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Low Complexity Energy-Efficient Collaborative Spectrum Sensing for Cognitive Radio Networks

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By

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ABSTRACT

Clustering approach is considered a management technology that arranged the distributed cognitive radio users into logical groups to improve the sensing performance of the network. A lot of works in this area showed that cluster-based spectrum sensing (CBSS) technique efficiently tackled the trade-off between performance and overhead issue. By employing the tree structure of the cluster, a multilevel hierarchical cluster-based spectrum sensing (MH-CBSS) algorithm was proposed to compromise between the gained performance and incurred overhead. However, the MH-CBSS iterative algorithm incurs high computational requirements. In this thesis, an energy-efficient low computational hierarchical cluster-based algorithm is proposed which reduces the incurred computational burden. This is achieved by predetermining the number of cognitive radios (CRs) in the cluster, which provides an advantage of reducing the number of iterations of the MH-CBSS algorithm. Furthermore, for a comprehensive study, the modified algorithm is investigated over both Rayleigh and Nakagami fading channels. Simulation results show that the detection performance of the modified algorithm outperforms the MH-CBSS algorithm over Rayleigh and Nakagami fading channels. In addition, a conventional energy detection algorithm is a fixed threshold based algorithm. Therefore, the threshold should be selected properly since it significantly affects the sensing performance of energy detector. For this reason, an energy-efficient hierarchical cluster-based cooperative spectrum sensing algorithm with an adaptive threshold is proposed which enables the CR dynamically adapts its threshold to achieve the minimum total cluster error. Besides, the optimal threshold level for minimizing the overall cluster detection error rate is numerically determined. The detection performance of the proposed algorithm is presented and evaluated through simulation results.

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DEDICATION

To my beloved parents, husband, and kids for their endless love, encouragement, and support.

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LIST OF ABBREVIATIONS

AWGN	Additive white gausain noise
AF	The amplify and forward protocol.
AP	access point.
CBSS	Cluster-based spectrum sensing.
CCSS	Centralized cooperative spectrum sensing.
CDR	Constant detection rate.
CFAR	Constant false alarm rate.
CH	Cluster head.
CMs	Cluster members.
CR	Cognitive radio.
CROC	Complementary receiver operating characteristic.
CSCG	Circularly symmetric complex gausain.
CSS	Cooperative spectrum sensing.
DF	The decode and forward protocol.
EGC	Equal gain combining.
FC	Fusion center.
FR	Fusion rule.
GH	Group head.
GSC	Generalized selection combining.
HTP	Hidden terminal problem.
HF	High-frequency.
IEDs	Improved energy detectors.
LOS	Line of sight.
LSS	Local spectrum sensing.
MCMG	Multi-cluster multi-group.
MDS	Minimal dominating set.
MHCBSS	Multi-level hierarchical cluster-based spectrum sensing.
MRC	Maximum ratio combining.

MME	Maximum Minimum Eigenvalue.
OSA	Opportunistic spectrum access.
pdf	probability density function.
PU	Primary user.
ROC	Receiver operating characteristic.
RSP	Received signal power.
SC	Selection combining.
SCM	Sample covariance matrix.
SDR	Software Defined Radios.
SINR	Signal to interference plus noise ratio.
SGH	Subgroup head.
SLC	Square law combining.
SNR	Signal to noise ratio.
SU	Secondary user.

LIST OF SYMBOLS

α	A predefined percentage of the saved energy.
B	The required number of reporting CRs.
β	Global probability of false alarm constraint.
$\lceil . \rceil$	Ceiling function.
ΔE	The percentage of saved total energy consumption.
ξ	Control channel gain.
f_s	Sampling frequency.
$\mathit{\Gamma}(m)$	The Gamma function.
$\mathit{\Gamma}(a, b)$	The incomplete Gamma function.
$\bar{\gamma}$	Average SNR.
γ_i	SNR for the ith CR.
$\gamma_{max,j}$	Maximum SNR in the jth subgroup.
H	Number of CRs in one subgroup.
h	Channel gain between transmitter and CR receiver.
H_0	Hypothesis of channel being idle.
H_1	Hypothesis of channel being busy.
H_j	Number of CRs in the jth subgroup.
I_0	0_{th} order modified Bessel function of the first kind.
k_1 and k_2	Fusion rule parameters.
K	A predefined integer.
$\bar{K}$	Rice factor.
L	Number of sensing sample.
λ	Sensing threshold.
λ_{opt}	The optimal sensing threshold.
M	Number of groups in one cluster.
m	Nakagami parameter.
M_s	Number of sensing samples in 1ms.
N	The total number of reported local decisions.

P_d	Probability of detection for a single CR.
P_{dSG}	Probability of detection for a subgroup.
P_f	Probability of false alarm for a single CR.
$\hat{P}_d$	Predefined probability of detection.
$\hat{P}_f$	Predefined probability of false alarm.
P_{md}	Probability of missed detection for a single CR.
$P(H_0)$	Probability of PU being absent.
$P(H_1)$	Probability of PU being present.
$P(T(y) > \lambda \mid H_0)$	Conditional probability density function of $T(y) > \lambda$ given H_0.
$P(T(y) > \lambda \mid H_1)$	Conditional probability density function of $T(y) > \lambda$ given H_1.
ψ	The percentage of reporting CRs in the cluster to the total number CRs in the cluster.
φ_e	Overall error detection rate.
$Q(\cdot)$	Q-function.
Q_d	Global probability of detection for CRN.
Q_f	Global probability of false alarm for CRN.
Q_m	Global probability of missed detection for CRN.
q_{dG}	Probability of detection for a group.
q_{fG}	Probability of false alarm for a group.
R	Number of subgroups in one group.
R_b	Bit rate.
σ_w^2	Noise power.
$T(y)$	The test statistic of the energy detector.
φ_e	Overall error detection rate.
$w(n)$	The received noise.
$x(n)$	The PU transmitted signal.
$y(n)$	A signal received by the CR.

CHAPTER 1

Introduction

The emergence of new applications coupled with the demand for higher data rates are growing because of the wide diversity of wireless devices and technologies. Radio frequency spectrum is getting extensively more congested. On top of that, given the limitations of the natural frequency spectrum, it becomes apparent that the existing static frequency allocation policy result in spectrum scarcity (i.e., spectrum underutilization). Spectrum utilization can be improved substantially by making it possible for an unlicensed user to exploit the unoccupied spectrum band (i.e., spectrum holes) of the primary user dynamically at a certain time and a specific geographic region.

A promising technique to deal with the problem of spectrum underutilization is cognitive radio (CR) technology. An essential function of the CR is to be aware of the primary user (PU) signals characteristics and, be able to learn and adapt its transmission parameters based on its own observations from the surrounding environment along with the CR users needs. Cognitive radio (CR) is a revolutionary technology proposed to perform dynamic spectrum access (DSA) techniques, which enables the unlicensed user to access the licensed user band with flexibility and minimum disturbance [2, 3].

Spectrum sensing is considered the most significant element to establish CR networks through which the CR identify the existence of the PU signal to improve spectrum utilization [2, 4]. When a particular frequency band is detected as unused by the licensed user at a specific time and selected geographical position, the secondary users (SUs) can utilize the spectrum (i.e., a spectrum opportunity can be found). Accordingly, spectrum sensing can be executed across the domains of time, frequency, and space [1]. The detection performance of CR user often critically deteriorates due to destructive radio circumstances such as deep multipath fading and heavy shadowing. As result, CR user may not be able to identify the existence of a primary transmitter (i.e., hidden terminal problem) [13]. Consequently, individual spectrum sensing cannot guarantee the desired reliability. To ensure accurate sensing results, cooperative detection approaches are implemented to alleviate this problem. Cooperative detection refers to spectrum sensing methods that allow many cognitive radios to share their local sensing information for more accurate primary transmitter detection. Cooperative spectrum sensing (CSS) procedure enhances the accuracy and reliability of cooperation gain (i.e., detection performance improvement) and mitigates the impact of harsh radio environment conditions. However, this improvement may also incur numerous collaboration costs (i.e., additional energy consumption, time, and complexity), which limit or even compromise the achievable cooperative gain. Thus, striking a balance between enhancing the collaboration gain and reducing the incurred overhead is an essential objective in CSS.

Therefore, the principle of clustering was imposed to CSS to enhance the performance while alleviating the overhead issue. Many works in this field revealed that cluster-based spectrum sensing (CBSS) technique efficiently addressed the trade-off the between performance and overhead issue. However, the design of energy efficient CBSS system is still considered a significant design issue in cognitive radio networks (CRNs).

1.1 Motivation and Research Objectives

Recently, the trend of research concentrates on designing an energy efficient CBSS system to strike a stability between the performance and cost (i.e., overhead). An iterative algorithm was introduced in [34] to develop multi-level hierarchical cluster based spectrum sensing (MH-CBSS) algorithm to balance between the achieved performance and incurred overhead. This performed by employing double fusion stages to reduce control overhead for a cluster with a significant number of devices. However, the MH-CBSS iterative algorithm incurs high computational burden. Moreover, most energy detection algorithms assume fixed detection threshold to differentiate between the PU signal and the noise. The performance of the energy detector depends considerably on the setting of the threshold. Therefore, it is crucial to set a proper threshold for the energy detector to gain a reliable and robust sensing ability.

The research work takes into consideration the following objectives.

1. Designing an energy efficient low computational hierarchical cluster-based CSS system over Rayleigh and Nakagami fading channels.

2. Designing an energy efficient hierarchical cluster-based CSS system with an adaptive threshold over Rayleigh fading channels.

1.2 Research Contributions and Significances

The two main contributions of this thesis are provided as follows:

1. Energy-efficient low computational hierarchical cluster-based cooperative spectrum sensing for CRNs.

   In previous research an iterative algorithm was developed in [34] to construct a multi-level hierarchical cluster based spectrum sensing MH-CBSS algorithm that compromise between the gained performances and incurred overhead. The MH-CBSS algorithm outperforms both the Conventional CBSS and MCMG algorithm in terms of probability of detection, throughput and reporting overhead. However, the MH-CBSS iterative algorithm incurs high computational requirements. In this thesis, we propose a modified version of the MH-CBSS algorithm that reduces the incurred computational burden. Moreover, we compare both versions over both Rayleigh and Nakagami fading channels. Simulation results show that the detection performance of the modified algorithm outperforms the MH-CBSS algorithm over Rayleigh and Nakagami fading channels.

2. Energy-efficient adaptive threshold based on hierarchical CBSS for energy detection.

   The second contribution developed the proposed MH-CBSS algorithm by considering the adaptive threshold instead of the conventional fixed threshold. A low computational energy-efficient hierarchical cluster-based spectrum sensing with an adaptive threshold is proposed. The proposed algorithm enables the CR dynamically adapts its threshold to achieve the minimum total cluster error. Moreover, the optimal threshold level for minimizing the overall cluster error rate is numerically determined. The detection performance of the proposed algorithm has been investigated and compared with the conventional fixed threshold over Rayleigh fading channels. The simulation results have shown that the proposed algorithm can provide higher primary user protection by improving the detection performance.

1.3 Outline of the Thesis

The thesis is organized as follows: **Chapter 2** provides an overview and background of spectrum sensing in cognitive radio networks used in this thesis including local spectrum sensing, cooperative spectrum sensing (CSS), the gain and overhead trade-off in CSS, and cluster-based CSS. An energy-efficient low computational hierarchical cluster-based spectrum sensing algorithm is introduced in **Chapter 3** which reduces the complexity of the MH-CBSS algorithm. The work in **Chapter 4** considers the adaptive threshold instead of the conventional fixed threshold which enables the CR dynamically adapts its energy threshold to achieve the minimal total cluster error. Moreover, the optimal threshold level for minimizing the overall cluster detection error rate is numerically determined. Conclusions and recommendations are shown in **Chapter 5** .

CHAPTER 2

An Overview of Spectrum Sensing in Cognitive Radio Networks

2.1 Introduction

Recently, the growth of wireless technologies and services has contributed to the insufficient utilization of available wireless resources and has increased the demands for extra bandwidths and higher data rates. This is exacerbated by the unexpected evolution of multimedia technologies and excessive development of its applications and subscribers which has led to the recent spectrum scarcity problem. Moreover, it becomes noticeable that the fixed spectrum assignment policies that are enforced by regulatory bodies and the government agencies are unable to satisfy the requirements of increasing number of higher data rate devices [1]. Consequently, innovative approaches that can offer new methods of exploiting the available spectrum are required.

A promising approach to tackle the problem of spectrum underutilization is cognitive radio CR technology. A fundamental function of the CR is to be able to sense, learn, and be aware of the PU signals characteristics. It is intended to take advantage of the underutilized licensed spectrum by dynamically exploiting the local vacant spectrum bands of the primary users (i.e., licensed users) during their inactive periods by secondary users (i.e., unlicensed users). Cognitive radio (CR) is a revolutionary technology proposed to perform dynamic spectrum access (DSA) techniques, which enables unauthorized user to access licensed user band with flexibility and minimum interference [2, 3].

2.2 Local Spectrum Sensing

Spectrum sensing is considered the most important functional element to establish CR networks through which the CR identify the existence of the PU signal to improve spectrum utilization [2, 4]. Detecting the presence of the PU is mainly based on spectrum sensing hypotheses, which are defined as:

$$\textbf{Testing hypotheses} = \begin{cases} H_0 \ (idle\ channel) & y(n) = w(n) \\ H_1 \ (occupied\ channel) & y(n) = h(n) \times x(n) + w(n) \end{cases} \tag{2.1}$$

where H_0 and H_1 , are the hypotheses for absence and presence of the PU, respectively. $y(n)$ is a signal received by the CR, $x(n)$ is the PU transmitted signal, $w(n)$ is the received noise, and $h(n)$ is the channel gain between the CR and PU. $n = 1, 2..., M_s$, where M_s is the number of sensing samples [5].

Different methods have been suggested to perform local spectrum (LSS) sensing such as energy detectors [5], cyclostationary detectors [7], matched filter [1], and eigenvalue-based detectors. However, while each method has its advantages, there are disadvantages.

2.2.1 Energy Detector

Energy detector is the most widely used technique in spectrum sensing due to its simple hardware implementation, low computational, and execution requirements as it requires no prior knowledge of PU signal's characteristics. In the energy detection method, CR users detect the existence/absence of a primary user through the energy of a received PU signal. First, the energy detector filters out the desired signal from the unwanted frequency band. Then, the received signal samples from the filter are squared and summed. Eventually, the accumulated energy of the M_s observation samples is compared with a predefined threshold to decide whether a primary user is present or not. The energy detector block diagram is given in Fig. 2.1, and the test statistic of the energy detector $T(y)$ is determined as follows [5]:

$$T(y) = \sum_{n=1}^{M_s} |y(n)|^2 \tag{2.2}$$

There are three main drawbacks to the energy detector scheme : (1) its setting of detection threshold, which should be selected carefully since it significantly affects the sensing performance of energy detection; (2) its poor performance at low signal-to-noise ratio (SNR) values; and (3) its inability to determine the presence of the signal in another wards it cannot distinguish among PU signals, secondary user signals and noise [6].

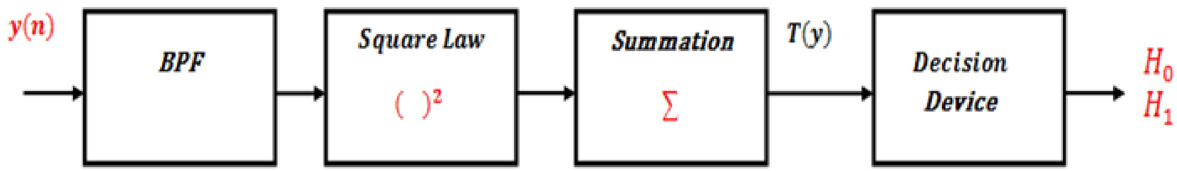

Figure 2.1: Diagram of energy detector.

2.2.2 Matched Filter

Its distinctive feature is the low execution time, but it demands full knowledge about the PU signal properties. Furthermore, perfect synchronization between the primary transmitter and cognitive radio user is needed. However, the main impairment of this method is the fact that its hardware implementation is complicated and it requires high computational complexity [1, 8].

2.2.3 Cyclostationarity Feature Detection

If partial knowledge about the primary user PU signal existed, feature detection might be employed. It usually exploits the periodicity in the received PU signal, which is frequently caused by the sine waves, pulse sequences or cyclic prefixes during modulation. Moreover, the statistical parameter of the primary user modulated signal, such as mean and autocorrelation, may also vary periodically, therefore, such statistical periodicity can be applied to identify the occupation of PUs signal. Unlike the energy detector, the feature detector is more effective with respect to noise uncertainty. In addition, it can distinguish between the noise and the PU signal which requires more computational complexity and hardware implementation [7].

2.2.4 Maximum-Minimum Eigenvalue (MME) Detector

MME detector is considered a blind spectrum sensing technique where the PU signal characteristics (i.e., expected received SNR, the typical values of the occupied bandwidth, and on top of that, the noise energy inside the band of interest) are concealed for the CR user. The distribution of the eigenvalues of the covariance matrix of the received signal has recently provided an attractive research topic. MME detection begins by estimating the sample covariance matrix (SCM) of the received signal. Then, the ratio of the maximum eigenvalue to the minimum eigenvalue can be utilized to detect the presence/absence of the PU signal. High probability of detection can be accomplished using MME detector, particularly at low SNR. However, this will be at the price of higher hardware complexity [9, 10].

A crucial factor in the success of cognitive transmission is the reliability of the obtained results from the spectrum sensing process. However, the detection performance of cognitive radio CR often harshly deteriorates due to adverse radio conditions (i.e., multipath fading and shadowing) [11]. Consequently, individual spectrum sensing cannot guarantee the desired reliability. To ensure accurate sensing results, CSS was proposed as an effective approach to mitigate the consequence of radio environment conditions and to improve the detection performance of the CRs.

2.3 Models of Cooperative Spectrum Sensing

To improve the performance of spectrum sensing especially when CR users experience unfavorable radio conditions, different secondary users allowed to collaborate by sharing

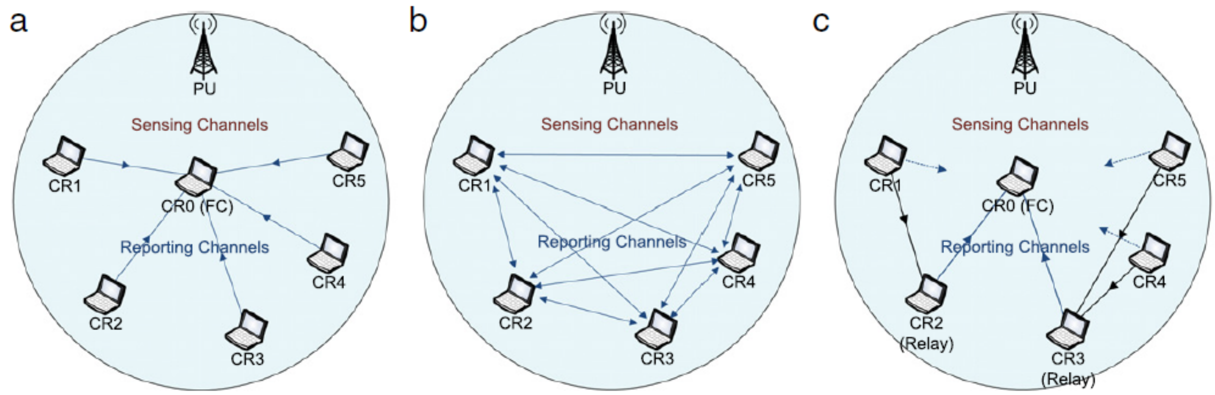

Figure 2.2: Models of cooperative spectrum sensing: (a) centralized, (b) distributed, and (c) relay-assisted.

their information. As a result, the participation greatly improves the probability of detection and the throughput while reducing the required sensing time [13]. There are three popular models for CSS networks that are classified based on how the collaborative SUs share the sensing information in the network: centralized CSS, decentralized CSS, and relay assisted CSS, as shown in Fig. 2.2, [2].

2.3.1 Centralized Cooperative Spectrum Sensing

In centralized cooperative spectrum sensing (CCSS), a central unit (i.e., Fusion Center, Base station) accumulates the sensing information from cognitive radio devices. First, every single cooperating CR performs local sensing autonomously to measure the signal of PU user. CR makes its decision about the existence of PU signal based on its local sensing information. Second, each CR reports its decision to the fusion center (FC) via reporting channel. The decision can be done in either one-bit form (i.e., hard-based scheme) or as large quantized number of bits form (i.e., soft-based scheme). Third, the central unit fuses all the received local decisions of collaborating CRs and then diffuses the final decision back, which is made according to a predefined rule, called fusion rule (FR) [2, 13].

In the case of a hard decision fusion scheme, the most well-known FR is the K-out-of-N rule, where CRs report their local decisions as one bit (i.e., $u_i = 0, 1$). if $u_i = 1$, then the CR decides that the spectrum is used. Otherwise, the spectrum is recognized as unused by the i^{th} CR. In this rule, N is the total number of reported local decisions, and K is a predefined integer between 1 and N. The concept of this rule is to compare the number of CRs whose local decisions have been received as 1 to K. If it is larger than or equal to K, then the spectrum is defined as used. Otherwise, the spectrum is determined to be unused. The following equation describes the function of K-out-of-N rule.

$$\textbf{Final decision} = \begin{cases} \text{used} & \text{If } \sum_{i=1}^{N} u_i \geq K \\ \text{unused} & \text{If } \sum_{i=1}^{N} u_i < K \end{cases} \tag{2.3}$$

OR and AND rule are considered special cases of the general K-out-of-N rule when K is 1 or N respectively [12, 14].

While in the case of a soft decision fusion scheme, CR users forward the entire sensing decision to the central unit as energy. Equal gain combination (EGC), maximal ratio combination (MRC), and square law combination (SLC) are the most widely adopted soft combining procedures. Though the soft scheme improves the reliability of centralized CSS decision, it may increase the overhead (i.e., bandwidth and power consumption) during reporting to central unit [15].

Many approaches were aimed at enhancing the detection performance such as the probability of detection and throughput which defined as the average successfully transmitted data by the involved CRs in CSS. As a result, a trade-off between the detection performance and the incurred overhead (i.e., energy consumptions, time costs and bandwidth occupation) should be analyzed carefully before designing the centralized CSS model. Therefore, many researchers have studied the trade-off between performance and overhead. Some researchers focused on optimizing different parameters of K-out-of-N rule targeting different objectives. For example, the researchers in [16] optimize the N (i.e., the total number of CRs) following two different scenarios: an energy-efficient setup and a throughput optimization setup. Moreover, a novel report scheme was introduced in [17], and it reduces the power consumption considerably by decreasing the number of reporting CRs without affecting the detection accuracy. A double thresholds fusion scheme was proposed in [18] to reduce the transmitted information and the incurred overhead while keeping the required detection performance.

2.3.2 Decentralized Cooperative Spectrum Sensing

This model implies the establishment of the CRs network without need for a central unit. In this model, each CR takes part to make the cooperative decision. At first, each CR senses the spectrum autonomously and regularly. Then every CR builds up a communication link with other CRs and shares the information about the present or absence of PU. Next, each cognitive radio makes its final decision based on the gathered information from other CRs and its local decision. Finally, if a definitive agreement about the PU existence is not achieved, the procedure is repeated until a final agreement is accomplished [19]. Compared with the centralized model, the distributed scheme is more favorable as there is no need for a backbone infrastructure and because it can reduce costs [1].

2.3.3 Relay Assisted Cooperative Spectrum Sensing

The cooperative relay is regarded as a key technology to develop spectrum diversity in the cognitive radio network and combat the influence of fading and shadowing in wireless communication networks. The underlying mechanism is to exploit the space diversity available among cooperating CRs. Some CR users do not require the entire accessible spectrum due to the low traffic demands (i.e., strong reporting channel and weak sensing channel). Those CR users can serve as relays or helpers that assist in forwarding the sensing results from the CR users who observe strong PU signal and low reporting channel [2, 20].

In this model, two relaying schemes are used most often: the amplify and forward (AF) protocol, and the decode and forward (DF) protocol. In AF scheme, CR simply amplifies and retransmits the noisy version of the received primary user signal to another CR in the network [21]-[23]. The relay based CSS was considered in [22] over Rayleigh fading channels. The relay CRs used an amplify-and-forward relaying strategy to deliver the information from primary user to cognitive center. Both single relay and multiple relays procedures are utilized. Moreover, two phenomena were evaluated: the impact of relays location between the primary user and cognitive receiver, and the effect of path loss by measuring the probability of false alarm and probability of detection. In [23], the authors analyzed the performance of the amplify-and-forward (AF) relay-based cooperative spectrum sensing system with generalized selection combining (GSC) over a Rayleigh fading channel. In addition, they derived a novel mathematical formulae for the average detection

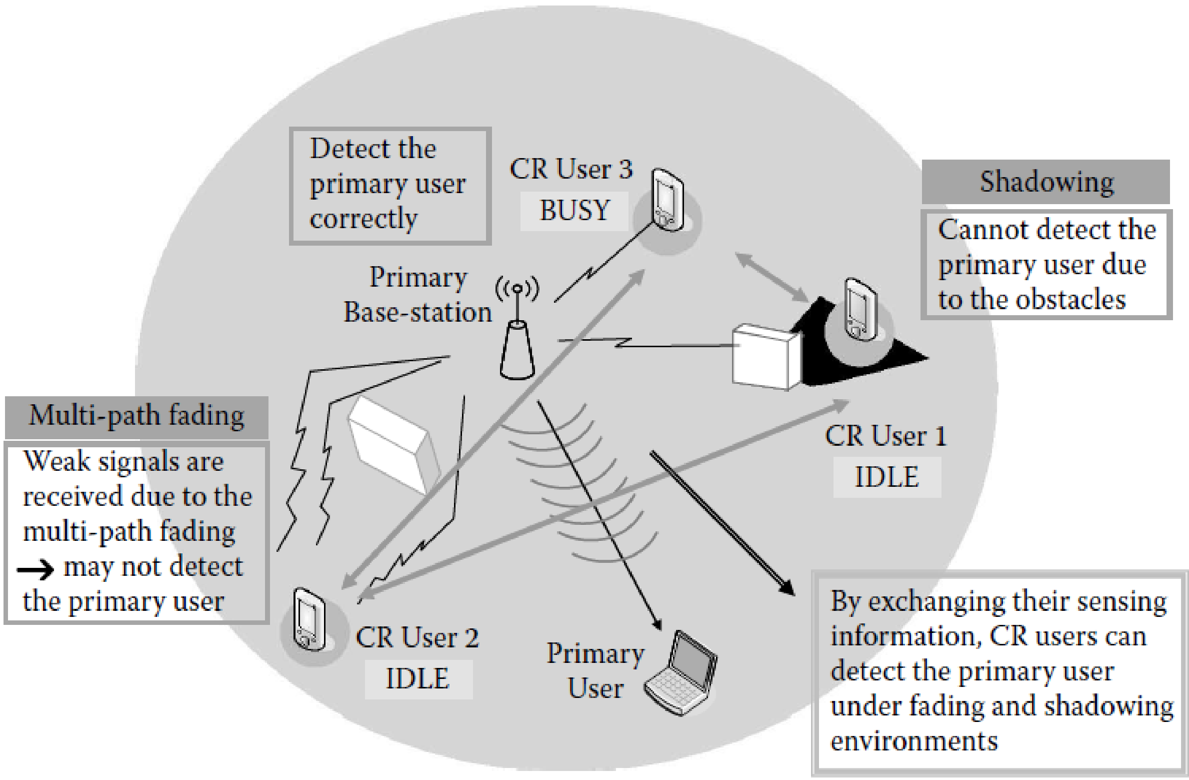

Figure 2.3: Cooperative Spectrum Sensing detection under highly faded and shadowed environment.

probability. The results were compared with the conventional diversity-combining schemes such as maximal-ratio-combining (MRC) and selection-combining (SC) schemes. It was shown that the GSC receivers achieve a more balanced compromise between the receiver performance and the implementation complexity compared to the MRC receivers.

2.4 Gain and Overhead Trade-off in CSS

Cooperative spectrum sensing CSS has been proposed to improve spectrum sensing capabilities over wireless channels. This procedure enhances the accuracy and reliability of cooperation gain (i.e., detection performance improvement) and mitigates the impact of harsh radio environment conditions. However, this improvement may also incur various collaboration costs (i.e., additional energy consumption, time, and complexity), which limit or even compromise the achievable cooperative gain. Therefore, striking a balance between enhancing the cooperation gain and reducing the incurred overhead is a crucial purpose in CSS. For the sake of achieving a compromise between the gain and the cost, many factors should be taken into account. One of these important factors is channel impairments.

2.4.1 Channel Impairments

In broadcast communication networks, as the radio waves travel from the transmitter to the receiver, the signal power could severely weaken due to harsh radio conditions, such as heavy shadowing and deep multipath fading. As a result, detection performance (i.e., cooperation gain) becomes progressively worse. At this point, the cooperative gain can be achieved by employing the concept of cooperative spectrum sensing to combat such effect.

The constructive and destructive combination of reflected, scattered and diffracted signal components of the PU signal creates a multipath fading effect. This impact results in multiple replicas of the transmitted signal that experience different attenuation and variations (i.e., envelope and phase fluctuations) at the receiver side. In addition, the fading caused by obstacles (i.e., natural or human-made features) in the radio bath affects the wave propagation between the PU transmitter and CRs. This is referred to as shadowing. Both of these effects can be seen in Fig. 2.3, [24].

2.4.2 Models of Fading Channels

The nature of the radio propagation environment can influence how effectively different models describe the statistical behavior of the multipath fading envelope.

2.4.2.1 Rayleigh Fading Channel

In the Rayleigh fading scheme the magnitude of a signal that has transmitted through a communications channel will fluctuate randomly according to a Rayleigh distribution. Also, Rayleigh fading is considered the most applicable model when there is no direct line of sight (LOS) path (i.e., radio waves travel in a direct path from the transmitter to the receiver).

The probability density function (pdf) of the signal-to-noise ratio (SNR), γ, over a Rayleigh fading channel is given by

$$f(\gamma) = \frac{1}{\bar{\gamma}}\, e^{-\frac{\gamma}{\bar{\gamma}}},\ \gamma \geq 0 \tag{2.4}$$

where $\bar{\gamma}$ is the average SNR [25].

2.4.2.2 Rician Fading Channel

It is usually utilized to model scattering environment consisting of one strong direct LOS component and several random contributions with less amplitude. In this situation, the fading channel of the received signal is characterized by a Rician distribution. Its pdf is given by

$$f(\gamma) = \frac{\bar{K}+1}{\bar{\gamma}}\, e^{\left(-\bar{K}-\frac{(\bar{K}+1)\,\gamma}{\bar{\gamma}}\right)} I_0\left(\sqrt{\frac{\bar{K}(\bar{K}+1)\gamma}{\bar{\gamma}}}\right),\ \gamma \geq 0 \tag{2.5}$$

where $\bar{K}$ is the Rice factor and I_0 is the 0_{th} order modified Bessel function of the first kind [26].

2.4.2.3 Nakagami Fading Channel

The Nakagami-m distribution was introduced by Nakagami in the early 1940s to describe the rapid fading in long-distance high-frequency (HF) channels. It provides greater flexibility and accuracy in matching some empirical data than the Rayleigh and Rician distributions. The Nakagami-m distribution describes the magnitude of the received envelope which follows the gamma distribution [28]. Hence, the pdf of Nakagami-m channel is:

$$f(\gamma) = \frac{1}{\Gamma(m)}\left(\frac{m}{\bar{\gamma}}\right)^m \gamma^{m-1}\, e^{(-\frac{m}{\bar{\gamma}})\gamma},\ \gamma \geq 0 \tag{2.6}$$

where m is the Nakagami parameter and $\Gamma(m)$ is the Gamma function.

The Nakagami-m distribution can represent different models of fading environments. It is a general case that includes the one-sided Gaussian distribution $(m = 1/2)$ and the Rayleigh distribution $(m = 1)$ as special cases. Furthermore, when $m > 1$ a close approximation can be used to obtain a Rician distribution. When the limit of $(m \to \infty)$, the Nakagami-m fading channel converges to a non-fading additive white gausain noise (AWGN) channel [26].

The performance of energy detector was presented in [29] for an unknown transmitted signal under both AWGN and different multipath fading channels. Closed form expressions for the probability of detection and the probability of false alarm over Rayleigh and Nakagami fading channels were proposed. The work also investigated the impact of diversity on Rayleigh channels. The results revealed an improvement in detection capability, especially for relatively low power applications when soft decision fusion rules, such square law combining (SLC), and square law selection (SLS) were employed.

The authors of [26] examined the performance of cooperative spectrum sensing CSS over different multipath fading channels such as Rayleigh, Nakagami, and Rician fading channels. Closed-form expressions of the average detection probability are employed to provide a comprehensive study of cooperative energy detection in various fading channels. It has been found that the cooperative among cognitive radios guarantees the enhancement of the detection performance by employing different data fusion rules. A comparison between the performances in these channels was presented and showed that spectrum sensing performance is lower in the presence of Rayleigh, Ricean, and Nakagami fading when compared to an AWGN channel. Further, because of the LoS path, the sensing performance of a Ricean channel is better than the other fading channels.

The influence of shadowing on the performance of the CSS system was viewed in [27]. In the study, an analytical framework was provided for the analysis and design of cooperative spectrum sensing methods over correlated log-normal shadowing by using the energy-based detector in each collaborative user. Approximation methods were proposed, and their accuracy was analyzed to compute the detection probability over correlated LogNormal shadowing. Consequently, the proposed framework provided reliable estimates that can overcome the impact of the correlated shadow fading on the system performance.

2.5 Cluster-Based Cooperative Spectrum Sensing

Clustering technique is considered a management technology that arranged the scattered cognitive radio users into logical groups to enhance the sensing performance of the network. In the conventional CSS systems, the reporting process of a vast number of participating CRs incurs high cooperation cost (i.e., energy consumption, control and transmission overhead). In addition, when the CRs are assigned in different radio circumstances the global decision by the base station BS may not include all the participating CRs which in turn will be reflected on the sensing performance [30, 31]. Hence, the main objectives of the cluster- based spectrum sensing technique (CBSS) is to improve sensing performance and address the overhead matters.

In CBSS technique (Fig. 2.4), CRs are separated into small groups (i.e., clusters) according to their geographical area and spectral circumstance. Each cluster has a cluster head (CH) and cluster members (CMs). Spectrum sensing is executed in a hierarchical framework. The collaboration process has two levels: the low level is carried out within the cluster, and the high level is performed between CHs. The CH is usually chosen as a CR with the greatest reporting channel gain in the cluster. The CMs (i.e., the lowest cooperation level) in a cluster detect the existence of the PU, and then forward their local sensing outcomes to the CH. The CH combines its observation with the aggregated observations to extract an accurate decision on the existence of the PU [30].

Lately, the research trend focuses on designing an energy efficient CBSS system in order to strike a stability between the performance and overhead.

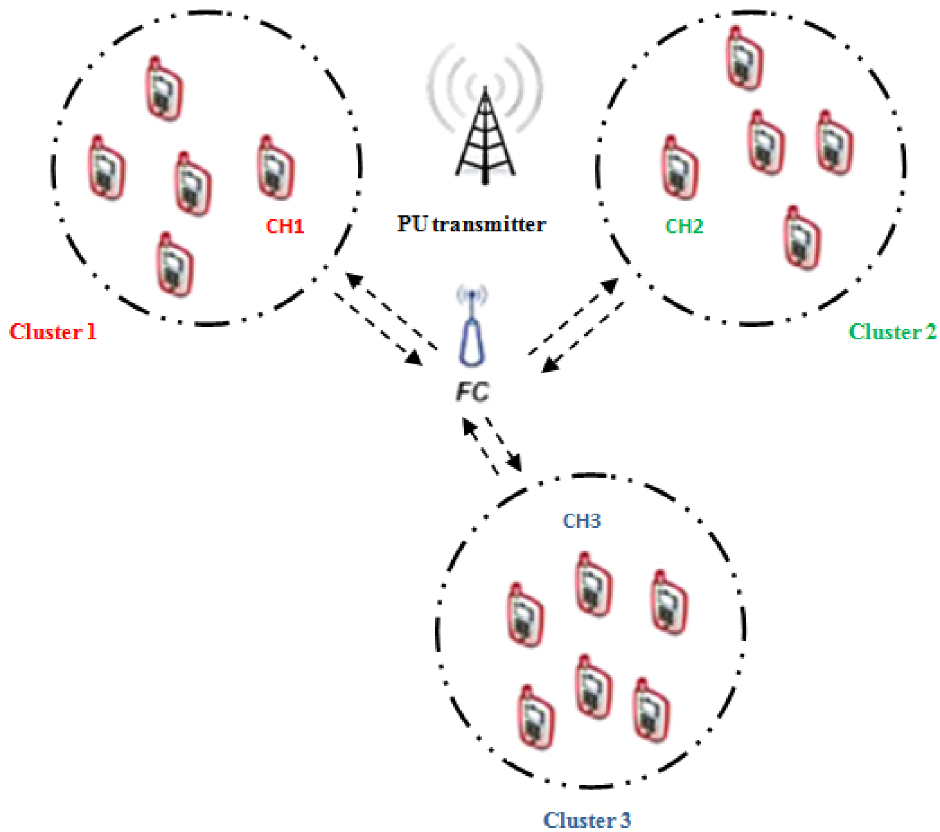

Figure 2.4: Cluster-based spectrum sensing technique (CBSS) structure

2.5.1 Strategies of Cluster-Based Spectrum Sensing Technique

Multiple approaches and algorithms have been recommended to form the clusters for CBSS scheme. The CBSS system can be classified into three main categories based on their objective: performance gain oriented models, overhead reduction oriented models, and combined metrics based models [30, 31].

2.5.1.1 Performance Gain-Oriented Strategy

The optimal number of clusters is achieved in [32] by balancing the trade-off between the cooperation cost and sensing reliability. A clustering approach has been proposed to group cognitive users with similar locations into the same cluster. The strategy has two phases;

cluster head election and cluster formation. Moreover, a closed form expression for a probability of detection based on polling rule was also derived. A multi-clusters multi-groups (MCMG) based CSS algorithm was introduced in [33] to improve the detection performance. By separating a cluster into various groups, the optimal number of groups is obtained by using K-out-of-N fusion rule which minimizes the error rate of a cluster.

An iterative algorithm was developed in [34] to construct suboptimal number of groups and subgroups in a multi-level hierarchical cluster based spectrum sensing (MH-CBSS) algorithm. This was done by employing double fusion stages to reduce the control overhead for a cluster with a great number of CRs. The idea of the algorithm is to split the CRs in one cluster into groups. Each group is then divided into subgroups. Each group has a group head (GH), and each subgroup has a subgroup head (SGH). The subgroup head polls the received PU signal with maximum strengths of its subgroup members and makes a subgroup decision, which is then forwarded to the GH of its group. The aggregated observations from subgroups will be combined by GHs using K-out-of-N rule first, and then the CH collects decisions from GHs and fuses them to the FC to extract clusters decision about PU presence also using K-out-of-N rule. A novel dynamic clustering based cooperative spectrum sensing (CSS) scheme with improved energy detectors (lEDs) was considered. In [35] a novel expression for dynamic clustering was proposed under the Rayleigh fading channels. Only the CRs with the best quality links and distinct access point (AP) were selected to make a cluster. In addition, the performance of clustered networks was also compared with the non-clustered network.

2.5.1.2 Overhead Reduction Oriented Strategy

Many paradigms for the development of CBSS were adopted to overcome the incurred sensing overhead. Clustering technique was developed in [36] to save energy consumption during the reporting and exchanging information stages. Also, frequency reuse distance was considered to reduce the transmission delay especially when the cluster CRs number is significant.

The minimal dominating set (MDS) clustering algorithm was proposed in [37] to achieve the minimal number of clusters that maintain the network connectivity. The recommended approach was pointed toward reducing the bandwidth required for reporting the results to the fusion center (FC) by decreasing the number of reporting CRs. Furthermore, sensing efficiency, sensing accuracy and throughput were also investigated by employing different parameters of the clustering system such as cluster size, a number of clusters, and a reporting channels error. It was revealed that throughput of cluster-based cooperative sensing system using MDS algorithm outperforms the conventional cooperative sensing system particularly when the reporting channels are subjected to a high probability of error. In addition to previous works, a new censoring method [18] was applied in the clusters to decrease the number of the transmission bits and saving the bandwidth. Two thresholds were given to measure the reliability of the CR information. Only the users with reliable information were allowed to give their local binary results, and the others will not make any decision. It was shown that the new method reduced the sensing bit number considerably at the cost of a little performance deterioration.

2.5.1.3 Combined Metric Based Strategy

Considering the trade-off between improvement of sensing performance and the reduction of incurred sensing overhead to reach a compromise is a significant goal of this type of CBSS schemes. The work in [38] aimed at a trade-off between the number of clusters and the detection performance in the cluster based cooperative spectrum sensing scheme. By characterizing the trade-off as an optimization problem, the optimal number of clusters was obtained. Base on the optimal cluster number the CR users are separated into different clusters according to the received signal power (RSP) from the CH. CR users choose the closest CH to join it according to the RSP. Moreover, the approximation of the optimal number of clusters was also derived, and simulation results proved the superiority of the suggested approach.

2.6 Conclusions

This chapter introduced a brief introduction to spectrum sensing in cognitive radio networks. Different methods have been presented to perform local spectrum sensing. Moreover, we present some fundamental models and fusion rules that can be adopted in cooperative sensing systems. A trade-off between the detection performance and incurred overhead has been discussed. Different models that are describing the multipath fading channels are briefly explained. Eventually, some information about the models of cluster-based spectrum sensing strategies has also been provided.

CHAPTER 3

Low Computational Hierarchical Cluster-Based CSS for CRNs

3.1 Introduction

Cooperative spectrum sensing (CSS) was proposed as an effective solution to minimize the impact of radio environment conditions and to enhance the detection performance of the collaborating cognitive radios [1]. On the other hand, the gained improvement attained by the CSS technique causes cooperative cost called overhead (i.e., bandwidth requirements, extra sensing time, delay, and energy consumption. Therefore, the principle of clustering was imposed to CSS to improve the performance while reducing the overhead [2].

In conventional cluster-based cooperative sensing (CBSS) scheme [40], all cooperating CRs are arranged according to their geographic locations into groups called clusters. Each cluster has a cluster head (CH) and cluster members (CMs). The CMs in a cluster detect the existence of the PU, and then forward their local sensing outcomes to the CH. The CH

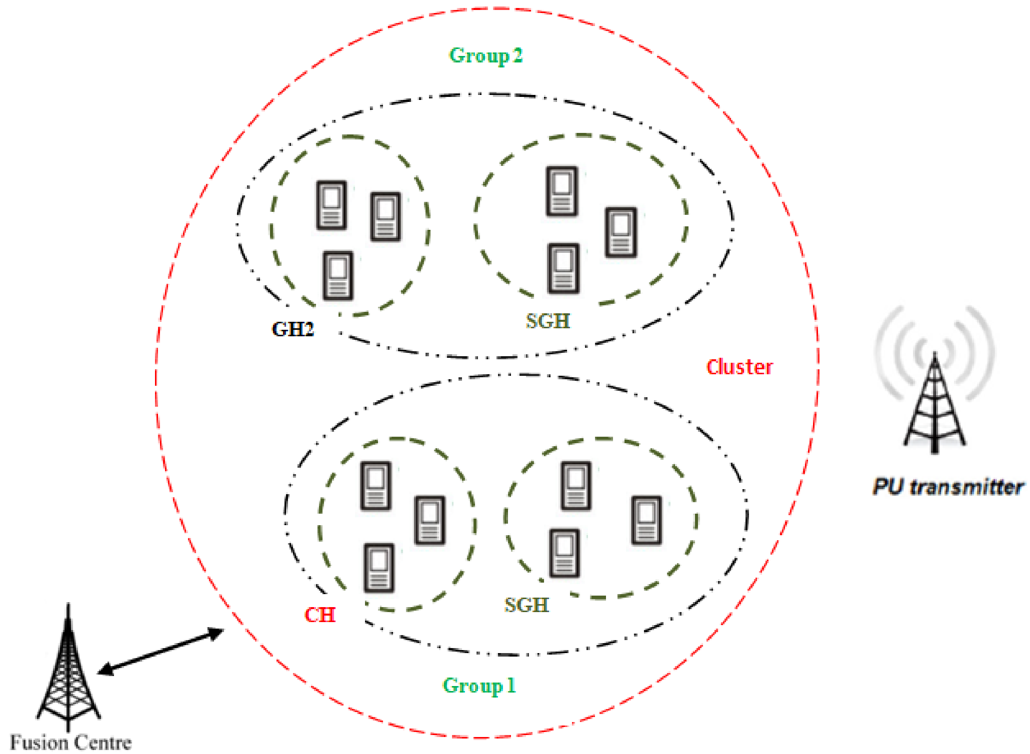

Figure 3.1: System model of the MH-CBSS algorithm.

combines its observation with the aggregated observations to extract an accurate decision on the existence of the PU. Lately, the trend of research focuses on designing an energy efficient CBSS system in order to strike a balance between the performance and overhead. An iterative algorithm with low complexity was proposed in [41] to extract the optimal number of CRs in a cluster that maximizes the probability of detection while satisfying the probability of false alarm constraint.

Multi-clusters multi-groups (MCMG) based CSS algorithm was introduced in [33], to improve the detection performance. An iterative algorithm was developed in [34] to construct multi-level hierarchical cluster based spectrum sensing (MH-CBSS) algorithm to compromise between the gained performances and incurred overhead. The MH-CBSS algorithm outperforms both the Conventional CBSS and MCMG algorithm in terms of probability of detection, throughput and reporting overhead. However, the MH-CBSS iterative algorithm incurs high computational requirements as shown in Fig. 3.1.

In this chapter, a modified version of the MH-CBSS algorithm that reduces the incurred computational burden is proposed. Moreover, we compare both versions over both Rayleigh and Nakagami fading channels. Simulation results show that the detection performance of the modified algorithm outperforms the MH-CBSS algorithm over Rayleigh and Nakagami fading channels.

This chapter is organized as follows: The MH-CBSS algorithm system model is described in Section 3.2. The modified version of the MH-CBSS algorithm is presented in Section 3.3. Simulation outcomes are presented and discussed in Section 3.4. while the conclusion is provided in Section 3.5.

3.2 System Model for MH-CBSS Algorithm

Assume a cluster with N CRs is separated into M groups. Each group is also divided into Sub- groups, each with H CRs. In subgroup level, H of CRs are considered to be very close to each other, therefore, they almost experience the same radio environment conditions such as SNR and fading. In group level, each group has R of SGHs; one SGH between other SGHs in the group is selected to be a GH. In cluster level, each cluster has M GHs; one of the GHs is chosen to be a CH. The probability of detection, P_d, and probability of false alarm, P_f, for any CR are provided in [42] as

$$p_d = Q\left((\frac{\lambda}{\sigma_w^2} - \gamma_i - 1)\sqrt{\frac{L}{2\gamma_i + 1}} \right) \tag{3.1}$$

$$p_f = Q\left((\frac{\lambda}{\sigma_w^2} - 1)\sqrt{L}\right) \tag{3.2}$$

where γ_i is the signal-to-noise ratio (SNR) at the i-th sensor, λ is sensing threshold, σ_w^2 is noise variance, L is the number of samples and $Q(\cdot)$ is Q-function.

According to MH-CBSS algorithm [34], the cluster is divided into M groups, each group has R subgroups, and each subgroup has H CRs. Moreover, in practice, the sensing channels between the CRs and the PU may experience multi-path fading. For the j_{th} subgroup, with H_j CRs, the probability density function of Rayleigh fading is provided in [29] as

$$f(\gamma_{max,j}) = \frac{H_j}{\gamma} e^{-\frac{\gamma_{max,j}}{\gamma}} \left(1 - e^{-\frac{\gamma_{max,j}}{\gamma}}\right)^{H_j - 1} \tag{3.3}$$

where $\gamma_{max,j}$ is the largest received SNR in the j_{th} subgroup.

For the j_{th} subgroup, the SGH polls a subgroups observation and then reports it to the GH The probability of detection of the SGH P_{dSG}, is calculated as:

$$P_{dSG} = \int_0^\infty P_d(\gamma_{max,j}) f(\gamma_{max,j}) d_{\gamma_{max,j}} \tag{3.4}$$

where P_{dSG} is numerically calculated using adaptive Gauss-Kronrod Quadrature technique [43].

For the n_{th} group with R subgroups, considering a perfect channel, the probability of detection, q_{dG} , and the probability of false alarm, q_{fG}, are computed as [34].

$$q_{dG} = \sum_{r=k_1}^{R} \binom{R}{r} P_{dSG}^{r} (1 - P_{dSG})^{R-r} \tag{3.5}$$

$$q_{fG} = \sum_{r=k_1}^{R} \binom{R}{r} P_{f}^{r} (1 - P_{f})^{R-r} \tag{3.6}$$

where $k_1 = \lceil \frac{R}{2} \rceil$ for majority rule, and $\lceil x \rceil$ is ceiling function.

The global probability of detection (Q_d) and global probability of false alarm (Q_f) for a cluster with M groups are formulated as:

$$Q_d = \sum_{m=k_2}^{M} \binom{M}{m} \beta_{d}^{m} (1 - \beta_{d})^{M-m} \tag{3.7}$$

$$Q_f = \sum_{m=k_2}^{M} \binom{M}{m} \beta_{f}^{m} (1 - \beta_{f})^{M-m} \tag{3.8}$$

where $k_2 = \lceil \frac{M}{2} \rceil$, $\beta_f = (1 - q_{fG})\bar{P}_e + q_{fG}(1 - \bar{P}_e)$,$\beta_d = (1 - q_{dG})\bar{P}_e + q_{dG}(1 - \bar{P}_e)$, and $\bar{P}_e$ is the probability of reporting error [34].

The criterion of designing MH-CBSS algorithm is provided in [6] as

$$\begin{aligned} \max_{M,R,k_1,k_2} \quad & \mathrm{Q_d} \\ \text{subject to} \quad & R \geq 1, M \geq 1 \\ & k_1 \geq 1, k_2 \geq 1 \\ & Q_f \leq \beta. \end{aligned} \tag{3.9}$$

where β is the global probability of false alarm constraint, R is the number of subgroups, M is the number of groups, k_1 is the fusion rule parameters at the group level and k_2 is the fusion rule parameters at the cluster level.

The required number of reporting CRs, B, in the cluster has been computed in [44] as

$$B = MR - 1 = \frac{N - H}{H} \tag{3.10}$$

3.3 Modified MH-CBSS Algorithm

Let ψ represents the percentage of reporting CRs in the cluster to the total number CRs in the cluster, which is computed as:

$$\psi = \frac{B}{N} = \frac{N - H}{NH} \tag{3.11}$$

In this section, in order to reduce the number of required iterations (i.e., computational runs) to compute $M, R,$ and H (i.e., number of hierarchical levels), we initially specify the required ψ. Therefore,

$$H = \left\lceil \frac{N}{1 + N\psi} \right\rceil \tag{3.12}$$

The required ψ will be initially predefined. Then, the number of CRs in the subgroups will be determined using (3.12), which provides an advantage of reducing the number of the iterations of MH-CBSS algorithm by around 30%, since only two parameters (i.e., R and M) will be determined using the proposed algorithm instead of determining three parameters (i.e., H, R and M) as in MH-CBSS algorithm. For a cluster with N CRs, the proposed modified iterative algorithm is as follows:

Algorithm 3.1. Proposed Low Computational MH-CBSS algorithm

1: **Specify** Ψ, **and compute** H.
2: **Specify** $\beta, \hat{P}_f$,**let** $\lambda = \sigma_w^2 \, (\frac{1}{\sqrt{L}} \, Q^{-1}(\hat{P}_f) + 1)$
3: **Find Factorization of** N **an determine its divisors** $\{1, a_1, a_2, \cdots, a_n\}$
4: **Let** $M_1 = \{1, a_1, a_2, \cdots, a_n\}$
5: **p=1**
For i=1:n
$M = M_1(i)$
$R = \frac{N}{M(i) \times H}$
If $R = fix(R)$, **compute** $P_{dSG}, P_{dG}, Q_d, P_{fSG}, P_{fG}$ and Q_f.
If $Q_f \leq \beta$
$M_2(p, :) = [Q_d \; M \; R \; H]$
$p = p + 1$
ELSE
END If
END If
END
6: $[i_1, i_2] = max(M_2(:, 1))$
7: $M = M_2(i_2, 2), R = M_2(i_2, 3)$

As an extended study of the characteristics of the MH-CBSS algorithm, we consider the case of Nakagami fading channel. Therefore, for the n_{th} subgroup, the fading probability density function (pdf) of the largest received SNR among H_n CRs is given as [29].

$$f(\gamma_{max,n}) = \frac{H_n \; m^m \gamma^{m-1}}{\bar{\gamma}^m \; \Gamma^{H_n} \; m} \; \Gamma^{H_n - 1} \left(m, m(\frac{\gamma_{max,n}}{\bar{\gamma}}) \right) e^{-m(\frac{\gamma_{max,n}}{\bar{\gamma}})} \tag{3.13}$$

where $\Gamma(m)$ is the Gamma function which is defined as $\Gamma(m) = \int_0^\infty x^{m-1} e^{-x} dx$, while $\Gamma(a, b)$ is the incomplete Gamma function which is defined as $\Gamma(a, b) = \int_0^b x^{a-1} e^{-x} dx$. The Nakagami-m distribution can represent different models of fading environments. It is the general case which includes the one-sided Gaussian distribution $(m = 1/2)$ and the Rayleigh distribution $(m = 1)$ as special cases. When the limit of $(m \rightarrow \infty)$, the

Nakagami-m fading channel converges to a non-fading AWGN channel [26].

3.4 Simulation Results

In this section, the simulation results of the proposed algorithm are presented. The simulation results of the modified algorithm are compared with the conventional CBSS using majority rule in [40], and the MH-CBSS algorithm in [34]. Simulation settings are assumed as, $N = 24$ CRs, sampling frequency $f_s = 6$ MHz, bit rate $R_b = 250$ kbps, time frame $T = 10$ ms, $P_f = 0.1$, and $\beta = 0.01$, while the reporting channel gain $\xi = 1$ dB.

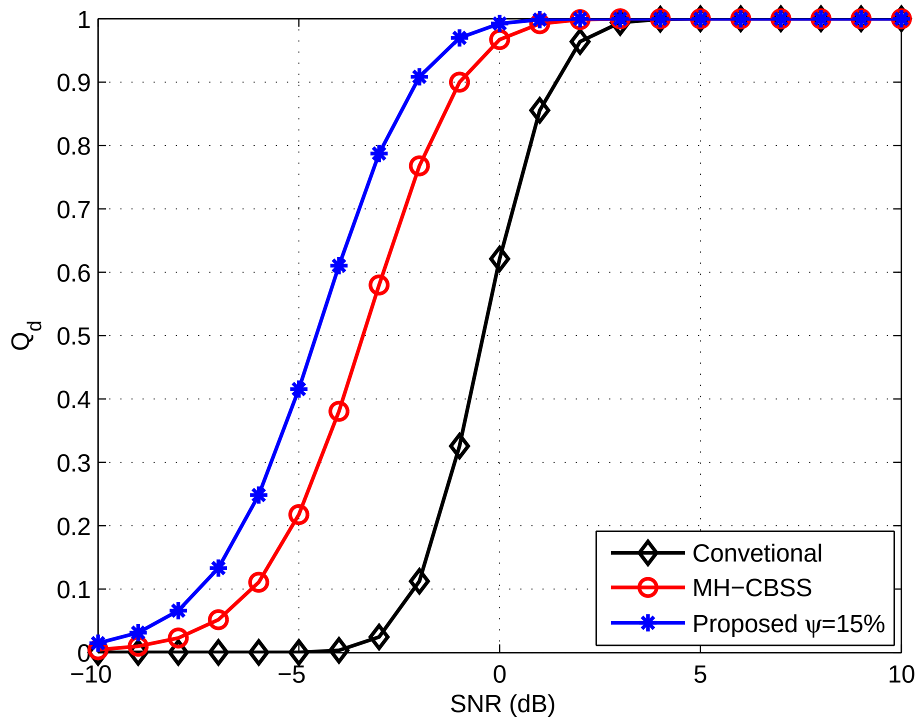

Figure 3.2: Global probability of detection for the modified algorithm compared to conventional and MH-CBSS algorithms over Rayleigh fading channel.

The proposed iterative algorithm is examined to assess its performance under different radio conditions, different fading channels. For a predefined percentage of reporting CRs,

$\psi = 0.15$, and using (3.12), the number of CRs in the subgroups, H, is 6. The best values for M and R obtained by the modified algorithm are 2 and 2, respectively.

It is shown in Fig. 3.2 that the proposed algorithm outperforms both the MH-CBSS and the conventional algorithms in terms of the global probability of detection over Rayleigh fading channel, especially, in low SNR scenarios, while it has almost the same total probability of detection of both algorithms in higher SNR (i.e., $\gamma > 2$ dB).

It can be observed from Fig. 3.3 that the modified algorithm outperforms both conventional and MH-CBSS algorithms over Nakagami-m fading channel at $m = 3$.

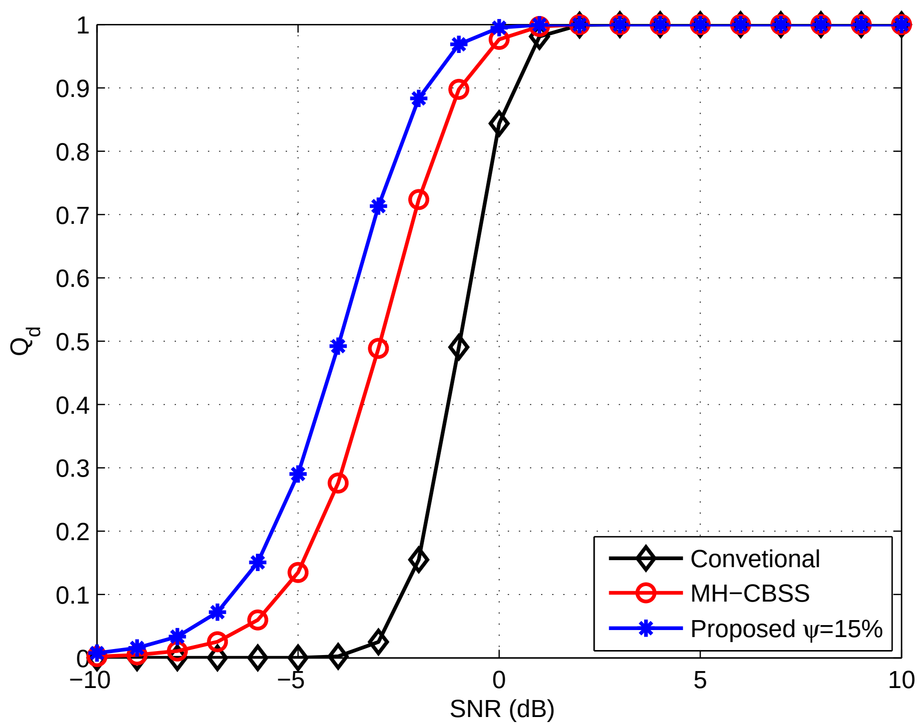

Figure 3.3: Global probability of detection for the modified algorithm, conventional algorithm and MH-CBSS algorithm over the Nakagami-m fading channel .

For a comprehensive study, we investigate the performance of the modified algorithm over the Nakagami fading for different values of Nakagami parameter, m, as depicted in

Fig.3.4.

It is noticeable from Fig. 3.4, that the detection performance of the modified algorithm slightly decreased as Nakagami parameter, m, increased. For the particular case at $m = 1$ the sensing performance of modified MH-CBSS algorithm will be exactly the same as the performance over Rayleigh fading channel.

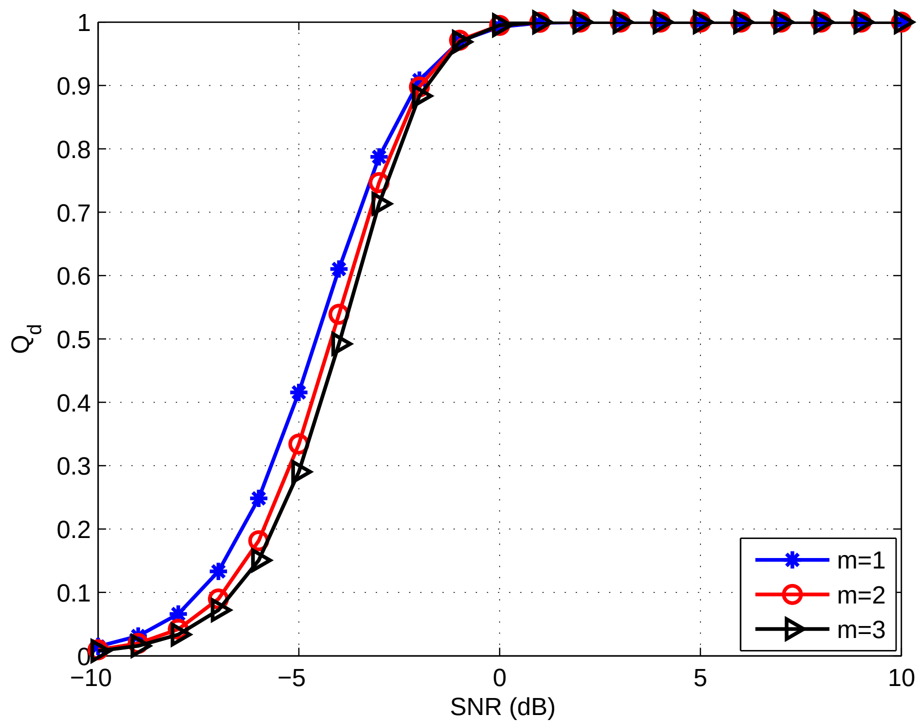

Figure 3.4: Global probability of detection for the modified algorithm over Nakagami fading channel with different values for m.

Figure 3.5 shows the complementary receiver operating characteristics (CROC) for the three available algorithms at SNR of 1 dB (i.e., $\gamma = 1$ dB) and reporting channel gain $\xi = 1$ dB. The figure shows that the modified algorithm has better detection performance than both the MH-CBSS and the conventional algorithms.

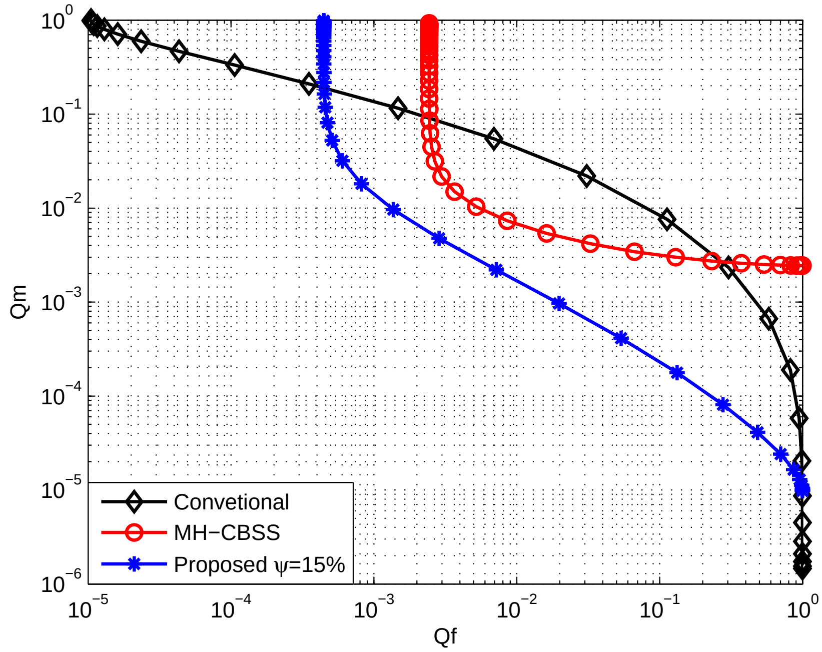

Figure 3.5: Complementary receiver operating characteristics for the three algorithms over Rayleigh fading channel.

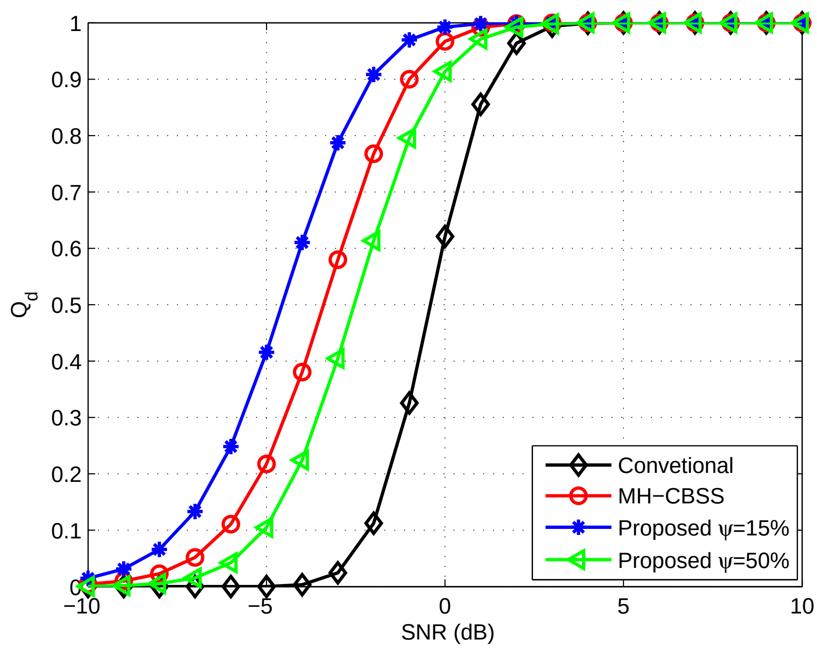

Figure 3.6: A comparison in global probability of detection between the conventional, the MH-CBSS algorithms and the modified algorithm at different values of ψ.

The impact of selecting the predefined percentage of reporting CRs, ψ, on the detection performance of the modified algorithm is investigated and illustrated in Fig. 3.6. It is shown in the figure that increasing the value of ψ degrades the detection performance of the modified algorithm.

3.5 Conclusions

A modified MH-CBSS algorithm has been proposed to reduce the computational complexity of the MH-CBSS algorithm. Moreover, the detection performance of the modified algorithm has been investigated and compared with the conventional and the MH-CBSS algorithms over the Nakagami and Rayleigh fading channels. The simulation results have shown that the modified algorithm provides higher primary user protection while maintaining the required reporting overhead.

CHAPTER 4

Hierarchical CBSS Based on Adaptive Threshold for Energy Detection

4.1 Introduction

A conventional energy detection algorithm is a fixed threshold based algorithm. Setting a detection threshold is of crucial importance in the performance of an energy detector. Therefore, it is essential to set a proper detection threshold value for the energy detector to achieve a reliable and robust sensing capability.

Unlike the conventional fixed threshold based detection algorithm, some current works investigate the adaptive sensing threshold. In [46], an adaptive threshold was determined according to the signal to interference plus noise ratio (SINR) for energy detection based spectrum sensing for individual CR user. The detection threshold was dynamically adjusted as a linear increasing function of the CRs SINR. The main goal is to maximize the CRs average transmission rate using an optimized policy function while keeping the average interference to the PU within a target level. Moreover, the policy function was obtained using very simple real-time linear calculation which maps the instantaneous SINR to a proper energy threshold. Simulation results revealed that the proposed method achieves a higher SU throughput compared to the fixed threshold based energy detector, while maintaining great stability in the probability of detection and probability of false alarm. In addition, the proposed algorithm in [47] was considered the detection error rate as a criterion to assess the performance of spectrum sensing algorithm. An optimal adaptive threshold level was determined to minimize the spectrum sensing error for given spectrum sensing constraint for a single CR. However, the individual CR user may not give accurate sensing results due to shadowing, multipath fading and hidden terminal problems of the wireless communication channel. Therefore, in [48] to deal with these problems, the proposed adaptive threshold approach had been analyzed under the cooperative spectrum sensing (CSS). Simulation results showed that the probability of detection clearly improved when more than one CR involved in the spectrum sensing. However, all previously mentioned algorithms did not consider a compromise between detection performance and incurred energy consumption for CSS system.

In this chapter, a low computational energy-efficient hierarchical cluster-based CSS with an adaptive threshold is proposed. The proposed algorithm enables the CR to dynamically adapt its detection threshold to meet the minimal overall cluster detection error. Moreover, the optimal threshold level for minimizing the overall cluster detection error rate is determined. The detection performance of the proposed algorithm is presented and evaluated through simulation results.

This chapter is organized as follows: Threshold Setting is described in Section 4.2.

The system model is presented in Section 4.3. The proposed algorithm for the adaptive threshold is introduced in 4.4. Simulation results are presented and discussed in Section 4.5 while the conclusion is provided in Section 4.6.

4.2 Threshold Setting

Before explaining the concept of adaptive threshold, the methods of fixed threshold will be discussed in this Section. Consider, the test statistic of the energy detector $T(y)$ is determined as follows.

$$T(y) = \sum_{n=1}^{M_s} |y(n)|^2 \tag{4.1}$$

where $y(n)$ is the signal received by the CR and M_s is the observation samples [5].

The performance metric of spectrum sensing can be determined by the detection probability P_d and the false alarm probability P_f.

$$P_d(\lambda, \gamma) = P(T(y) > \lambda \mid H_1) = Q\left((\frac{\lambda}{\sigma_w^2} - \gamma - 1)\sqrt{\frac{L}{2\gamma + 1}} \right) \tag{4.2}$$

$$P_f(\lambda) = P(T(y) > \lambda \mid H_0) = Q\left((\frac{\lambda}{\sigma_w^2} - 1)\sqrt{L} \right) \tag{4.3}$$

where γ is the signal-to-noise ratio (SNR) at the CR, λ is the sensing threshold, σ_w^2 is the noise variance, L is the number of samples, $Q(\cdot)$ is Q-function and, H_0 and H_1, are the testing hypotheses for absence and presence of the PU, respectively.

Setting an optimal threshold is one of the most critical challenges to implement detection techniques. Therefore, it should be selected carefully; since it significantly affects the sensing performance of energy detector. The threshold can be set as either fixed or dynamic (i.e., adaptive threshold); two methods can be used to set a fixed threshold: (1) constant false alarm rate (CFAR) and (2) constant detection rate (CDR).

(1) The threshold λ_{Pf} can be set for CFAR as

$$\lambda_{Pf} = \sigma_w^2\,(\frac{1}{\sqrt{L}}\,Q^{-1}(\hat{P}_f) + 1) \tag{4.4}$$

(2) The threshold λ_{Pd} can be set for CDR as

$$\lambda_{Pd} = \sigma_w^2\,(\sqrt{\frac{2\gamma+1}{L}}Q^{-1}(\hat{P}_d) + \gamma + 1) \tag{4.5}$$

where $\hat{P}_d$ and $\hat{P}_f$ are the targeted detection probability and targeted false alarm probability, respectively.

If the cognitive radio user is expected to guarantee PU's safely utilize of the spectrum, the probability of detection should be set to satisfy a predefined probability of detection called targeted probability of detection ($\hat{P}_d$) and the probability of false alarm should be minimized as much as possible. This condition is referred to as CDR method. From the other perspective, if the CR user aims to ensure the spectrum efficiency of the SUs, the probability of false alarm should be set to satisfy a predefined targeted probability of false alarm ($\hat{P}_f$), and the detection probability should be maximized as much as possible. This condition is referred to as CFAR method [39]. Therefore, a compromise between the two methods can be achieved in the best possible way by using an adaptive threshold.

4.3 System Model for MH-CBSS Algorithm

In the MH-CBSS model, the PU is assumed to be static, a cluster with N CRs is arranged into M groups. Each group is also separated into R subgroups. Each subgroup has H CRs. Every group and subgroup have group head GH and sub-group head SGH, respectively. The heads are selected to have the greatest reporting channel gain between their neighbors. In other words, the nearest CR to FC usually has the largest reporting channel gain and the FC is in charge of clustering and choosing the CH [34]. For more details about the system model please refer to Section 3.2.

The overall cluster detection error rate φ_e is calculated as

$$\varphi_e = P(H_1)\, Q_m + P(H_0)\, Q_f \tag{4.6}$$

where is $Q_m = 1 - Q_d$ the global probability of missed detection and, $P(H_1)$ and $P(H_0)$, are the probabilities of presence and absence of the PU, respectively.

An accurate performance improvement cannot be attained by blindly increasing or decreasing the sensing threshold. Therefore, to satisfy the target total error rate, an optimal detection threshold must be determined. Moreover, identifying the optimal threshold contributes to improving the probability of detection and the usage level of the unused spectrum. The optimal threshold is determined by minimizing the total error as provided in (4.7).

$$\lambda_{opt} = \arg \min_{\lambda} \quad (\varphi_e) \tag{4.7}$$

The solution to this problem is the threshold value that makes the derivative of the overall cluster error equal to zero as described in (4.8).

$$\frac{\partial \, \varphi_e(\lambda)}{\partial \lambda} \mid_{\lambda=\lambda_{opt}} = \; P(H_0)\frac{\partial \, Q_f(\lambda)}{\partial \lambda} - P(H_1)\frac{\partial \, Q_d(\lambda)}{\partial \lambda} = 0 \tag{4.8}$$

The optimization problem for MH-CBSS is formulated based on minimizing the overall detection error as

$$\begin{aligned} \min_{\lambda} \quad & (\varphi_e) \\ \text{subject to} \quad & R \geq 1, M \geq 1 \\ & k_1 \geq 1, k_2 \geq 1. \end{aligned} \tag{4.9}$$

where R is the number of subgroups, M is the number of groups, k_1 and k_2 are the fusion rule parameters at the group level and fusion rule parameters at the cluster level, respectively.

4.4 The Proposed Algorithms

In this section, the main objective is to propose a low computational algorithm that optimizes the detection performance of the MH-CBSS algorithm by minimizing the total error of the system. The idea is to compute the H (i.e., the number of CRs in a subgroup) that can satisfy the objective. The H is determined based on the required percentage of saved energy (ΔE), as computed in [34]:

$$\Delta E = \frac{N(H-1)}{H(N-1)} \tag{4.10}$$

where N is the total number of CRs in the cluster.

In order to reduce the number of required iterations (i.e., computational runs) to compute $M, R,$ and H (i.e., the number of hierarchical levels), it is assumed that $\Delta E \leq \alpha$, based on (4.10), the number of CRs in a subgroup H can be calculated as

$$H = \left\lceil \frac{N}{N + \alpha - N\alpha} \right\rceil \tag{4.11}$$

Using (4.11), the number of CRs in the subgroups will be determined by initially specifying the required percentage of saved energy, ΔE, which will reduce the number of the iterations of the MH-CBSS algorithm by approximately 30%. As a first step, we investigate the case of energy efficient adaptive hierarchical structure with adaptive detection threshold to achieve the minimum total error. For this purpose, after determining H, all possible combinations of M and R will be determined based on the computed H, using (4.11). Then, the overall detection error for all combinations will be calculated by using (4.6). Finally, at each single threshold, the best combination will be obtained based on the minimum total error rate.

Based on the aforementioned step, for a predefined percentage of saved energy, $\alpha = 60\%$, and using (4.11), the number of CRs in the subgroup, H, is 3. It is shown in Fig. 4.1 for a cluster with 24 CRs at $\gamma = 1$ dB. These are all possible combinations (i.e., hierarchical levels) of M and R. Figure 4.2 illustrates the comparison between the total error rate

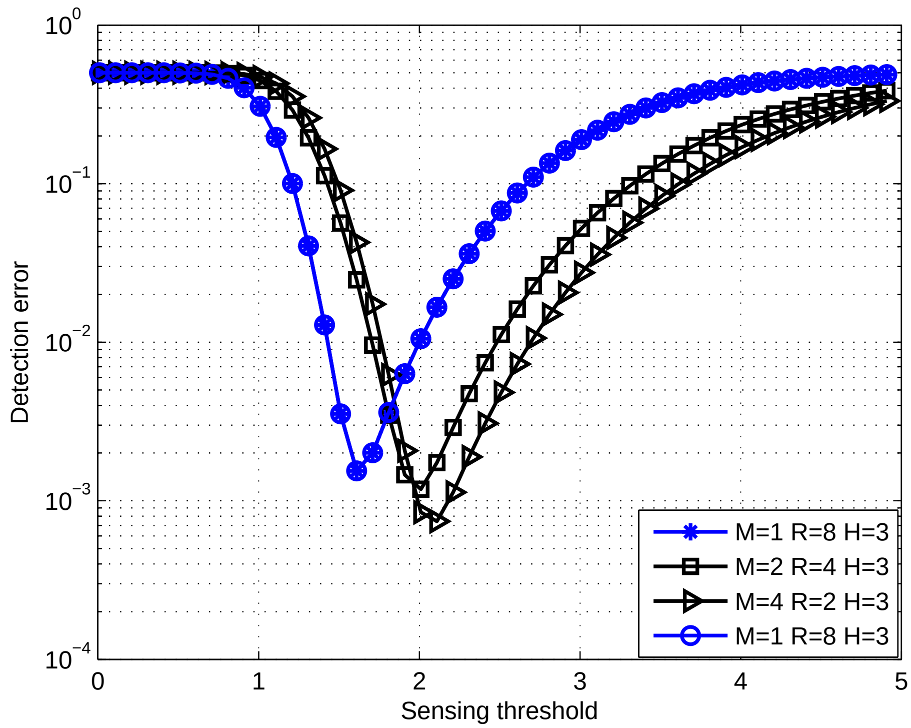

Figure 4.1: Error detection rate vs. sensing threshold for a cluster with 24 CRs at $\gamma = 1$ dB and $\alpha = 60\%$.

and detection threshold for the two and three levels hierarchy. It is observed that at higher values of detection threshold the three levels considerably outperforms the two levels by achieving lower detection error ; in other words, a higher detection probability. On the other hand, the two levels perform greater at lower values of detection threshold at the expense of some sensing performance loss. It can also be noticed that the difference in the minimum total error rate at the optimal threshold values for two levels (i.e., $\varphi_e(\lambda_{opt} = 1.6) = 0.0015)$ and three levels (i.e., $\varphi_e(\lambda_{opt} = 2) = 0.0007)$ hierarchy is very small. Therefore, the local minimum detection threshold will be selected as a reference. Furthermore, designing an energy efficient adaptive hierarchical structure with adaptive sensing threshold could be a computational burden. Accordingly, a suboptimal algorithm is proposed to design an en-

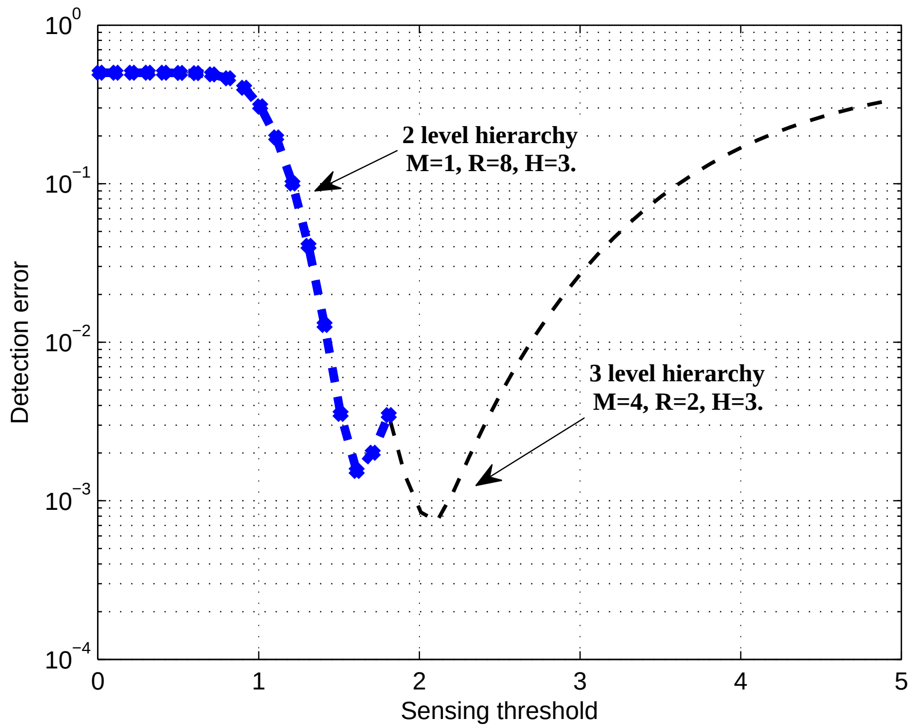

Figure 4.2: A comparison in total error rate between 2 and 3 levels hierarchy with 24 CRs at $\gamma = 1$ dB and $\alpha = 60\%$.

ergy efficient fixed hierarchical structure with adaptive detection threshold that minimizes the total error rate.

4.4.1 The Proposed Iterative Algorithm for Threshold Optimization

By determining the value of, λ, that solves (4.8) the optimal threshold that minimize the spectrum sensing error can be determined. However, it is hard to extract a closed-form expression for the optimal threshold, therefore, it is better to be determined numerically using line search methods such as bisection method. As a result, an iterative algorithm is proposed to determine the optimal threshold (λ_{opt}) as provided in Algorithm 4.1.

Algorithm 4.1. The proposed iterative algorithm to determine the optimal threshold

1: **Specify** α, **and compute** H using (4.11).
2: **Provided** P_0 and P_1.
3: **Determine** all possible combinations of (M, R).
4: **Compute** φ_e for all combinations using (4.6).
5: **Determine** the hierarchical structure according to the local minimum φ_e.
6: **Use** Bisection method to find optimal $\lambda_{opt} \in (0, \lambda_{max})$
(i.e., λ_{max} is arbitrarily selected).
let $n = 100, \Delta\lambda = \frac{\lambda_{max}}{n}$
7: **For** $i = 1 : n$
If $\varphi_e(i+1) \leq \varphi_e(i)$
$\lambda_{i+1} = \lambda_i + \Delta\lambda$
else $\lambda_{i+1} = \lambda_i - \Delta\lambda$
end If
end For
8: **Return** $\lambda_{opt} = \lambda_{i+1}$, $Q_{D(Suboptimal)} = Q_d(\lambda_{opt})$, $Q_{F(Suboptimal)} = Q_f(\lambda_{opt})$
and $\varphi_{e(Suboptimal)} = \varphi_e(\lambda_{opt})$.

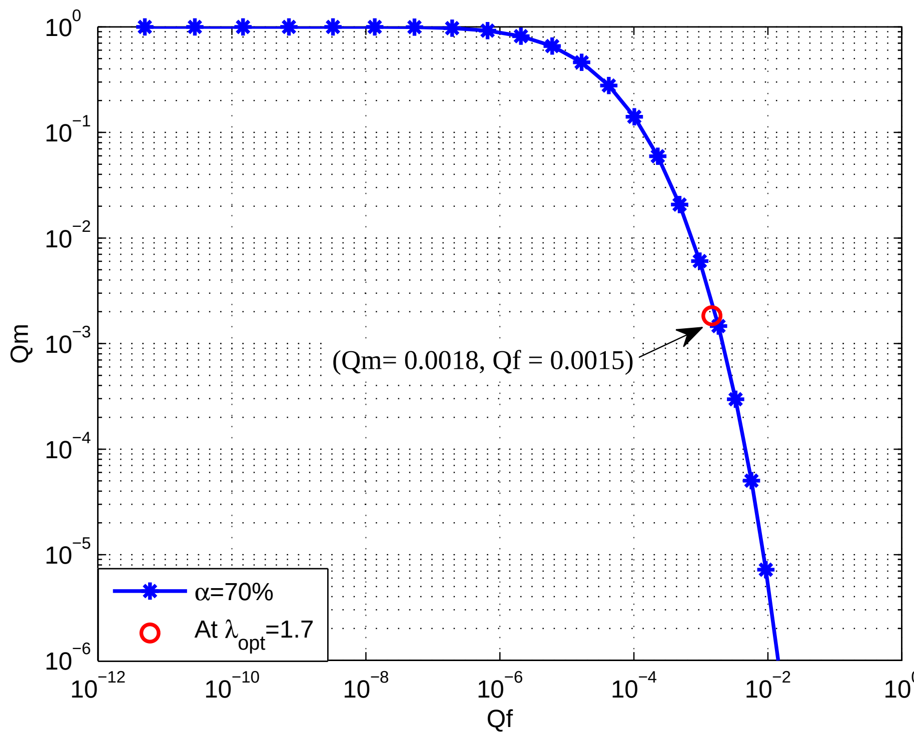

Figure 4.3: Complementary receiver operating characteristic of the proposed iterative algorithm (4.1), for $N = 24, \gamma = 1$ dB and $\alpha = 70\%$.

For instance, if the predefined percentage of saved energy is $\alpha = 70\%$. Using (4.11), the number of CRs in the subgroup, H, will be 4. The cluster structure is selected as ($M = 1$, $R = 6$, $H = 4$) based on the local minimum error. Based on Algorithm 4.1, the optimal threshold level for the energy detector at the minimum error (i.e., $\varphi_e(min) = 0.0016$) equals to ($\lambda_{opt} = 1.7$). The corresponding optimal global probability of missed detection Q_m and false alarm Q_f are 0.0018 and 0.0015, respectively. Besides, the optimal global probability of detection can be calculated as ($Q_d = 1 - Q_m = 0.9982$). Figure 4.3 represents the complementary receiver operating characteristic (CROC) for the aforementioned example at $N = 24$ and signal-to-noise ratio (i.e., $\gamma = 1$ dB). It is shown that the global false alarm and missed detection probabilities are monotonically increased and decreased, respectively.

4.4.2 The Proposed Algorithm for Hierarchical CBSS with an Adaptive Threshold

If each cognitive user in the cluster dynamically adjusts its threshold to minimize the overall cluster error this will enhance the performance of energy detector, and hence improve spectrum efficiency. In Algorithm 4.2, the SNR is changed through a set of values in the range [SNR$_{min}$: SNR$_{max}$], and the corresponding optimal threshold λ_{opt} is simultaneously determined for each SNR value by using Algorithm 4.1.

Using Algorithm 4.2, we investigate the impact of SNR at three different values (i.e., SNR=$-5, 0, 5$.) on the sensing threshold. It has been recognized from Fig. 4.4 as the SNR increase the optimal sensing threshold at each SNR monotonically increases. Consequently, the overall detection error reduced which in turn will enhance the Q_d.

Algorithm 4.2. An adaptive threshold based algorithm for hierarchical CBSS

1: **Specify** α, **and compute** H using (4.11).
2: **Provided** P_0 *and* P_1.
3: **Determine** all possible combinations of (M, R).
4: **Compute** φ_e for all combinations using (4.6).
5: **Determine** the hierarchical structure based on the local minimum φ_e.
6: **For** $i = \text{SNR}_{min} : \text{SNR}_{max}$
7: **Use** algorithm (4.1) to find the $\lambda_{(opt)i}$
8: **Return** $\lambda_{(opt)i}$, $Q_{D(Suboptimal)} = Q_d(\lambda_{(opt)i})$, $Q_{F(Suboptimal)} = Q_f(\lambda_{(opt)i})$ and $\varphi_{e(Suboptimal)} = \varphi_e(\lambda_{(opt)i})$.
end For

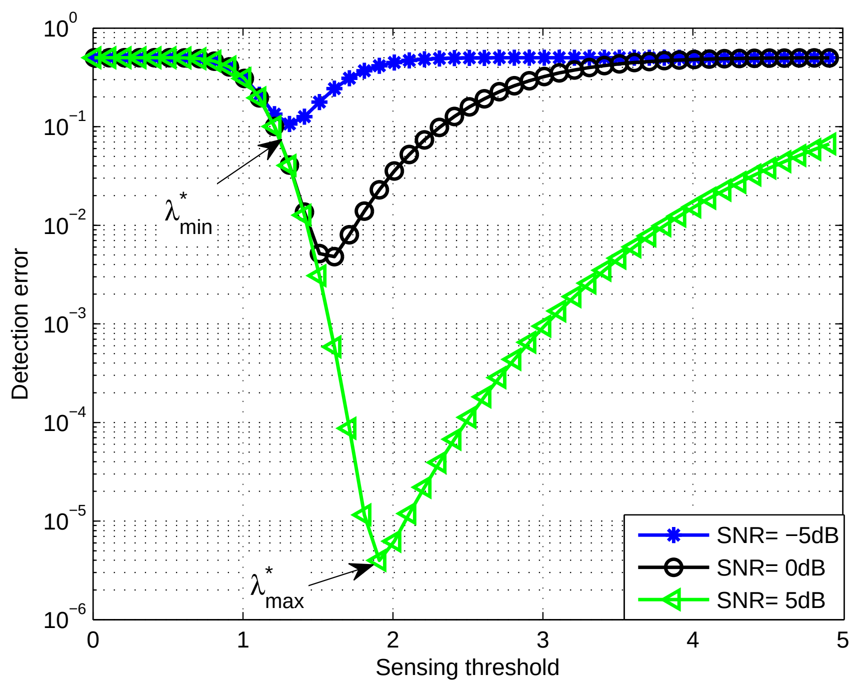

Figure 4.4: Error detection rate vs. sensing threshold at three different SNR values.

The search for the optimal threshold will be considered only between $(\lambda^*_{min}, \lambda^*_{max})$, where those values refer to the thresholds at the minimum and maximum SNR, respectively as indicated in Fig. 4.4. This particular search will save computations that required to find the optimal threshold in the conventional search (i.e., from 0 to λ_{max}). As proposed in Algorithm 4.3. In addition, from Fig. 4.5, it is noticeable that the detection performance starts to deteriorate after the sensing threshold reaches its optimal point. Using this fact, we were motivated to modify Algorithm 4.2 to reduce the computational burden.

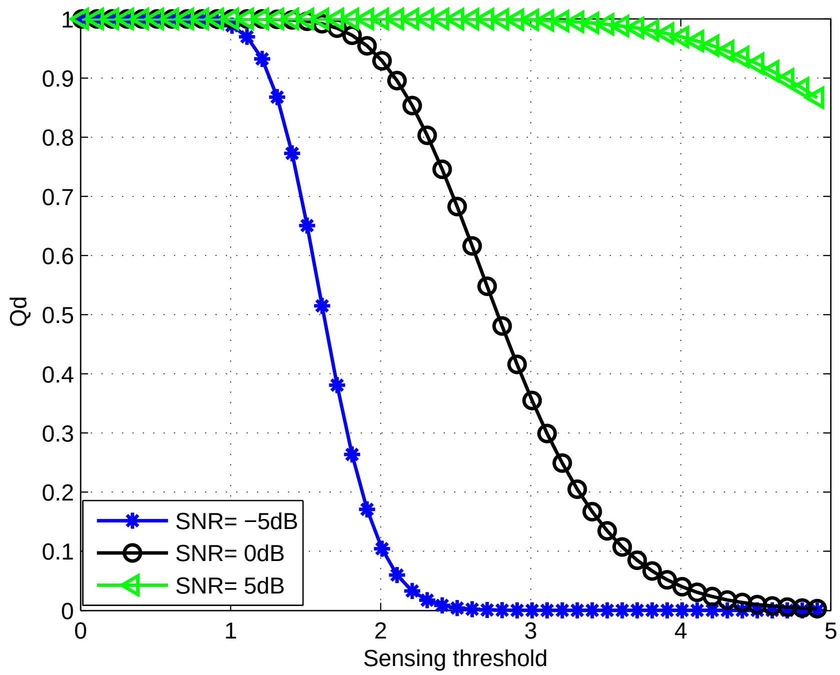

Figure 4.5: Overall probability of detection vs. sensing threshold of three different SNR.

Algorithm 4.3. Low computational adaptive threshold based algorithm for hierarchical CBSS

1: **Specify** α, **and compute** H using (4.11).
2: **Provided** P_0 *and* P_1.
3: **Using Bisection method compute** λ^*_{min} at SNR$_{min}$ and λ^*_{max} at SNR$_{max}$.
4: **Specify** $\varphi_e(\lambda^*_{min})$.
let $n = 100, \Delta\lambda = (\lambda^*_{max} - \lambda^*_{min})/n$.
5: **Use** Bisection method to find optimal threshold $\lambda_{opt} \in (\lambda^*_{min}, \lambda^*_{max})$.
$i = 1$
6: **While** SNR $>$ SNR$_{min}$
If $\varphi_e(i+1) \leq \varphi_e(i)$
$\lambda^*_{i+1} = \lambda^*_i + \Delta\lambda$
end If
7: **Return** $\lambda_{opt} = \lambda^*_{i+1}$, $Q_{Di(Suboptimal)} = Q_d(\lambda_{opt})$, $Q_{Fi(Suboptimal)} = Q_f(\lambda_{opt})$ and $\varphi_{ei(Suboptimal)} = \varphi_e(\lambda_{opt})$.
end While

4.5 Simulation Results

Simulation settings are assumed as, $N = 24$ CRs, sampling frequency $f_s = 6$ MHz, bit rate $R_b = 250$ kbps, time frame $T = 10$ ms, $P_f = 0.1$ for fixed threshold, and $\beta = 0.01$, while the reporting channel gain $\xi = 1$ dB. We consider the predefined percentage of saved energy is $\alpha = 60\%$. Using (4.11), the number of CRs in the subgroup, H, will be 3. The cluster structure is selected as ($M = 1$, $R = 8$, $H = 3$) based on the local minimum error. It is shown in Fig. 4.6 that the proposed adaptive threshold algorithm outperforms the conventional fixed threshold algorithm in terms of the global probability of detection over Rayleigh fading channel, especially, in low SNR scenarios, while it has almost the same total probability of detection of both algorithms in higher SNR (i.e., $\gamma > 1$ dB).

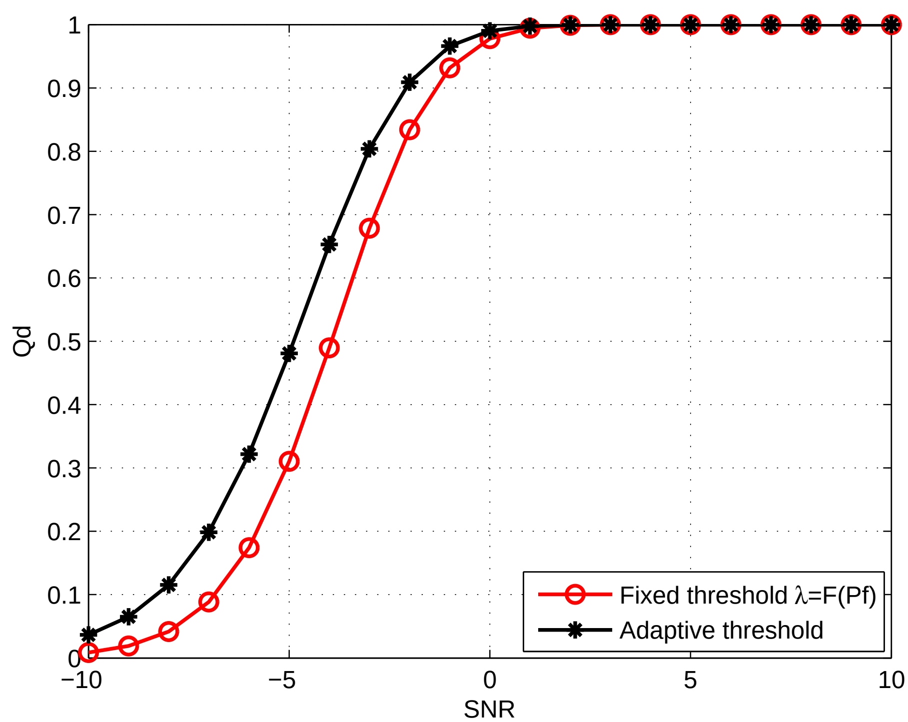

Figure 4.6: Overall probability of detection of the proposed algorithm compared to a fixed threshold at $\alpha = 60\%$.

Figure 4.7 depicts the total error detection rate vs. SNR of the proposed adaptive threshold algorithm compared with the fixed threshold based algorithm. It can be seen that the proposed algorithm minimizes the overall detection error noticeably compared with the fixed threshold based algorithm. Moreover, at the high SNR the detection error of the fixed threshold scheme is almost steady (i.e., $\varphi_e = 2 \times 10^{-5}$), because Q_d approaches its maximum value (i.e., $Q_d = 1$) at the high SNR, in this case, Q_m will be zero. Therefore, the dominant factor on the overall detection error is Q_F because the probability of false alarm P_f for the CRs in the fixed threshold based algorithm is a predefined value.

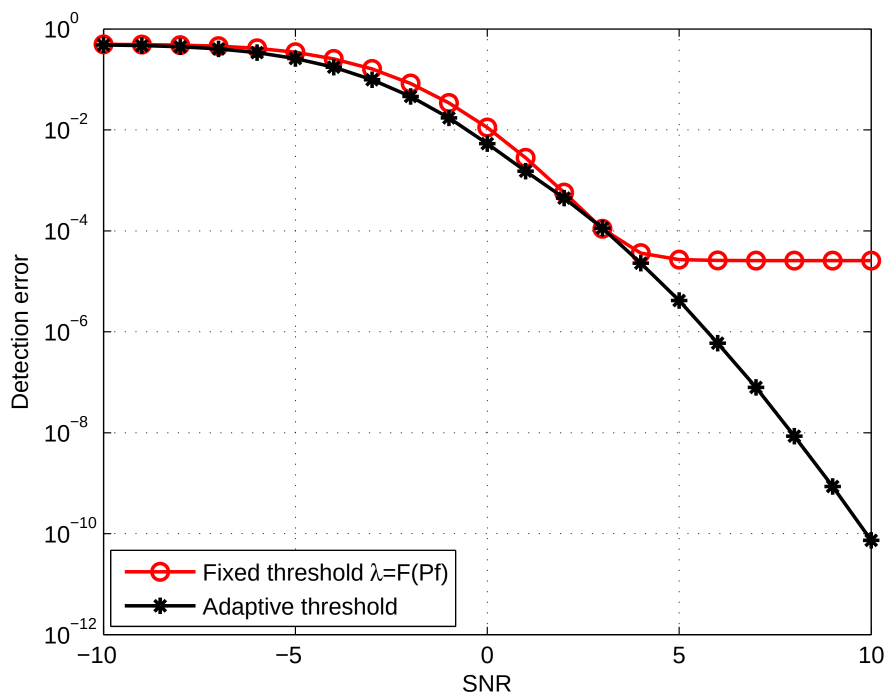

Figure 4.7: Error detection rate vs. SNR of the proposed algorithm compared to a fixed threshold,at $\alpha = 60\%$.

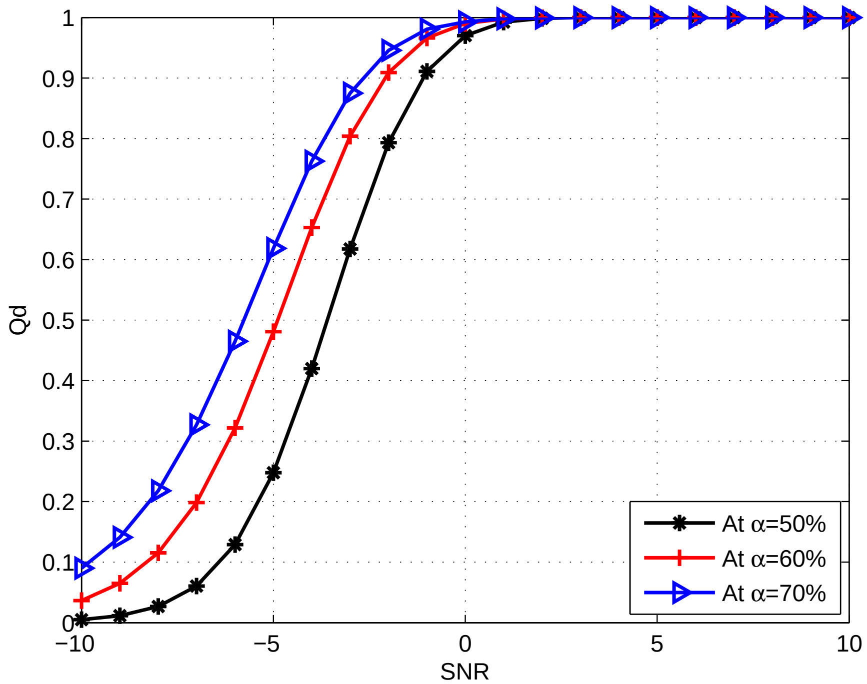

Figure 4.8: A comparison in a global probability of detection for adaptive threshold algorithm at different values of α.

The impact of selecting the percentage of saved energy, α, on the detection performance of the proposed adaptive threshold algorithm is investigated and illustrated in Fig. 4.8. It is noted that increasing the value of α enhances the detection performance. The reason behind that is increasing the percentage of saved energy means increasing the number of CRs in the subgroups while reducing the number of reporting CRs.

4.6 Conclusions

In this chapter, the optimal threshold level that minimizes the overall cluster detection error rate has been investigated. Moreover, an adaptive threshold MH-CBSS algorithm has been proposed which allows the CR dynamically adjusts its energy threshold to attain the minimal total cluster error. The detection performance of the proposed algorithm has been investigated and compared with the conventional fixed threshold over Rayleigh fading channels. The simulation results have shown that the proposed algorithm can provide higher primary user protection by improving the detection performance.

CHAPTER 5

Thesis Conclusions and Recommendations

5.1 Conclusions

A low computational MH-CBSS algorithm has been proposed to reduce the complexity of the MH-CBSS algorithm. Using the proposed algorithm the number of CRs in the sub-groups has been determined based on the predefined ψ, which provides an advantage of reducing the number of the iterations of MH-CBSS algorithm by around 30%, since only two parameters (i.e., $R\, and\, M$) will be determined using the proposed algorithm instead of determining three parameters (i.e., $H, R\, and\, M$) as in MH-CBSS algorithm. Moreover, the detection performance of the modified algorithm has been investigated and compared with the conventional and the MH-CBSS algorithms over the Nakagami and Rayleigh fading channels. The simulation results have shown that the modified algorithm provides higher primary user protection while maintaining the required reporting overhead.

Conventionally, most energy detection algorithms assume fixed detection threshold. The performance of the energy detector depends considerably on the setting of the threshold. Thus, it is essential to set a proper threshold for the energy detector to gain a credible and robust sensing capability. Therefore, the work in chapter 4 developed to consider the concept of the adaptive threshold. The number of CRs in the subgroups has been determined by specifying the required percentage of saved energy, ΔE, which provides an advantage of reducing the number of the iterations of the MH-CBSS algorithm. In addition, the optimal threshold level that minimizes the overall cluster detection error rate has been determined. An adaptive threshold MH-CBSS algorithm has been proposed which allows the CR dynamically adjusts its energy threshold to attain the minimal total cluster error. The detection performance of the proposed algorithm has been examined and compared with the conventional fixed threshold over Rayleigh fading channels. Besides, the simulation results have shown that the proposed algorithm noticeably improves the detection performance which provides higher protection of the PU user.

5.2 Recommendations

Cooperative spectrum sensing has recently emerged as an attractive and versatile research topic that interests many researchers. The recommendation for future works will be considered as follow

1. Energy detection is a widely adopted method for spectrum sensing because it has low implementation complexity and it does not depend on any prior knowledge about

primary signals. Most current works on energy detection assumed that the noise power is perfectly and previously known. However, the fact is that the noise power changes from time to time in a practical environment. Therefore, energy detection has practical limitation. As a future research point, conventional detection methods can be implemented using Software-Defined Radios (SDR) which can be employed as a sensing unit for single CR instead of energy detection in a real environment.

2. In the previous point, the work can be extended to implement CSS in order to improve detection performance of the system. Moreover, various radio environmental conditions such as Rayleigh fading, and shadowing can be granted to have a comprehensive study. Also, the work can be continued to implement cluster-base spectrum sensing (CBSS). Accordingly, the detection performance of the proposed algorithms can also be investigated in real time world.

3. Furthermore, the effect of mobility on the detection performance of the proposed algorithms in the thesis can be considered as a point for a future research.

REFERENCES

[1] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE communications surveys & tutorials*, vol. 11, no. 1, pp. 116–130, 2009.

[2] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Physical communication*, vol. 4, no. 1, pp. 40–62, 2011.

[3] L. Lu, X. Zhou, U. Onunkwo, and G. Y. Li, "Ten years of research in spectrum sensing and sharing in cognitive radio," *EURASIP Journal on Wireless Communications and Networking*, vol. 2012, no. 1, p. 28, 2012.

[4] J. Ma, G. Y. Li, and B. H. Juang, "Signal processing in cognitive radio," *Proceedings of the IEEE*, vol. 97, no. 5, pp. 805–823, 2009.

[5] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in *Signals, systems and computers, 2004. Conference record of the thirty-eighth Asilomar conference on*, vol. 1. Ieee, 2004, pp. 772–776.

[6] H. Tang, "Some physical layer issues of wide-band cognitive radio systems," in *New*

frontiers in dynamic spectrum access networks, 2005. DySPAN 2005. 2005 first IEEE international symposium on. IEEE, 2005, pp. 151–159.

[7] Y. Mingchuan, L. Yuan, L. Xiaofeng, and T. Wenyan, "Cyclostationary feature detection based spectrum sensing algorithm under complicated electromagnetic environment in cognitive radio networks," *China Communications*, vol. 12, no. 9, pp. 35–44, 2015.

[8] Z.-H. Hao, Y.-X. Tang, and J.-X. Xia, "A distributed cooperative spectrum sensing based on network code in cognitive radios," in *Apperceiving Computing and Intelligence Analysis, 2009. ICACIA 2009. International Conference on*. IEEE, 2009, pp. 9–13.

[9] M. Hamid, N. Björsell, and S. B. Slimane, "Energy and eigenvalue based combined fully blind self adapted spectrum sensing algorithm," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 2, pp. 630–642, 2016.

[10] Y. Zeng and Y.-C. Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio," *IEEE transactions on communications*, vol. 57, no. 6, 2009.

[11] A. Ghasemi and E. S. Sousa, "Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs," *IEEE Communications magazine*, vol. 46, no. 4, 2008.

[12] S. Althunibat, M. Di Renzo, and F. Granelli, "Optimizing the k-out-of-n rule for cooperative spectrum sensing in cognitive radio networks," in *Global Communications Conference (GLOBECOM), 2013 IEEE*. IEEE, 2013, pp. 1607–1611.

[13] A. Ghasemi and E. S. Sousa, "Collaborative spectrum sensing for opportunistic access in fading environments," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*. IEEE, 2005, pp. 131–136.

[14] S. Maleki, S. P. Chepuri, and G. Leus, "Optimal hard fusion strategies for cognitive radio networks," in *Wireless Communications and Networking Conference (WCNC), 2011 IEEE*. IEEE, 2011, pp. 1926–1931.

[15] D. Teguig, B. Scheers, and V. Le Nir, "Data fusion schemes for cooperative spectrum sensing in cognitive radio networks," in *Communications and Information Systems Conference (MCC), 2012 Military*. IEEE, 2012, pp. 1–7.

[16] S. Maleki, S. P. Chepuri, and G. Leus, "Energy and throughput efficient strategies for cooperative spectrum sensing in cognitive radios," in *Signal Processing Advances in Wireless Communications (SPAWC), 2011 IEEE 12th International Workshop on*. IEEE, 2011, pp. 71–75.

[17] S. Althunibat and F. Granelli, "Novel energy-efficient reporting scheme for spectrum sensing results in cognitive radio," in *Communications (ICC), 2013 IEEE International Conference on*. IEEE, 2013, pp. 2438–2442.

[18] Z. Bai, L. Wang, H. Zhang, and K. Kwak, "Cluster-based cooperative spectrum sensing for cognitive radio under bandwidth constraints," in *Communication Systems (ICCS), 2010 IEEE International Conference on*. IEEE, 2010, pp. 569–573.

[19] Z.-H. Hao, Y.-X. Tang, and J.-X. Xia, "A distributed cooperative spectrum sensing

based on network code in cognitive radios," in *Apperceiving Computing and Intelligence Analysis, 2009. ICACIA 2009. International Conference on*. IEEE, 2009, pp. 9–13.

[20] Q. Zhang, J. Jia, and J. Zhang, "Cooperative relay to improve diversity in cognitive radio networks," *IEEE Communications Magazine*, vol. 47, no. 2, pp. 111–117, 2009.

[21] L. Zhang, J. Yang, H. Zhou, and X. Jian, "Optimization of relay-based cooperative spectrum sensing in cognitive radio networks." IEEE Publishing, September 2011, pp. 1–4.

[22] N. Zarin, S. A. Mahmud, and I. Khan, "Relay based cooperative spectrum sensing in cognitive radio networks over rayleigh fading channel with path loss effects," in *Multitopic Conference (INMIC), 2012 15th International*. IEEE, 2012, pp. 291–296.

[23] V. Kumar, D. C. Kandpal, R. Gangopadhyay, and S. Debnath, "Amplify-and-forward relay based spectrum sensing with generalized selection combining," in *Personal, Indoor, and Mobile Radio Communications (PIMRC), 2016 IEEE 27th Annual International Symposium on*. IEEE, 2016, pp. 1–5.

[24] Y. Xiao and F. Hu, *Cognitive radio networks*. CRC press, 2008.

[25] M. K. Simon and M.-S. Alouini, *Digital communication over fading channels*. John Wiley & Sons, 2005, vol. 95.

[26] J. Duan and Y. Li, "Performance analysis of cooperative spectrum sensing in differ-

ent fading channels," in *Computer Engineering and Technology (ICCET), 2010 2nd International Conference on*, vol. 3. IEEE, 2010, pp. V3–64.

[27] M. Di Renzo, F. Graziosi, and F. Santucci, "Cooperative spectrum sensing in cognitive radio networks over correlated log-normal shadowing," in *Vehicular Technology Conference, 2009. VTC Spring 2009. IEEE 69th*. IEEE, 2009, pp. 1–5.

[28] T. S. Rappaport *et al.*, *Wireless communications: principles and practice*. Prentice Hall PTR New Jersey, 1996, vol. 2.

[29] F. F. Digham, M.-S. Alouini, and M. K. Simon, "On the energy detection of unknown signals over fading channels," *IEEE Transactions on communications*, vol. 55, no. 1, pp. 21–24, 2007.

[30] L. Wang, J. Wang, G. Ding, F. Song, and Q. Wu, "A survey of cluster-based cooperative spectrum sensing in cognitive radio networks," in *Cross Strait Quad-Regional Radio Science and Wireless Technology Conference (CSQRWC), 2011*, vol. 1. IEEE, 2011, pp. 247–251.

[31] K.-L. A. Yau, N. Ramli, W. Hashim, and H. Mohamad, "Clustering algorithms for cognitive radio networks: A survey," *Journal of network and computer applications*, vol. 45, pp. 79–95, 2014.

[32] C. Guo, T. Peng, S. Xu, H. Wang, and W. Wang, "Cooperative spectrum sensing with cluster-based architecture in cognitive radio networks," in *Vehicular Technology Conference, 2009. VTC Spring 2009. IEEE 69th*. IEEE, 2009, pp. 1–5.

[33] W. Kim, H. Jeon, S. Im, and H. Lee, "Optimization of multi-cluster multi-group based cooperative sensing in cognitive radio networks," in *MILITARY COMMUNICATIONS CONFERENCE, 2010-MILCOM 2010*. IEEE, 2010, pp. 1211–1216.

[34] F. A. Awin, E. Abdel-Raheem, and M. Ahmadi, "Optimization of multi-level hierarchical cluster-based spectrum sensing structure in cognitive radio networks," *Digital Signal Processing*, vol. 36, pp. 15–25, 2015.

[35] K. Yadav, A. Bhowmick, S. D. Roy, and S. Kundu, "Cooperative spectrum sensing based on dynamic clustering with improved energy detector," in *Recent Advances in Information Technology (RAIT), 2016 3rd International Conference on*. IEEE, 2016, pp. 46–49.

[36] W. Xia, S. Wang, W. Liu, and W. Chen, "Cluster-based energy efficient cooperative spectrum sensing in cognitive radios," in *Wireless Communications, Networking and Mobile Computing, 2009. WiCom'09. 5th International Conference on*. IEEE, 2009, pp. 1–4.

[37] S. Hussain and X. Fernando, "Approach for cluster-based spectrum sensing over band-limited reporting channels," *IET communications*, vol. 6, no. 11, pp. 1466–1474, 2012.

[38] C. Guo, T. Peng, S. Xu, H. Wang, and W. Wang, "Cooperative spectrum sensing with cluster-based architecture in cognitive radio networks," in *Vehicular Technology Conference, 2009. VTC Spring 2009. IEEE 69th*. IEEE, 2009, pp. 1–5.

[39] E. Peh and Y.-C. Liang, "Optimization for cooperative sensing in cognitive radio

networks," in *Wireless Communications and Networking Conference, 2007. WCNC 2007. IEEE*. IEEE, 2007, pp. 27–32.

[40] C. Sun, W. Zhang, and K. B. Letaief, "Cluster-based cooperative spectrum sensing in cognitive radio systems," in *Communications, 2007. ICC'07. IEEE International Conference on*. IEEE, 2007, pp. 2511–2515.

[41] F. A. Awin, E. Abdel-Raheem, and M. Ahmadi, "Designing an optimal energy efficient cluster-based spectrum sensing for cognitive radio networks," *IEEE Communications Letters*, vol. 20, no. 9, pp. 1884–1887, 2016.

[42] Y.-C. Liang, Y. Zeng, E. C. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE transactions on Wireless Communications*, vol. 7, no. 4, pp. 1326–1337, 2008.

[43] D. Calvetti, G. Golub, W. Gragg, and L. Reichel, "Computation of gauss-kronrod quadrature rules," *Mathematics of Computation of the American Mathematical Society*, vol. 69, no. 231, pp. 1035–1052, 2000.

[44] F. A. Awin, E. Abdel-Raheem, and M. Ahmadi, "Agile hierarchical cluster structure-based cooperative spectrum sensing in cognitive radio networks," in *Microelectronics (ICM), 2014 26th International Conference on*. IEEE, 2014, pp. 48–51.

[45] A. Bagwari, J. Kanti, and G. S. Tomar, "New cooperative spectrum detection technique in cognitive radio networks," 2016.

[46] X. Ling, B. Wu, H. Wen, P.-H. Ho, Z. Bao, and L. Pan, "Adaptive threshold con-

trol for energy detection based spectrum sensing in cognitive radios," *IEEE Wireless Communications Letters*, vol. 1, no. 5, pp. 448–451, 2012.

[47] D.-C. Oh and Y.-H. Lee, "Energy detection based spectrum sensing for sensing error minimization in cognitive radio networks," *International Journal of Communication Networks and Information Security (IJCNIS)*, vol. 1, no. 1, 2009.

[48] M. Gupta, G. Verma, and R. K. Dubey, "Cooperative spectrum sensing for cognitive radio based on adaptive threshold," in *Computational Intelligence & Communication Technology (CICT), 2016 Second International Conference on*. IEEE, 2016, pp. 444–448.

[49] N. Wang, Y. Gao, and X. Zhang, "Adaptive spectrum sensing algorithm under different primary user utilizations," *IEEE Communications Letters*, vol. 17, no. 9, pp. 1838–1841, 2013.

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