS algorithm is proposed based on the first one, which uses the local decision of the coarse detection to improve the energy efficiency of the algorithm with the same length of sensing time. However, the detection performance of the second TSEEOB-CSS algorithm is worse than the first TSEEOB-CSS algorithm. Thus, we should make a trade-off between the energy efficiency and detection performance to choose the proper algorithm in practical applications.

Chapter Three

System And Mathematical Model

3.1. Energy Efficient Spectrum Sensing Techniques for Cognitive Radio Networks

Some of the energy efficient spectrum sensing techniques are discussed below.

3.1.1. Reinforcement Learning Based Energy Efficient spectrum Sensing

Reinforcement learning [26] is a trial-and-error machine learning approach in which the decision maker, called the agent, observes the state of the environment and chooses actions that lead to rewards and new states. Actions leading to desired outcomes are given higher rewards, which reinforce these actions, thus making them more likely to be chosen again in similar situations in the future. Consequently, in reinforcement learning, the agent or agents are faced with the exploitation versus exploration tradeoff, i.e., whether to exploit the current best action or to explore other actions in hope of finding a better one. Energy efficiency is achieved by minimizing the number of assigned sensors per each sub band under a constraint on miss detection probability. The Reinforcement Learning Based Spectrum Sensing Policy balances between exploring and exploiting different parts of the radio spectrum and different sensing assignments.

3.1.2. History Assisted energy efficient Spectrum sensing

The history assisted energy efficient spectrum sensing scheme [27] employs an Iteratively developed history processing database. The usage of history helps predicting PU activity and results into reduced spectrum scanning by SUs thereby improving the sensing related energy consumption. Despite the fact that continuous scanning of the spectrum can fully capture the opportunities for the SUs, however it incurs costs in terms of increased energy consumption and sensing time. The history assisted spectrum sensing technique employs a database to process the spectrum sensing history and help SUs make a decision towards utilization of an empty space or to perform continued spectrum sensing. It is shown that the increased history utilization helps SUs conserve energy during the spectrum sensing.

3.1.3. Wireless sensor network assisted Cognitive Radio Networks

An energy efficient network architecture that consists of ad hoc (mobile) cognitive radios (CRs) assisted by infrastructure wireless sensor nodes can reduce the energy consumption by the cognitive radios as the spectrum sensing is done solely by the sensor network. Here sensor nodes within communications range of each CR are grouped into a cluster and the clusters of CRs are regularly updated according to the random mobility of the CRs. . An ad hoc CR, which is a cluster head, is surrounded by a cluster of infrastructure sensor nodes within one-hop communication range of the CR, and each cluster is further partitioned into subsets. The energy consumption is reduced by dividing each cluster into disjoint subsets with overlapped sensing coverage of primary user (PU) activity. Sleep wake scheduling for the subsets based on the statistical behavior of the PU can impart further energy efficiency of the CRN [28].

3.1.4. Energy efficiency through adaptive spectrum probing

There is an optimal spectrum sensing interval which reduces total energy consumption. In the an adaptive spectrum sensing time interval strategy, SUs can adjust the next spectrum sensing time interval according to the current spectrum sensing results (namely, channel status).It's a dynamic spectrum sensing strategy in which the next spectrum sensing time is adaptive and based on current spectrum sensing results. That is, spectrum sensing time interval is not fixed, according to the current sensing result [29].

3.2. Threshold setting and performance analysis

The parameters are important to the proposed algorithms, so in this section, the threshold setting is discussed. In addition, the energy efficiency and time-saving performance of the algorithms are further analyzed .

3.3. Analysis of threshold setting

There are three important parameters in the two proposed TSEEOB-CSS algorithms, $\lambda1$, $\lambda2$, and Δ. These parameters affect the detection performance greatly. Thus, we discuss the parameters setting, and give some rules as follows.[30]

3.3.1. The rules in setting Δ

Remark 1. For a fixed value of $\lambda1$, the larger the value of Δ is, the better the detection performance can be achieved with longer sensing time. Assume the square of the sampled signal $x(n)$, $|x(n)|^2$, follows a distribution with mean μ and variance σ^2. The sensing result of the first stage detection can be described as

$$T = \frac{1}{\alpha Ns} \sum_{n=1}^{\alpha Ns} |x\ (n)|^{\ 2} \tag{3.1}$$

which follows Gaussian distribution with mean μ and variance $\sigma^2/(\alpha Ns)$ according to the central limit theorem. Therefore, the probability the final decision obtained at each SU after the first stage coarse detection can be expressed as

$$p = 1- \int_{\lambda 1-\Delta}^{\lambda 1+\Delta} \frac{1}{\sqrt{2\pi\alpha Ns\sigma}}\ e^{-\frac{(x-\mu)2}{2\sigma 2/(\alpha Ns)}}\, dx \tag{3.2}$$

Hence, when Δ is larger, and the probability $(1 - P)$ indicating the need of second stage fine detection correspondingly becomes larger, which means the sensing time becomes longer. Also, the detection performance becomes better for the probability of second stage detection is larger. Remark 2: Δ should be smaller as the sample number αNs of the first stage coarse detection becomes larger. Assume the background noise $\omega(n)$ in (1) follows Gaussian distribution with zero mean and unit variance (i.e., $\omega(n) \sim N(0, 1)$), and thus the square of $\omega(n)$, $|\omega(n)|^2$, follows chi-square distribution with 1 degree of freedom. The mean of $|\omega(n)|^{\ 2}$ is 1, and its variance is 2. The first stage coarse energy detection result can be expressed as

$$T = \frac{1}{\alpha Ns} \sum_{n=1}^{\alpha Ns} |\omega\ (n)|^{\ 2} \tag{3.3}$$

when no PU exists, and it follows Gaussian distribution with mean 1 and variance σ^2 H0 = $2/(\alpha Ns)$ according to the central limit theorem. We set

$$\Delta = a\sigma H0 = a \sqrt{2/(\alpha Ns)} \tag{3.4}$$

where a is a positive constant. When the number of samples becomes larger, e.g., $Ns_2 = 2\alpha Ns$, the variance of the first stage coarse energy detection result changes to $2/(2\alpha Ns) = 1/(\alpha Ns)$, and hence Δ should be set as a $\sqrt{1/(\alpha Ns)}$ accordingly. Therefore, the larger the number of samples is, the smaller the value of Δ should be.[30]

3.3.2. The rules in setting λ1

Remark 3: λ1 should be set according to the requirement of the false alarm probability (Pf). In Case I as shown in Figure (3.1), λ1 is set relatively low (e.g., below 1). If no PU exists, the distribution of the first stage energy detection result is shown in Figure (3.1). The probability that the detection result is larger than λ1 + Δ is so large that Pf cannot be set small (e.g., Pf = 0.01). In Case II as shown in Figure (3.1), λ1 is set relatively high (e.g., above 1). The probability that the detection result is smaller than λ1 − Δ is so large that Pf cannot be set large (e.g., Pf = 0.5). For Pf above 0.5 is not meaningful in practical networks, λ1 is usually set above 1. Furthermore, if certain Pf can be achieved, the detection performance is better when λ1 is smaller. However, when λ1 becomes smaller, the probability indicating the need of second stage fine detection becomes larger when

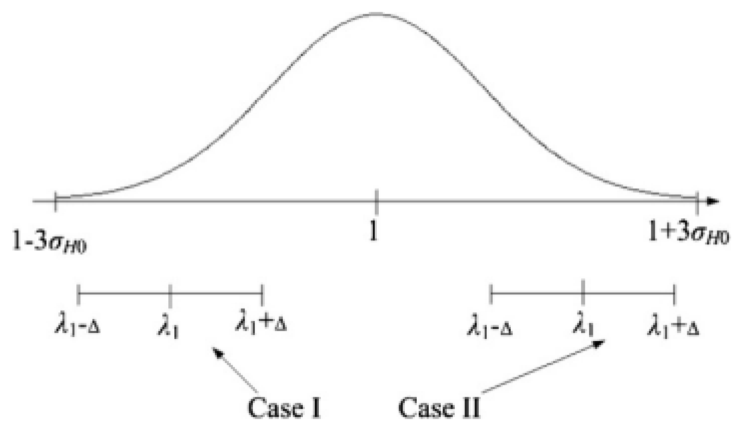

Figure (3.1): The distribution of the first stage energy detection.

SNR is low or no PU exists, which means the sensing time becomes longer and the energy consumption becomes larger.[30]

3.3.3. The rules in setting λ2

As analyzed above, we know that the parameters Δ and λ1 determine the detection performance and the computational complexity of the algorithms. Thus, Δ and λ1 should be set first according the requirements of the detection performance and energy consumption when applied to practical systems. λ2 can be set according to the values of Δ and λ1 When Δ is fixed, λ2 should be set larger with smaller λ1. When λ1 is fixed, λ2 should be set larger with larger Δ. With certain values of Δ and λ1, the value of λ2 is deterministic. Thus, after λ1 and Δ are set, λ2 can be set according to the required value of Pf through measurements in advance. The above rules in setting Δ, λ1, and λ2 are all suitable for both of the two proposed TSEEOB-CSS algorithms.[30]

3.4. Analysis of energy-efficiency and time-saving performance

Remark 4: The energy consumption and sensing time of the proposed schemes are reduced significantly compared to the conventional CSS scheme with the same number of samples, especially when the SNR of the PU signal is high or no PU exists. The probability of the local decision D1i in the first stage coarse detection at the ith SU equal to 1 and 0 can be expressed, respectively, as

$$P1 = Q\left((\lambda 1 + \Delta - \gamma - 1)\sqrt{\frac{\alpha Ns}{2(\gamma+1)2}} \right) \Pr(H1) + Q\left((\lambda 1 + \Delta - 1)\sqrt{\frac{\alpha Ns}{2}} \right) \Pr(H0) \quad (3.5)$$

$$P0 = \left(1 - Q\left((\lambda 1 - \Delta - \gamma - 1)\sqrt{\frac{\alpha Ns}{2(\gamma+1)2}} \right) \right) \Pr(H1) + \left(1 - Q\left((\lambda 1 - \Delta - 1)\sqrt{\frac{\alpha Ns}{2}} \right) \right) \Pr(H0) \quad (3.6)$$

where Pr(H1) and Pr(H0) = 1 − Pr(H1) denote the probabilities of the presence and absence of the primary signal, respectively.[31] The energy consumption of the spectrum sensing is mainly caused by the energy detection using the samples of the received signal at all the SUs, and we can define the energy consumption of the conventional CSS algorithm through a function of the number of the samples as

$$E_{CSS} = KN_s e_0 \quad (3.7)$$

where K is the number of SUs in the CSS, N_s is the number of samples at each SU in the detection, and e_0 is the energy consumption corresponding to one sample of the detection.[31] The energy consumption of the first and second proposed TSEEOB-CSS algorithms can be expressed as

$$E1 = K\alpha N_s e_0 + K((1-\alpha)N_s)e_0 \left(1 - \sum_{i=\left[\frac{k}{2}\right]+1}^{k} \binom{k}{i} P_1^{i} (1-P_1)^{K-i} - \sum_{i=\left[\frac{k}{2}\right]+1}^{k} \binom{k}{i} P_0^{i} (1-P_0)^{K-i} \right) \quad (3.8)$$

$$E2 = K\alpha N_s e_0 + K((1-\alpha)N_s)e_0 \left(1 - \sum_{i=\left[\frac{k}{2}\right]+1}^{k} \binom{k}{i} P_1^{i} (1-P_1)^{K-i} - \sum_{i=\left[\frac{k}{2}\right]+1}^{k} \binom{k}{i} P_0^{i} (1-P_0)^{K-i} \right) (1 - P1 - P0) \quad (3.9)$$

From (3.8),(3.9), we can easily obtain

$$E2 < E1 < E_{CSS} \quad (3.10)$$

Thus, we can conclude that the energy consumption is reduced significantly by the two proposed CSS schemes, and the energy consumption of the second TSEEOB-CSS algorithm is much lower than that of the first algorithm. Similarly, assuming the sensing time of the CSS algorithms is mainly determined by the energy detection using the samples of the received signal at all the SUs, the sensing time of conventional CSS algorithm can be defined through a function of the number of the samples as

$$T_{CSS} = N_s t_0 \qquad (3.11)$$

where t_0 is the duration corresponding to one sample of the detection. The sensing time of the first and second proposed TSEEOB-CSS algorithms is the same, and can be represented as

$$T1 = T2 = \alpha N_s t_0 + ((1-\alpha)N_s)t_0 \Big(1 - \sum_{i=\left[\frac{k}{2}\right]+1}^{k} \binom{k}{i} P_1^i (1-P_1)^{K-i} - \sum_{i=\left[\frac{k}{2}\right]+1}^{k} \binom{k}{i} P_0^i (1-P_0)^{K-i} \Big) \qquad (3.12)$$

From (3.11) and (3.12), we can obtain that

$$T1 = T2 < TCSS \qquad (3.13)$$

Thus, we can conclude that the time consumption is reduced significantly by the two proposed CSS schemes, and the time consumption of the two algorithms is the same. [30]

The time and energy consumption of the proposed algorithms can be reduced effectively, and we will clarify it briefly. When there are PUs in the network, the first stage coarse energy detection result T follows a distribution with the mean of $1 + \mu s$. If the SNR of PU signal is larger, $1 + \mu s$ will be larger, and thus the probability that $T > \lambda 1 + \Delta$ will also become larger. This means the probability indicating the need of second stage fine detection becomes smaller, and thus the sensing time and energy consumption will be reduced due to the low probability of the need of second stage fine detection.[32] When no PU exists in the network, the probability that $T < \lambda 1 - \Delta$ is relatively large because $\lambda 1$ is usually set above 1. Therefore, the probability indicating the need of second stage fine detection is relatively small, and the sensing time and energy consumption will also be reduced greatly when no PU exists. From the above analysis, we can conclude that the sensing time and energy consumption is reduced greatly when the SNR of PU signal is high or no PU exists in the proposed two algorithms, and it enables a "green" CR network.[32]

Chapter Four

Simulink And Result

4.1. Simulating the Signal in MATLAB

As we know that CR promises the secondary users access the spectrum which is allocated to a primary user, so avoiding interference to potential primary users is a basic requirement. Therefore, we should detect the primary user status through the continuous spectrum sensing.

We use MATLAB to encode the output signal from the integrator with zero-mean AWGN. The output signal is in Chi-square distribution, we assume the Chi-square distribution as Gaussian distribution when samples are large, so we can encode the output signal from the integrator as: sig=sqrt(sigmas^2+sigman^2)*randn(100,N), which obeys the Gaussian distribution. Sigmas^2 is the variance of the signal waveform, sigman^2 is the variance of AWGN, the operation randn distributes random numbers and arrays. Then we set the values of the parameters to simulate the signal:

SNR = -10 dB (we take an example); the bandwidth W = 1×10^5 ; the observes time ts = 1×10^{-2} s; samples N = 2 × ts × W; the variance of the noise $\sigma_n^2 = 1\times10^{-2}$; the variance of the received signal $\sigma_s^2 = (\sigma_s \times 10^{-1})^2$ (SNR= -10 dB);

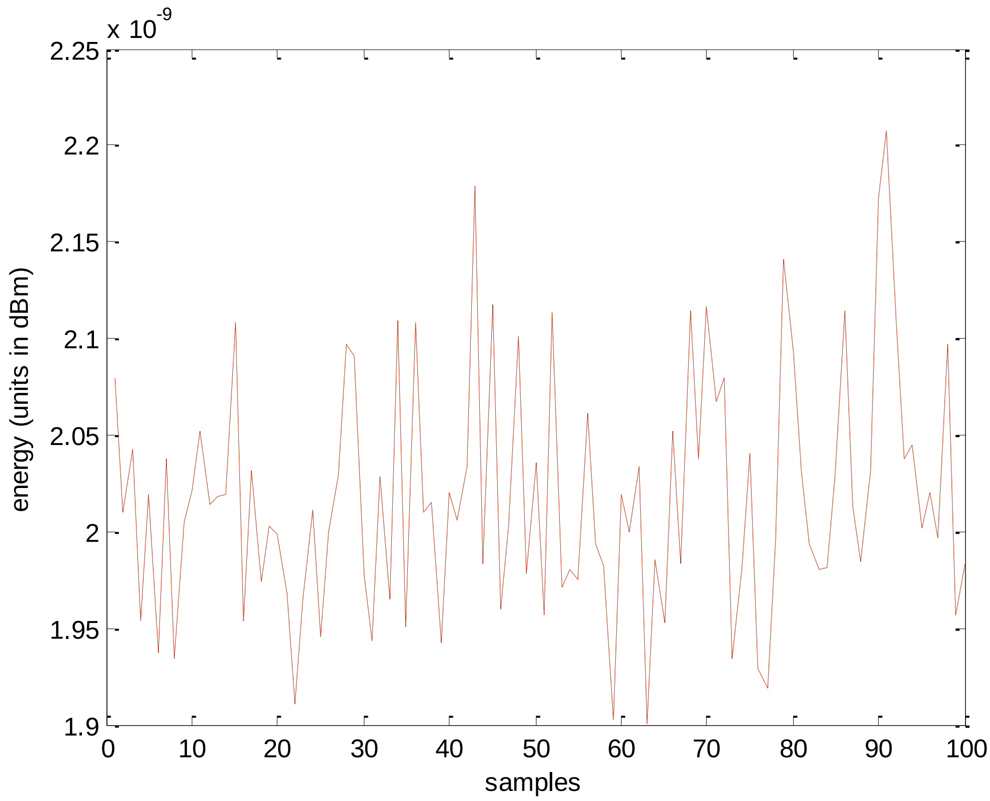

Figure (4.1): output signal with AWGN

Figure (4.1) is the simulated output signal with AWGN. The x-axis shows the samples we take and the y-axis shows the energy (units in dBm) of the signal. The figure shows the different signals‟ energy at different samples.

4.2. Probability of false alarm and probability of miss detection

The proposed scheme provides better probability of detection, reduced probability of false alarm and probability of miss detection and thus outperforms the existing hard decision-based technique for varied SNR conditions. The ROC plot between Probability of false alarm and probability of detection (Pd) for SNR=-10 dB

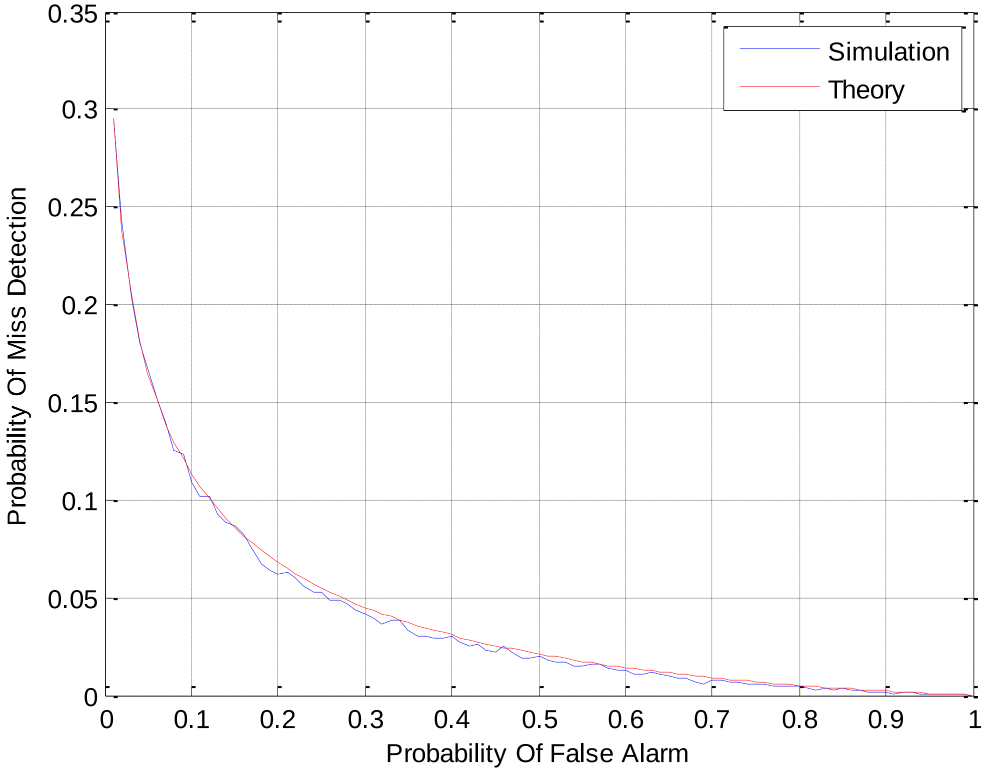

Figure (4.2): ROC plot between Probability of false alarm (Pfa) and probability of miss detection

The ROC plot between Probability of false alarm (Pfa) and probability of miss detection for SNR = −10 dB is shown in Figure (4:2). The probability of miss detection is very low compared with the existing scheme.

4.3. Receiver operating characteristic curve for simple energy detection

This plot is for receiver operating characteristic curve for simple energy detection, when the primary signal is real Gaussian signal and noise is additive white real Gaussian. Here, the threshold is available analytically.

It can also be thought of as a plot of the power as a function of the Type I Error of the decision rule (when the performance is calculated from just a sample of the population, it can be thought of as estimators of these quantities).

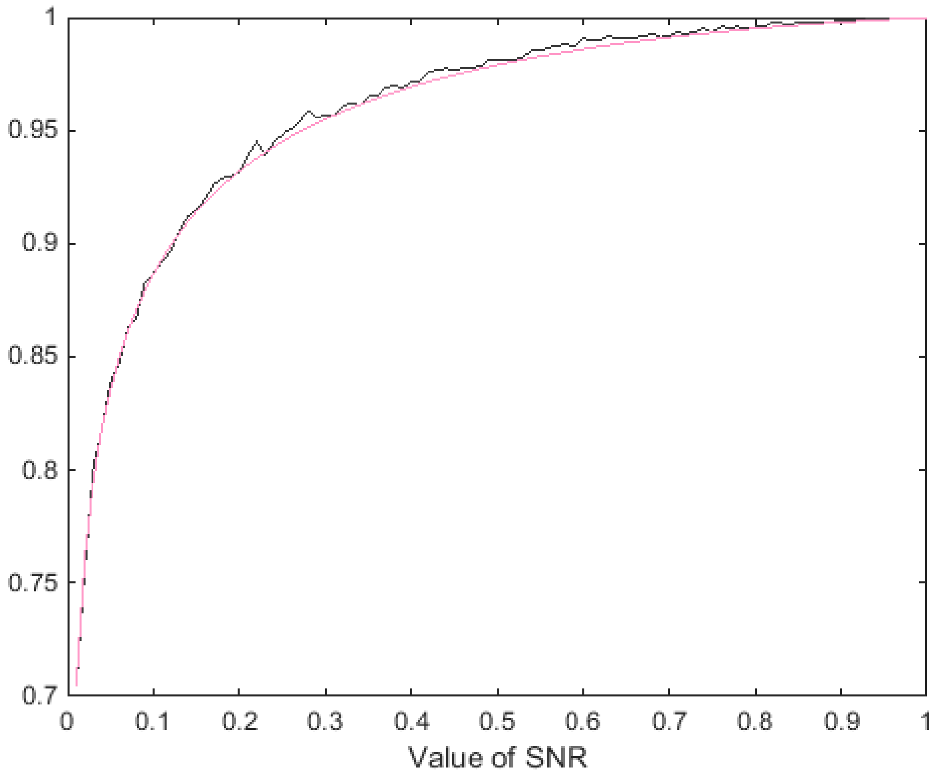

Figure (4.3): receiver operating characteristic curve for simple energy

The ROC curve is thus the sensitivity or recall as a function of fall-out. In general, if the probability distributions for both detection and false alarm are known, the ROC curve can be generated by plotting the cumulative distribution function of the detection probability in the y-axis versus the cumulative distribution function of the false-alarm probability on the x-axis.

ROC analysis provides tools to select possibly optimal models and to discard suboptimal ones independently from (and prior to specifying) the cost context or the class distribution. ROC analysis is related in a direct and natural way to cost/benefit analysis of diagnostic decision making.

4.4. Probability of Detection in Energy Detection in Cognitive Radio

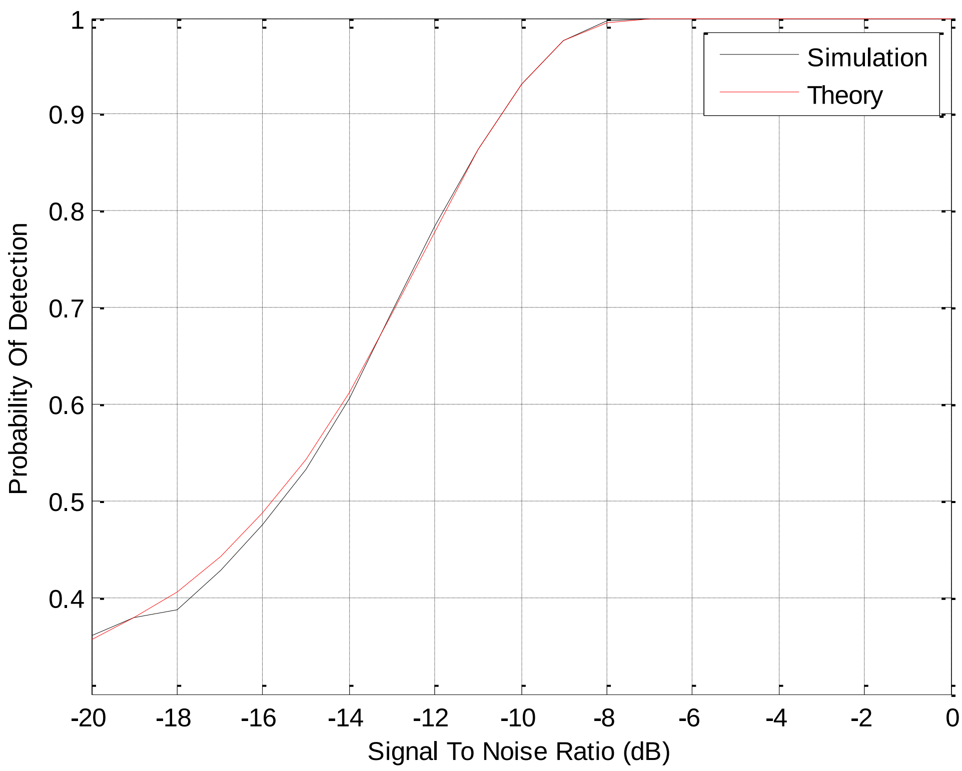

Figure (4.4): ROC curve for SNR vs probability of detection

SNR VS Probability of detection (P d) for P f = 0.01 From Figure 6, it can be easily observed that the probability of detection for both cases proposed threshold result is more preferable than fixed threshold under low SNR values.

This other example shows simulation for energy detection method of signal detection in cognitive radio and its probability of detection for different snr values with AWGN channel.

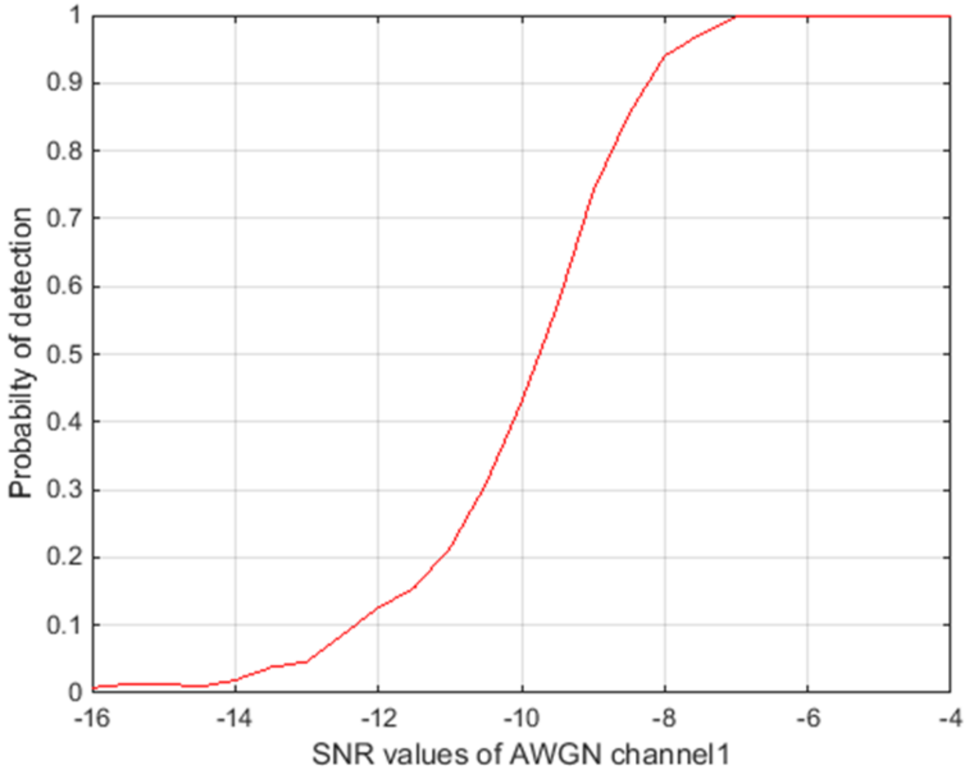

Figure (4.5): Probability of Detection in Energy Detection in Cognitive Radio

with the increasing of the SNR (from 10 dB to 0) the detections we get also increased and within 7 dB and 5 dB, the increasing slope is the largest. So, the SNR influences the detections. It indicates that with the increasing of the SNR, the more spectrums which are occupied we can detect.

4.5. Cooperative sensing with AND rule under AWGN.

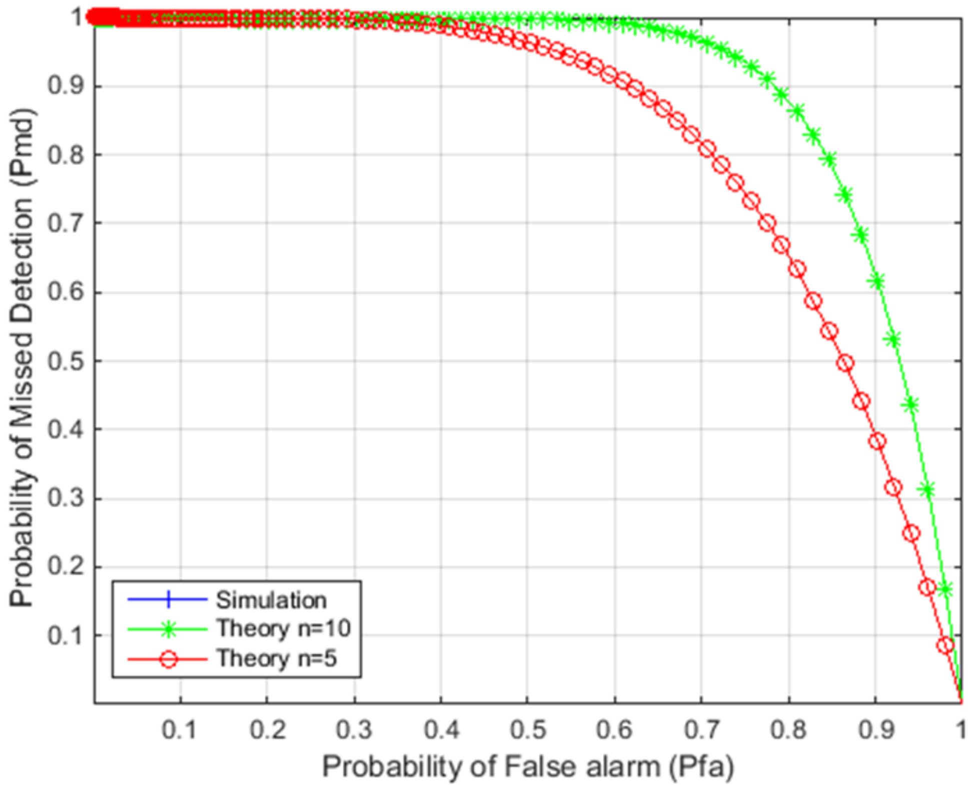

Figure (4.6): Complementary ROC of Cooperative sensing with AND rule under AWGN.

This assessment showed that the cooperation among CR users can result into significant improvement on the detection performance and compensating the degradation of the spectrum sensing execution caused by the possibly weak PU signals. Finally, the paper provided a verification of the validity of the OR- and AND- fusion schemes which were used for combining the individual decisions of CR users, where the deleterious impact for the fading effectively can be cancels by using these fusion decisions of various secondary users.

4.6. Calculate the threshold in energy detection by simulation.

This is a general method and applicable to all scenarios for energy detection.

We assume that all the signals are complex Gaussian.

Algorithm:

1. Assume only noise is received, i.e., primary user is absent.

2. If the only noise energy lies above the threshold, it corresponds to false alarm

3. Run this scenario for some number of iterations.

4. Probability of False Alarm = energy above threshold/No. of Iteration.

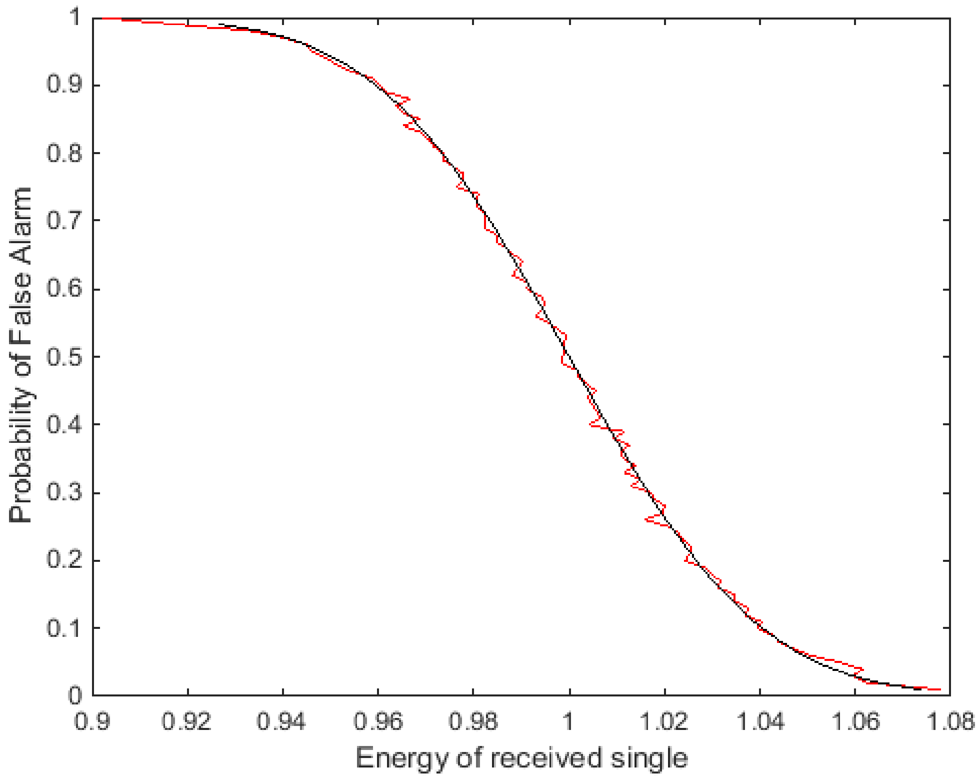

Figure (4.7): The threshold in energy detection by simulation.

4.7. Optimization of Cooperative spectrum sensing in Cognitive radio network.

This plot is for optimization of Cooperative spectrum sensing in Cognitive radio network.

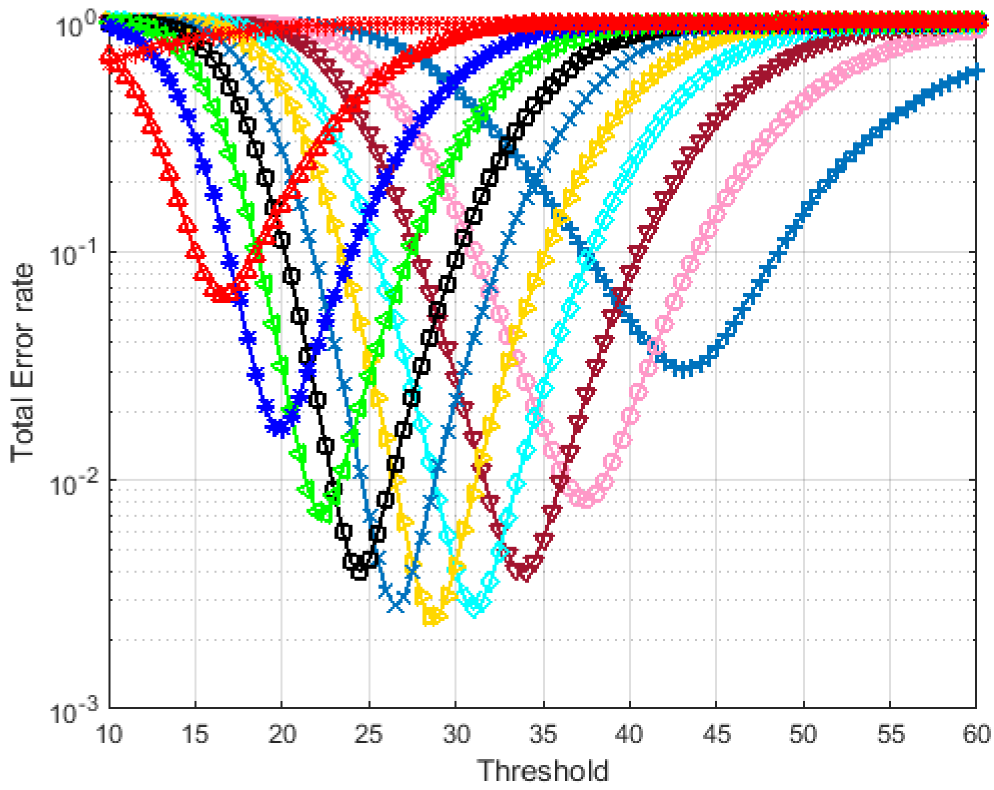

Figure (4.8): Optimization in cooperative spectrum sensing.

Cooperative spectrum sensing and adapting to the environment, a cognitive radio is able to fill spectrum holes and serve without causing harmful interference to the licensed user. We consider optimization of cooperative spectrum sensing with energy detection to minimize the total error rate.

Chapter Five

Conclusion And future work

5.1. Conclusion

In the past few years, with the growing demand for spectrum in various wireless applications and due to the inefficient spectrum utilization, there is a need to efficiently utilize the limited spectrum. Cognitive Radio plays an important role in such scenario and spectrum sensing is a vital aspect in CR. In this book various energy efficient spectrum sensing methods are studied. The usage of these techniques are application dependent. One can select a suitable sensing technique according to their application but they are not without demerits. The Energy efficient spectrum sensing techniques increases the overall network life time of the cognitive radio networks. But they are with their own merits and demerits. History assisted technique has an advantage that reduced SS saves energy but increased delay and loss of quality for time sensitive traffic is a demerit. In WSN assisted CRNs main advantage is that no energy is wasted by CRN through SS except for the cost of a dedicated sensor network.

In RL based SS energy efficiency is achieved by minimizing the number of assigned sensors per each sub band under a constraint on miss detection probability but RL applications in clustering algorithms is still at infancy stage.

Recent trends of EE SS are utilizing history or employing a dedicated WSN for SS. Integration of different techniques together can further improve energy efficiency. Residual energy per node is taken care the most in History assisted SS while other techniques concentrate only on overall system life time. RL is a better way of EESS compared to others but is still at the infancy stage. Apart from the cost of a dedicated WSNs, WSN sensing the spectrum for CRNs is the best of all techniques as energy wasted by CRN in SS is almost zero.

5.2. Future Work

This phenomenal growth in wireless usage will be driven by new applications that embed computing power into the physical world around us, helping to make the world safer and more accessible. Radio technology will be at the very heart of the future computing world - one in which billions of communicators, we anticipate that cognitive radio technology will soon emerge from early-stage laboratory trials and vertical applications to become a general-purpose programmable radio that will serve as a universal platform for wireless system development, much like microprocessors have served a similar role for computation. Also can be serve electronic circuit through design oscillator and FPGA systems [33,34] .

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