Spectrum Sensing in Cognitive Radio: Multi-detection Techniques based Model

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Cognitive radio (CR) paradigm is a new radio technology proposed to solve spectrum scarcity and underutilization. Central to CR is spectrum sensing (SS), which is responsible for detecting unoccupied frequencies. Since Detection techniques differ in their performance, selecting the optimal detection method to locally perform SS has received significant attention. This research work aims to enhance the reliability of local detection decisions, under low SNR, by developing a spectrum sensing that can take advantage of multiple detection techniques. This model can either select the optimal technique or make these techniques cooperate with one another to achieve better sensing performance. The model performance is measured with respect to detection and false alarm probability as well as sensing time. To develop this model, the performance of three detection techniques is evaluated and compared. Furthermore, the voting and the maximum a posteriori probability (MAP) fusion models were developed and employed to combine spectrum sensing results obtained from the three techniques. It is concluded that the cyclostationary feature detection technique is a superior detector in low SNR situations. MAP fusion model is found to be more reliable than the voting model.

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Without you all and Allah's guidance, I would have never made it.

Dedication

This is dedicated to the soul of my father (Mohamed Ali Maatug) and to my mother (Amna Ibrahim El-Makki)

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Chapter 1

Introduction

1.1 Introduction

Communication networks, wired and wireless, play a vital role in each aspect of modern life: social, economic, healthcare, and others. During the last two decades, there has been enormous demands for wireless communication services. The transmission medium for such services is the space where the data are transmitted as electromagnetic waves over a specific radio frequency. Wireless communications can be transmitted over frequencies between 3 kHz to 300 GHz; this range is called the radio spectrum. In fact, the radio or frequency spectrum is a natural and valuable limited resource. Therefore, it must be efficiently exploited or utilized.

Radio spectrum is managed by certain regulations. The International Telecommunications Union (ITU) coordinates global spectrum use, while the spectrum regulator of each country is responsible for managing and monitoring national use. Basically, the radio spectrum is divided into three categories: licensed bands, unlicensed bands, and restricted bands for emergency or security use. Anyone can transmit over unlicensed bands such the industrial, scientific and medical (ISM) bands. Therefore, these bands do not provide high quality of services because of the high interference among unlimited numbers of expected users. On the other hand, only the owners or licensees can use licensed bands. This exclusive access guarantees the absence of interference from other spectrum users. Conventionally, spectrum users request a specific frequency band from the spectrum regulator, responsible for assigning frequencies according to spectrum regulations.

Due to the ever-growing demand for the radio spectrum and the exclusive access to licensed bands, it has become increasingly difficult for the Federal Communications Commission (FCC) and regulators of many countries to assign spectrum for new wireless services [1]. However, studies indicate that allocated licensed frequencies are largely underutilized in specific regions as depicted in Figure 1.1 [2, 3]. These findings open a new area of research to find a solution for spectrum scarcity and spectrum underutilization and to achieve efficient spectrum use and high-quality services. Recent studies have proposed a new approach to spectrum management whereby secondary users are given access to licensed bands which otherwise would be allocated for the restricted access of the license holders. This approach requires a secondary user to be able to detect the unused frequency and vacate this frequency at the time the licensed user accesses it without affecting its transmission. In other words, the new approach is to develop an intelligent radio that actively senses its environment so as to detect unoccupied frequencies and reconfigure its transmission parameters, such as centre frequency, bandwidth, power, modulation type, encryption type, and frame size. This is the basic concept of cognitive radio (CR).

1.2 Cognitive Radio

The main objective of cognitive radio is to achieve efficient spectrum use by enabling dynamic spectrum access. FCC has defined cognitive radio as “a radio that can change its

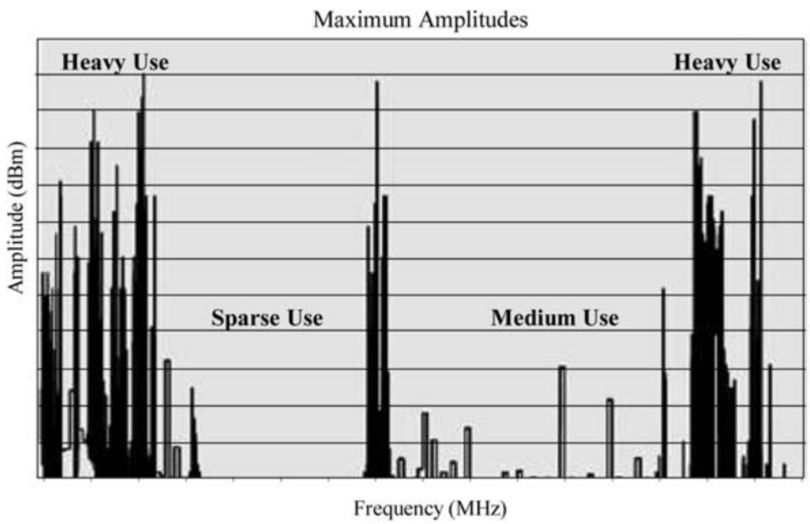

Figure 1.1: Spectrum Utilization [3]

transmitter parameters based on interaction with the environment in which it operates" [4]. Cognitive radio users are called secondary users (SUs), while the owners of licensed bands are referred to as primary users (PUs). A network that uses CR technology is called Cognitive Radio Network (CRN), as shown in Figure 1.2.

Many studies have been conducted to develop radio devices with CR characteristics. Mitola is the first to present the idea of CR based on a software-defined radio platform [5]. In [3], Akyildiz et al. demonstrate the main characteristics of CR, which are cognitive capability and reconfigurability. Cognitive capability enables CR users to interact with the spectrum environment, while reconfigurability allows CR devices to change their transmission parameters. They also define the cognitive cycle, as shown in Figure 1.3. In order to perform this cycle, CR must have four components. The first and most vital component is spectrum sensing (SS), which is the ability to detect unused frequencies. The second

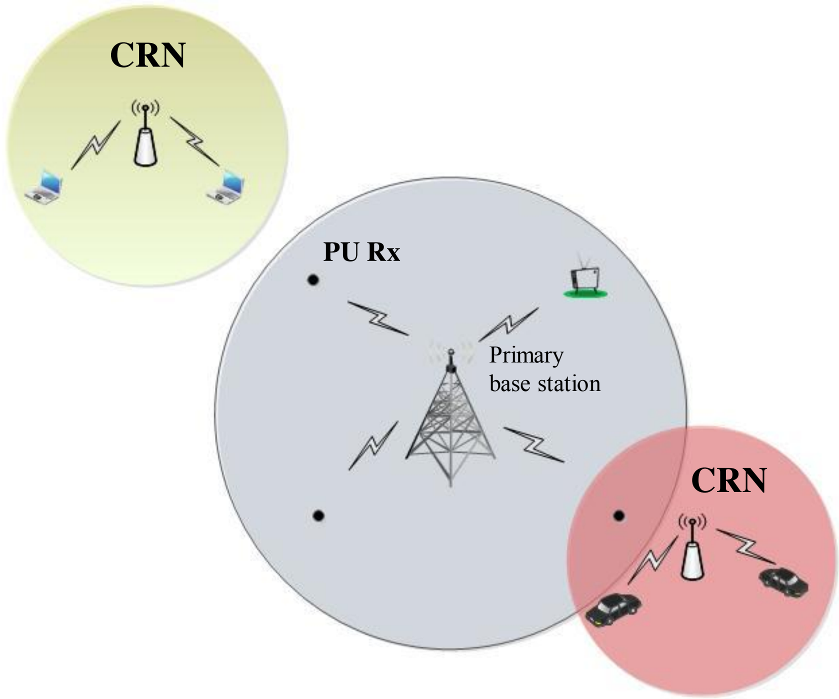

Figure 1.2: Cognitive Radio Network

component is spectrum management, which is the analysis of the available frequency holes so as to choose the one that satisfies certain quality-of-service requirements [6]. The third component is spectrum mobility or handoff that guarantees that secondary users are able to seamlessly transit to use another frequency with no connection loss once the primary user is detected. The forth component is a spectrum-sharing technique that determines the spectrum-scheduling mechanism. Figure 1.4 shows the four CR components. Using cognitive radio also requires significant changes to current regulations and policies on spectrum use, which may open a secondary market for the spectrum [7].

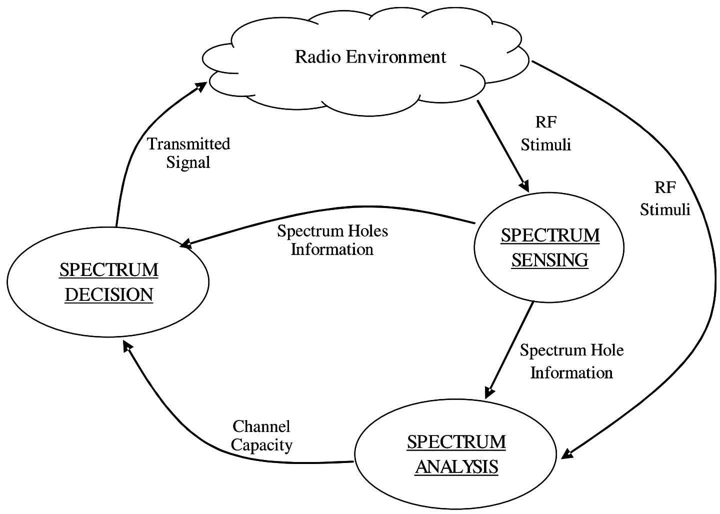

Figure 1.3: Cognitive Cycle [3]

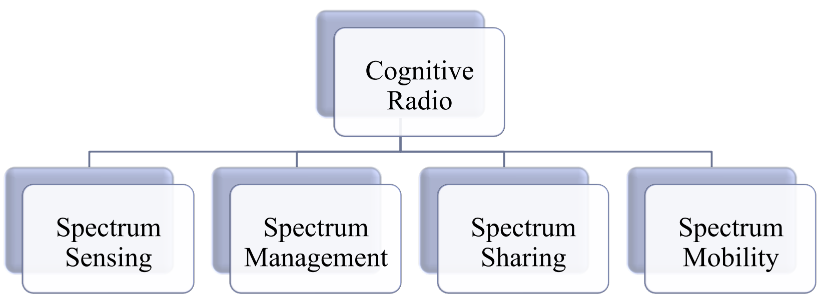

Figure 1.4: Cognitive Radio Components

1.3 Research Motivation

Spectrum sensing is a CR component that to a great extent defines the effectiveness of CR components. Therefore, extensive research has been conducted to develop and evaluate spectrum sensing techniques. Cognitive users perform spectrum sensing during the quiet period. Since no transmission occurs during this period, it should be as short as possible.

Consequently, spectrum-sensing must be able to detect unoccupied frequencies as fast as possible. To meet such time constraints, simple signal detection methods are employed to perform spectrum sensing. However, it has been found that simple detection techniques cannot achieve reliable and accurate sensing results under low signal-to-noise (SNR) and deep fading situations [2, 8]. To enhance spectrum detection reliability and accuracy, some researchers propose fusion of multiple local detection decisions, cooperative spectrum sensing (CSS) [9, 10].

Since detection techniques differ in their performance, selecting the most suitable detection method to locally perform spectrum sensing has been considered as a major challenge. For example, while energy detector (ED) cannot detect signals with low SNR, cyclostationary feature detector (CSFD) can achieve that but at the cost of time and complexity. Matched Filter (MF) is the optimal detection technique if PU's information is known. In contrast to matched filter and cyclostationary feature detector, energy detector requires no prior knowledge of the PU signal. These observations raise the question of whether it would be possible to enhance the sensing performance if different detection techniques collaborate to perform local spectrum sensing, and if so, at what cost. Recent studies proposed two-stage spectrum sensing model in which a simple detection method performs SS in the first stage, and more powerful method is used in the second stage [11, 12].

This research aims to enhance local decisions reliability by developing a spectrum-sensing models based on the fusion of multi-detection techniques. This model can either select the optimal technique or make these techniques cooperate with one another to achieve better sensing performance. The collaboration is achieved by fusing decisions obtained by different techniques to compute more accurate and more reliable local decisions. The model performance is measured with respect to detection and false alarm probability, as well as sensing time. The objective of this model is to maximize the probability of detection (low interference with PUs) and to minimize the probability of false alarm (high spectrum utilization), with minimum complexity and sensing time.

1.4 Research Contributions

The contributions of this thesis are as follows: First, a spectrum sensing model in which the local decision is a result of fusing decisions of three detection techniques was proposed. Second, the dynamic threshold setting method based on minimizing the total error rate as proposed in [13] for energy detector is investigated and employed to set a dynamic threshold of the other two techniques (MF and CSFD). Third, this study provides a comparison between the fixed and dynamic threshold setting methods for the three selected techniques. In addition, this research provides a performance comparison among energy detector, matched filter, and cyclostationary feature detector. Finally, this study shows how the results of these techniques can be combined to enhance local detection in low SNR environment based on certain decision fusion models.

1.5 Thesis Outline

This thesis is composed of seven chapters: Chapter 1 provides an introduction to the thesis. Chapter 2 provides a literature review on the topic related to the research conducted in this thesis. Chapter 3 describes the proposed multi-techniques spectrum sensing based model. Chapter 4 introduces the detection unit of the proposed model. Chapter 5 introduces the fusion unit. Chapter 6 reports and discusses simulation results of the proposed SS model. Chapter 7 summarizes the work conducted in this thesis and provides concluding remarks and recommendations for future directions.

Chapter 2

Background and Related work

2.1 Introduction

Spectrum sensing (SS), is the detection of temporal unoccupied frequencies, called spectrum opportunities or spectrum holes [14]. Hence, spectrum sensing must be made in with respect to time, frequency, space, code and angle of transmission to detect unutilized frequencies [2]. Optimally, spectrum-sensing techniques must be able to quickly, securely, frequently, accurately and reliably identify spectrum holes and any change of frequency-in-use status. Figure 2.1 shows the main requirements of spectrum sensing. However, many challenges make it hard to develop a cognitive radio with spectrum sensing capability that meets all these requirements. The detection results dramatically affect the accuracy of the other CR components. Therefore, spectrum sensing is a crucial issue in cognitive radio, and that has recently received the attention of many researchers.

This chapter provides background information about spectrum sensing and literature review. Section 2.2 discusses some of the spectrum sensing challenges. Section 2.3 introduces two main categories of spectrum sensing techniques. Sections 2.4, 2.5, and 2.6, respectively, provide a review of literature on local spectrum sensing, cooperative spectrum

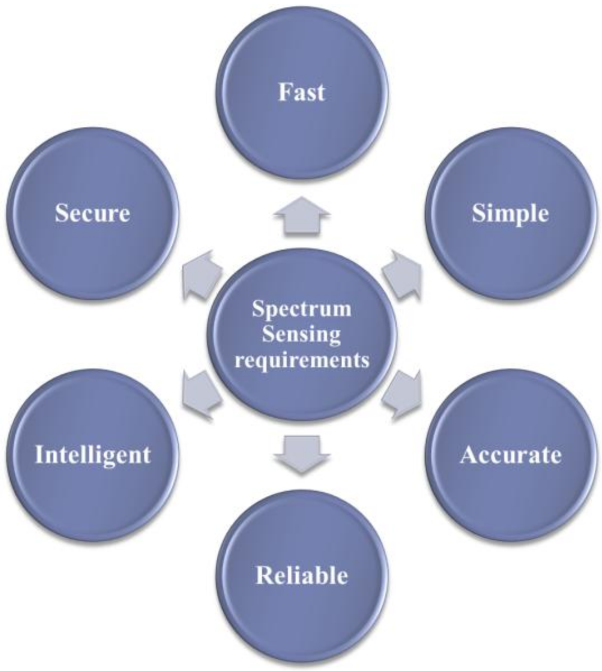

Figure 2.1: Spectrum Sensing Requirments

sensing and external spectrum sensing. Section 2.7 summarizes this chapter.

2.2 Spectrum Sensing Challenges

Designing an efficient spectrum-sensing technique is a fundamental and most problematic functionality in the cognitive radio paradigm. Spectrum sensing approaches differ in the level of complexity, accuracy, reliability, computational cost and speed. Indeed, it is hard for any given technique to achieve high performance with respect to all spectrum sensing requirements; therefore, tradeoff among these requirements is necessary to achieve satisfactory overall spectrum-sensing results. Some of the challenges that make spectrum sensing a challenging task are:

1. **Hardware and Software Constraints**

   Several hardware requirements must be taken into account by the designer of a cognitive radio device, namely, cost, complexity, and size. Most cognitive radio target applications imply low-power, low-cost, and low-size devices. Wireless sensor networks and Ad hoc vehicle networks are two examples of such applications. On the other hand, cognitive radio requires high speed computational capability for processing signals, and hence may benefit from embedded technologies such as FPGA and DSP [2]. In addition, CR devices must be able to sense a wide range of frequencies to obtain better sensing results; consequently, they must have powerful antennas, power amplifiers, high sampling time, and high-resolution ADCs [2, 15]. These requirements make meeting the power, cost and size constraints of CR a significant challenge.

   Several CR hardware implementations have been developed. For example, Communications Research Centre Canada designed a hardware CR prototype board [16]. GNU Radio, Universal Software Radio Peripheral and Shared Spectrum's XG Radio are examples of CR hardware and software platforms that use an energy detection method to sense the spectrum [2].

2. **Hidden Primary Users Problem**

   It is hard to detect PUs in a multi path fading environment. Shadowing, due to the presence of obstacles such as buildings in the propagation path, may cause misdetection of the primary users [2]. As discussed in Section 2.5, one of the proposed solutions to overcome this problem is to use a cooperative spectrum sensing.

3. **Noise Uncertainty**

   The level of noise power is required to estimate the SNR. Nevertheless, it is difficult to measure the exact level of the noise power. Some studies assume the noise power to be known and fixed, but, in fact, it is time variant and real time measurement must be used to determine its exact value. Certain detection techniques such as the energy detection are so susceptible to noise uncertainty [17, 18]. By considering noise uncertainty in performing SS, it was shown that PU's signals cannot be detected under a certain SNR value even for long sensing time [19]. This value is called the SNR wall, the exact value of which depends on the detection technique used. The SNR wall is expressed as follows [20]:

$$SNR_{wall} = 10log_{10}[10^{x/10} - 1] \tag{2.1}$$

where x is noise uncertainty in dB.

4. **Hopping Problem**

   Some wireless communications use a spread spectrum technique, or frequency hopping that uses spread frequencies with a wide bandwidth, to provide a promising security level and low probability of detection and interference. Because of these characteristics, hopping is one of the main concerns in PU detection, and it requires prior knowledge of the hopping pattern of the PUs [2].

5. **Sensing Period**

   Another crucial design concern in CR spectrum sensing is to identify sensing time length and how often it should be done (i.e, sensing frequency). During the sensing period, data transmission is suspended, thus reducing network throughput and increasing end-to-end delay. Therefore, sensing time should be chosen to be as short as possible. However, short sensing time may negatively affect detection performance. Sensing must be repeated frequently to ensure accurate PUs status of channel usage. In other words, sensing must be active most of the time, consequently effecting network performance. Choosing suitable detection time is therefore crucial. Sensing time can be fixed or random, and can be performed actively or proactively depending on the PUs' services and operational frequencies [21]. For example, a cognitive radio network that works in the white space of the TV bands does not require sensing to be as frequent as it is in other applications. It depends also on the place of operation, whether it is a remote rural area or an urban area.

6. **Sensing Frequency Band**

   Another fundamental design parameter of spectrum sensing is the frequency bands to be sensed. Sensing a wide frequency band guarantees identifying more frequency opportunities at the expense of time and hardware cost. In [22] a parallel sensing mechanism is proposed whereby secondary users sense different frequencies at the same time, and subsequently send their estimations to a fusion centre. This approach may enable rapid sensing of wider frequency bands. Another issue is to determine which frequency bands are most effective for the given cognitive radio environment so as to provide high quality of services for both PUs and SUs. The selection criteria are based on PU applications and the nature of the geographical area - remote, rural or urban.

7. **Security**

   Cognitive radio not only inherits the security concerns of wireless communication but also raises new security concerns. Among these concerns are the primary user emulation attack and belief manipulation attack [23, 24]. Malicious actions may harmfully affect the performance of spectrum sensing and other CR functionalities. However, security concerns have not been adequately taken into consideration in most current proposed spectrum sensing techniques [23, 25]. Therefore, security in cognitive radio is an open issue that requires significant attention.

8. **Multiple Cognitive Users**

   There is a high possibility that multiple secondary user networks competing to work in the same licensed bands. In this case, sensing becomes more challenging due to the competition with other users, and interference may occur if they use the same frequency at the same time. Consequently, coordination among SUs is necessary [21]. Current efforts to mitigate this problem involve employing external sensing to enable coordination among different CR networks [26].

2.3 Spectrum Sensing Techniques

Spectrum sensing techniques can be classified, based on the detection mechanism, into two main types: Primary transmitter (PTx) detection and interference based detection [27]. Figure 2.2 shows the main classification of SS techniques. In PTx detection, one of signal detection techniques, such as energy detection (ED), is used to detect the presence of PTx. In interference-based detection, a specific interference temperature at the PU receiver is used to detect the spectrum holes that meet this interference limit.

Spectrum sensing techniques are also classified into either non-cooperative or cooperative spectrum sensing (CSS). In non-cooperative spectrum sensing (NCSS), each SU independently decides whether the primary user is present or absent based on one of the detection techniques. On the other hand, in CSS, a number of secondary users collaborate to achieve more reliable decision by combining their local decisions. Further information regarding CSS is presented in Section 2.5.

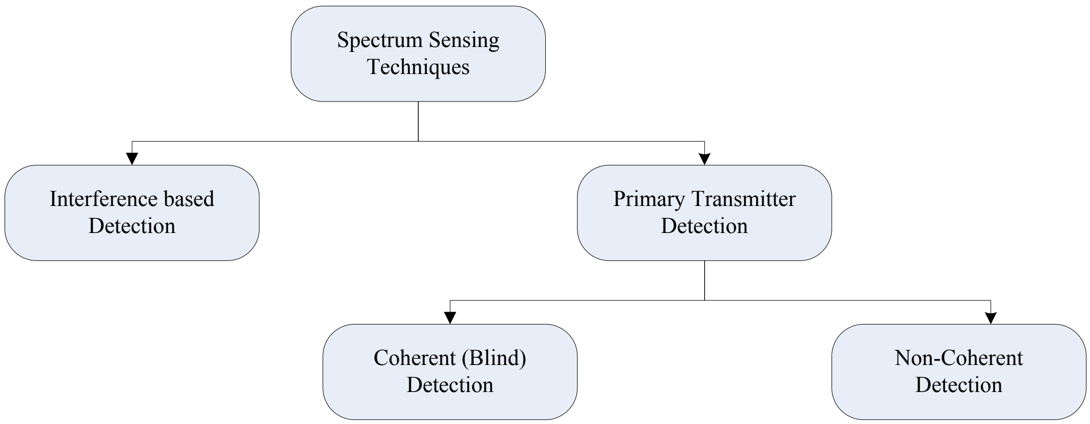

Figure 2.2: Spectrum Sensing Techniques

2.3.1 Primary Transmitter Detection Techniques

Spectrum sensing based on detection of PTx is the most common technique. In this technique, the detection of spectrum holes is achieved by studying the received signal characteristic and features using a digital signal processing method. Signal detection techniques differ in their requirements and performance. Generally, they are categorized into either coherent or non-coherent [28, 27]. In contrast to non-coherent detection, coherent detection does not require prior knowledge of PU signals. This section presents the most common detection techniques that are employed in spectrum sensing. Interested readers can refer to [2, 27, 28, 29] for information about other techniques.

1. **Matched Filter Technique**

   Matched filtering (MF) detects a signal by calculating the correlation between the received signal and a known copy of it [30]. The primary user transmitter sends a pilot signal with data for receiver synchronization. The MF technique can be used to detect this pilot signal. This technique is considered to be optimal, but it requires prior knowledge about the primary user's pilot signal, including its modulation type, packet format, carrier frequency and pulse shaping. In addition, without perfect synchronization, the MF technique cannot properly perform due to its sensitivity to frequency offset [31]. Although the detection time of MF is relatively short, it requires information about all primary users who work in the sensed frequency range [2, 30]. Inaccurate information about the primary users may result in poor performance [32].

2. **Energy Detection Technique**

   This method detects PUs by measuring the power of received signals in a specific frequency band. It requires no prior knowledge of the PU's signal; consequently, it is the most suitable detection method if the primary user's information is unknown. Furthermore, its implementation is relatively simple [29].

   There are several drawbacks to this technique. First, the accuracy of detection is dramatically affected by noise uncertainty. In addition, differentiating among modulated signals and noise cannot be achieved, and determining the optimal threshold is difficult [29]. Furthermore, achieving a proper performance in a fading environment is highly problematic [18].

3. **Feature Detection**

   This detection technique measures certain features of the PU signals such as the cyclostationary feature. Using this method, noise can be effectively differentiated from the modulated signal; therefore, it can detect the PU signals even with low SNR [21]. On the other hand, it requires a long detection time and complex computational process. There are several implementation methods of cyclostationary feature detector (CSFD). In [33, 34, 35], different CSFD implementation algorithms for cognitive radio are presented.

2.3.2 Interference-based Detection

In the underlay dynamic spectrum access, secondary and primary users can both utilize spectrum at the same time if the SUs' transmission do not interfere with that of the PUs'. To achieve this, FCC proposed that a certain interference temperature at the PU receiver must be defined in order for detection of the spectrum holes that meet this interference limit [36]. However, measurement of the interference temperature is not easy to achieve. In addition, it is difficult to discriminate between PU's signals, noise and interference [32].

2.4 Related Work

A considerable amount of literature has been published on cognitive radio and dynamic spectrum access. Many studies such as [20] and [37] introduce important research issues related to cognitive radio. Since spectrum sensing is the first component of cognitive radio, much research has been conducted to evaluate and compare the performance of signal detection techniques in order to find the best candidate technique that meets spectrum sensing requirements. In [29, 28, 38, 27, 8], several spectrum sensing techniques are surveyed and compared. According to these studies, energy detection method is the most common detection technique because of its simplicity. However, it cannot detect signals with low SNR.

Xuping and Jianguo have studied the effects of noise uncertainty and fading on the performance of ED [18]. They show that ED is not reliable for detecting low power signals, and it is not robust against deep fading and shadowing. Consequently, they propose a distributed cooperative spectrum sensing that improves detection reliability. An experimental study of an adaptive energy detection model is presented in [39]. The proposed model adapts the window size to detect narrow signals. In [17], Ye et al. introduce an SS model based on ED that estimates the noise power to be used to set the threshold.

Cabric et al. [31] conduct an experimental study to evaluate the energy detector and matched filter. Their results show that energy detection is vulnerable to noise uncertainty while matched filter is vulnerable to frequency offset. In their study, they propose collaborative detection method based on ED to enhance detection reliability. In [40], Bhargavi and Murthy evaluate and compare the energy detector, matched filter and two cyclostationary feature detectors, based on spectral correlation density (SCD) and magnitude squared coherence (MSC). The results and their analysis show that MSC cyclostationary feature detection outperforms the other techniques in low SNR environments.

Two-stages spectrum sensing has been proposed to improve local detection. The first stage (coarse sensing) uses a simple detection technique such as energy detector, while more powerful technique is used in the second stage. In [11], a two-stage SS technique based on combining energy detector and One-Order cyclostationary feature detector is proposed. The detection performance of the proposed model is compared to the performance of energy detector. The results show that the two-stage SS model outperforms ED with reasonable cost of time and complexity.

Luo et al. [41] propose two-stage spectrum sensing model for dynamic spectrum access in TV-band application. In their model, the local sensing is performed by both an energy detector and cyclostationary feature detector. The results show that the proposed model is more reliable and faster than ED. In [42], Maleki et al. also advance two-stage spectrum sensing based on the model proposed in [41]. The detection threshold was optimized in order to maximizing detection probability. Maleki et al. found that detection time of their model is shorter than detection time of cyclostationary feature detection method. Nair et al. [12] present a spectrum sensing model that enhances the speed of the proposed model in [42].

To overcome the noise uncertainty problem, Khalaf et al. [43] advance an SS model based on two detectors, (ED and CSFD). In their model, two threshold values for ED are set to determine the range within which ED is not reliable. If the energy of the received signal is within this range, CSFD is used to detect PU's signals. In addition, the threshold values are adjusted according to CSFD results. The authors claim that their SS model eventually works as an ED. However, the performance of proposed model is not supported by experimental results.

Kappr and Singh [44] propose a local hybrid spectrum sensing model that includes three detection techniques: the energy detector, matched filter, and cyclostationary feature detector. First, the authors demonstrate these techniques then explain how they can work together to enhance SS performance. However, there are no results that show the efficiency of their proposal.

2.5 Cooperative Spectrum Sensing

Cooperative detection requires collaboration among secondary users. Generally, this approach significantly increases detection reliability and certainty. Nevertheless, it may add a lot of network overhead and degrade throughput of the CR network. In addition, this approach requires control channels. In other words, cooperative spectrum sensing arises new challenges including detection delay, coordination algorithms, control channels, and asynchronous sensing [15].

Designing an efficient cooperative spectrum sensing technique involve several steps. First, it requires a user selection technique, which is responsible for determining how many and which users are going to participate. Moreover, a suitable network architecture for cooperative sensing must be chosen. Finally, selecting an optimal fusion rule that combines local decisions.

This collaboration can be accomplished by either a centralized or distributed network architecture [15]. In centralized spectrum sensing, secondary users send the sensed information about possible frequency opportunities to a central node which is responsible for fusing this information (fusion centre) and broadcasting it to other secondary users [45]. In contrast, in a distributed approach, sensed information is shared among SUs but each one makes the decision about what frequency will be used by individually fusing the shared information [46]. Figure 2.3 shows centralized and distributed cooperative spectrum sensing network.

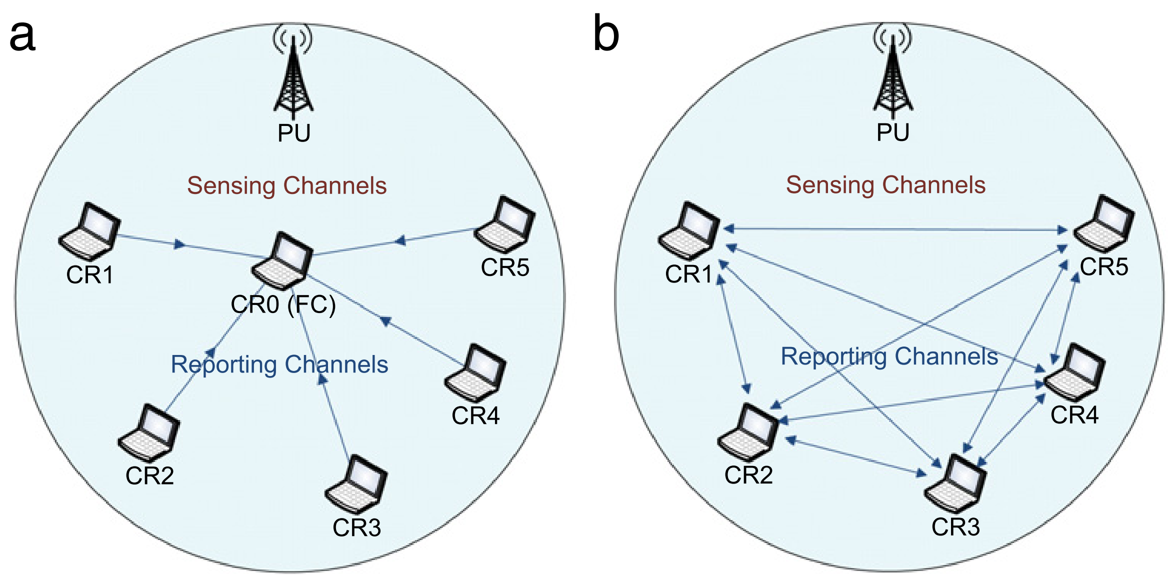

Figure 2.3: a) Centralized b)Distributed Cooperative Spectrum Sensing [47]

Much research has been conducted in cooperative spectrum sensing. Interested readers can refer to [48, 49, 30] regarding recent surveys related to CSS. In [50], Quan et al. propose an optimal solution of cooperative spectrum sensing by combining local test statistics from each secondary user at a fusion centre with a specific weight that determines the contribution of each user in the final decision. Users with better environments in terms of fading and noise are assigned a high weight for their local estimations. Conversely, low weights are assigned to local decisions of users experiencing a low SNR or high level of fading.

In [22], a parallel cooperative spectrum sensing model is proposed based on selecting a number of SUs to simultaneously sense different channels in order to improve sensing efficiency and maximize throughput. In [51], Joshi et al. present an "adaptive spectrum sensing with noise variance estimation" [51] using a discrete Fourier transform filter bank to decrease the harmful effects of noise on detection certainty.

In [52], Lie et al. applied fuzzy integral theory to develop a cooperative spectrum sensing model that alleviates detection uncertainty. Another model that exploits the Kriged Kalman filter is presented in [53]. This model effectively reduces the impacts of fading and shadowing on detection accuracy. In [54], a new approach to alleviate multi-path fading effects during PU location identification is presented; this model exploits the Lass algorithm to estimate sparsity of spectral power distribution. In [55], Song et al. introduce a scheme enhancing detection efficiency and reducing the cost using channel usage characteristics to determine an optimum sensing time rather than a fixed sensing period.

2.6 External sensing

Another proposed solution for developing an effective spectrum sensing mechanism is to perform sensing using an external network that broadcasts the results to all cognitive users. This advantageous approach increases network performance by eliminating network overhead and exploiting sensing time in transmission. It can also be an efficient solution that guarantees coordination among different CRNs. In [26], Han et al. advance an alternative solution based on developing powerful spectrum sensing devices. These devices are placed in PU networks by service providers of secondary users to solve a hidden PU problem, exploit sensing time in transmission and keep SUs devices as simple and cheap as possible. These devices are responsible for admitting transmissions for SUs. Han et al. also proposes a low-temperature handshake technique between secondary users and sensing devices without the necessity of using a separate control channel [26].

2.7 Summary

The cognitive radio paradigm is a new radio technology that provides an efficient use of the spectrum. As discussed, designing an efficient spectrum sensing model has attracted many researchers. It is difficult to design an accurate and quick spectrum sensing technique that both satisfies hardware constraints and mitigates spectrum environment challenges such as fading and noise uncertainty. Previous studies have shown that the performance of local detection techniques is limited under certain environment. Therefore, cooperative spectrum sensing is the promising solution for overcoming spectrum sensing challenges, but at the expense of increasing network overhead due to processing and transmitting sensing results.

Designing a cooperative spectrum sensing model for a cognitive radio network is the main interest for researchers working in the area of cognitive radio. This chapter represents a literature review of a research regarding this issue. This research aims to develop a spectrum sensing model based on using multiple detection techniques. This model either selects the optimal technique according to spectrum environment's characteristics or makes these techniques cooperate with one another to achieve better sensing results. The next chapter introduces the proposed spectrum sensing model.

Chapter 3

Spectrum Sensing: A Multi-detection Techniques Based Model

3.1 Introduction

In cognitive radio, each secondary user can individually use one of the signal detection techniques to decide whether the primary user is present or not. However, the hidden primary users' problem due to deep fading or shadowing dramatically affects the reliability and accuracy of the local sensing results. In other words, misdetection is highly probable due to fading and shadowing. In order to overcome this problem and enhance the detection performance, cooperative spectrum sensing has been proposed. In a cooperative approach, a number of secondary users experiencing different degrees of fading collaborate to improve the reliability and accuracy of their detection performance; of course at the cost of complexity and latency.

In current centralized SS models, independent secondary users (SUs) locally perform spectrum sensing based on one of the signal detection methods; for simplicity, the energy detection method is commonly used. After secondary users obtain sensing results, their local decisions are sent to a fusion centre, which applies one of the fusion rules to combine all the local decisions into one global decision. This final decision, which determines whether the sensed frequency is occupied or not, is reported to secondary users. Many studies have attempted to determine the best candidate detection techniques for local spectrum sensing as discussed in Chapter 2.

This chapter proposes a spectrum sensing model in which local sensing is based on multi-detection techniques. Section 3.2 defines the research problem. Section 3.3 defines certain assumptions. Section 3.4 introduces the proposed spectrum sensing model. The model formulation is presented in Section 3.5, while the model implementation is demonstrated in Section 3.6. Section 3.7 provides a summary of this chapter.

3.2 Problem Definition

Cognitive radio enhances spectrum utilization by enabling secondary access of unutilized licensed bands. Spectrum sensing is responsible for identifying spectrum opportunities. For this process to be practical, a fast accurate reliable detection method is needed. Due to various issues associated with spectrum sensing, already discussed in Chapter 2, the requirements and detection performance of spectrum sensing techniques may differ. For example, energy detection method is highly dependent on sensing minute change in the SNR, which leads to misdetection of signals with a low SNR. Several studies have determined that energy detector cannot detect signals with an SNR below -20 dB with 0.1 dB noise uncertainty [20]. On the other hand, cyclostationary feature detector can detect signals even with an SNR below this value [43]. However, cyclostationary feature detector is associated with relatively high implementation complexity and long processing time. In addition, cyclostationary feature detection and other techniques such as matched filter require prior knowledge of the primary user signals. Other techniques such as energy detection do not have that requirements.

Since the performance if each technique is dependent on the environment, it is quite conceivable that certain techniques can operate at times when others fail to deliver. In other words, these techniques can complement each other. However, it is important at first to determine whether the collaboration between different detection techniques can significantly enhance sensing performance. Moreover, we need to investigate the means by which each technique can be implemented.

The research of this thesis aims to develop a collaborative spectrum sensing model. This model must be able to utilize various detection techniques to obtain more reliable detection decisions. Much of the recent research in this area has been focused on multi-stages spectrum sensing [11], [12], [44]. However, up to the author's knowledge, current proposed models do not use the decision fusion principle to combine the results of the two stages. Furthermore, these models use only two detection techniques, but the proposed model can accommodate more than two techniques.

Another aspect of the spectrum sensing problem to be determined in this thesis is defining the performance indices. For the purpose of this research, the probability of detection and false alarm are both considered in the performance indices. In addition, sensing time is also deemed to be a significant performance index. The model developed in this thesis makes use of these performance indices. The problem now is to implement a spectrum sensing model that achieves reliable detection decision while maintaining reasonable sensing time.

3.3 Model Assumptions

The spectrum environment randomly changes at any moment. For instance, at the beginning of a sensing period, primary users may be either active or idle, and the sensing results is based on the status of primary users at that specific moment. However, this status could change during sensing time. Consequently, the results of spectrum sensing would be totally wrong. In case the PU's status changes from *off* to *on* and sensing results indicate the absence of the primary users, the secondary user may start using the same frequency used by the primary user. This problem is more likely to occur when a sensing period is relatively long; therefore, it must be considered by designers of spectrum sensing models. Since the main goal of this thesis is to examine the performance of multi-detection methods, it is assumed that the status of the primary users does not change during sensing time.

All detection techniques require an estimate of the noise power to calculate the SNR. Measuring the noise power is problematic. First, it cannot be exactly estimated. In addition, it is not fixed but changes with time. Therefore, it is important to evaluate spectrum sensing under certain noise uncertainty. However, for simplicity, the proposed model is based on the assumption that the noise power is known and invariant.

Another important issue is to determine whether the cognitive radio users are stationary or remote. Spectrum sensing identifies the unused frequencies in specific locations at certain times, but remote secondary users may change their location during the sensing period. Therefore, this possibility must be considered for any spectrum sensing model used by remote users. The proposed spectrum sensing model focuses on a stationary secondary users' network.

3.4 Model architecture

The proposed model includes two main units that process local data of each user (i.e., technique selector and detection unit), and a fusion unit that combines local decisions. Figure 3.1 shows the model architecture. In what follows, the components and function of these units are presented.

1. Technique Selector Unit

   This unit determines which techniques work better in a certain spectrum environment. It performs a situation assessment and technique weighing. A situation assessment is needed to quickly estimate which detection method can be performed according to its sensitivity, for instance, to SNR. These techniques are weighted based on this estimate. Figure 3.2 shows the proposed technique selector unit (T1, T2 and T3 indicate detection techniques).

2. Detection Unit

   This unit provides an initial prediction of the primary user status and contains two or more detection techniques. The unit's input is the received signal and the output of the selector unit, and its output is a detection decision corresponding to each technique. The most important step in building this unit is to decide which detection methods will be implemented.

   To implement this unit, the best candidate detection techniques must be chosen first. The selection criteria depend on the techniques' performance under certain spectrum environments. In other words, the performance of the selected techniques under low SNR and deep shadowing must not be identical; otherwise redundant results will be produced that add no value to the detection efficiency. Therefore, first, the

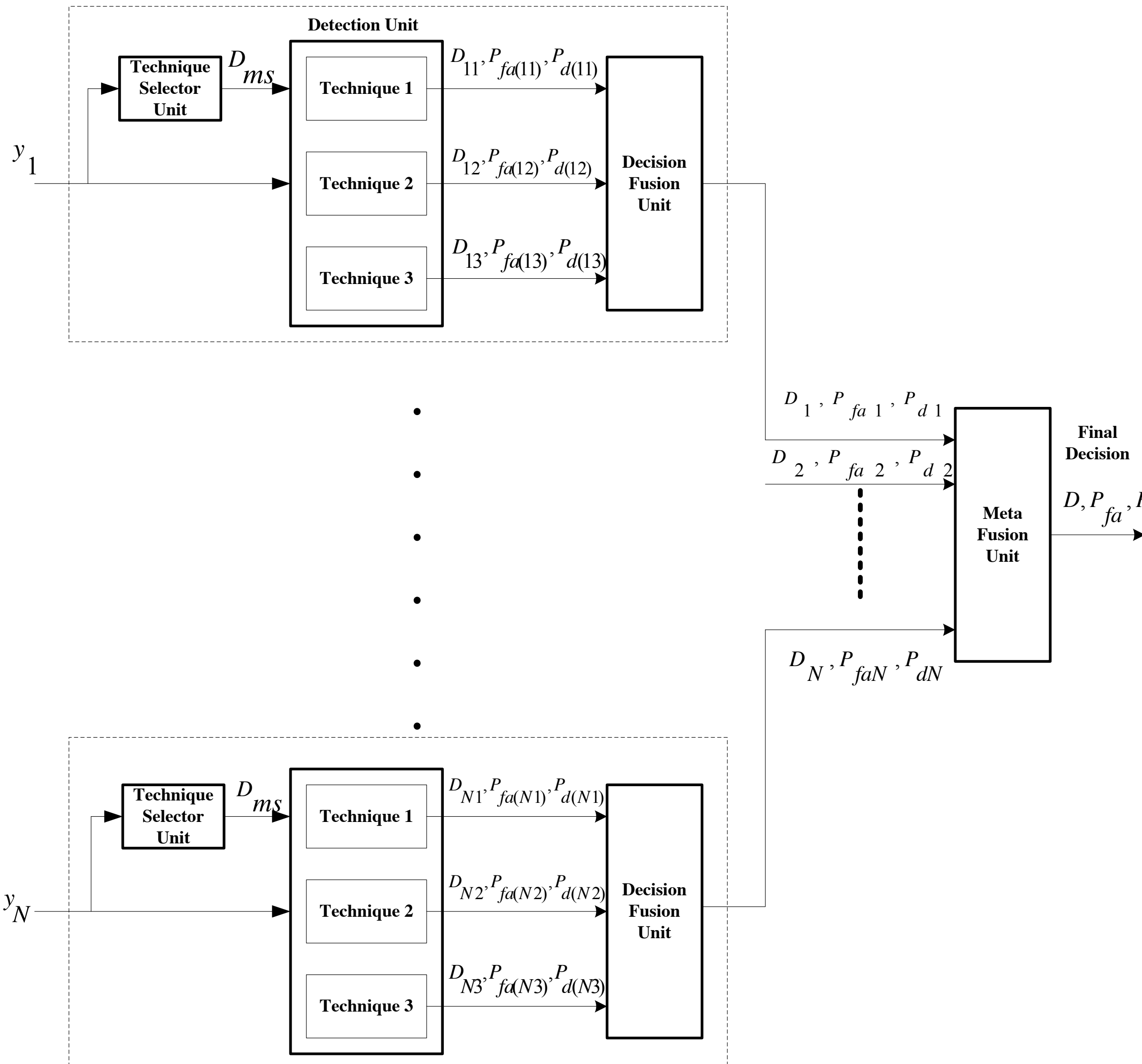

Figure 3.1: The blockdiagram of the proposed model

correlation of the chosen detection methods, which indicates the relationship between their results, must be investigated. Chapter 4 demonstrates the implementation of this unit.

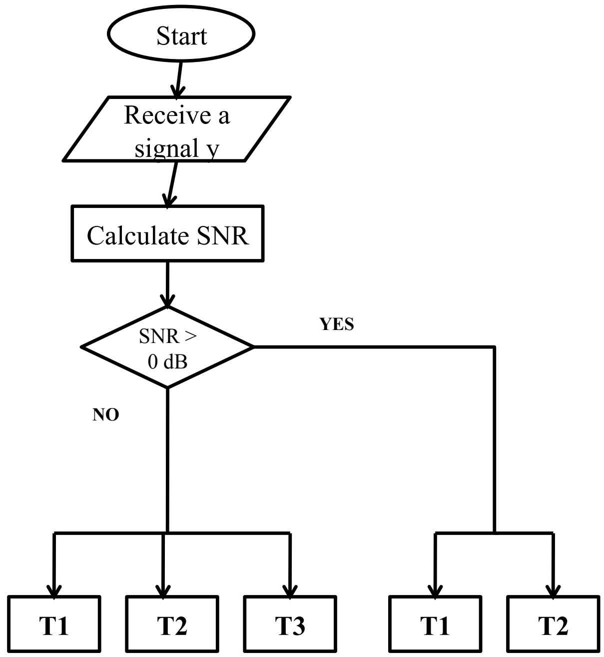

Figure 3.2: Technique Selector Unit

3. Decision Fusion Unit

   Data fusion combines raw data from different sources to obtain new raw data or to produce decisions that are more efficient than if each raw data is individually processed. The process of combing several decisions into one decision is called decision fusion and is thus a sort of data fusion.

   The proposed model requires two decision fusion processes. The first combines the output of the detection unit in one decision based on a specific fusion model. The fused decision must be more reliable than the decisions obtained from each technique. If the number of users who performs spectrum sensing is N, N fused decisions will be inputs of the second fusion unit that combines these N decisions. Since this process combines fused data, it is called the meta-fusion unit.

Several fusion models can be employed to perform decision fusion. These models differ in their complexity and requirements. Since two decision fusion processes are performed, different decision fusion models can be employed in each process. For example, a simple fusion model can be used to combine techniques decisions, and a powerful fusion model can be used in the meta-fusion unit. Chapter 5 demonstrates the implementation of the fusion unit.

3.5 Model Formulation

Let us assume that the received signal at CR user i is y_i where

$$y_i(t) = \begin{cases} s_i(t) + w_i(t), & \text{if PU is present} \\ w_i(t), & \text{if PU is absent} \end{cases} \tag{3.1}$$

$s(t)$ is the primary signal, which is assumed to be a Gaussian random process with variance σ_s^2, and $w(t)$ is the additive white Gaussian noise (AWGN) with zero mean and variance σ_w^2.

From the receiver signal, the technique selector assesses the current spectrum situation to decide which technique will perform the sensing. The selection is also based on the available information that is required to perform technique j, where $j = 1, 2, ...M$, and M the number of detection methods. Let us assume this decision to be D_{ms}. After the selection is made, the selected techniques will perform spectrum sensing.

The detection problem is modelled as a binary hypothesis problem with two hypotheses: H_1, primary user is present, and H_0, primary user is absent. Let us assume that the detection decision of user i obtained by technique j is D_{ij}, and that $D_{(td)} = \{D_{i1}, D_{i2}, ...D_{iM}\}$ is a decision vector of the detection unit output. The corresponding probability of false alarm is $P_{fa(td)} = \{P_{fa(i1)}, P_{fa(i2)}, ..., P_{fa(iM)}\}$, and probability of detection is $P_{d(td)} = \{P_{d(i1)}, P_{d(i2)}, ...P_{d(iM)}\}$.

D_{ij} can be expressed as

$$D_{ij} = \begin{cases} +1, & \text{if } H_1 \text{ is declared} \\ -1, & \text{if } H_0 \text{ is declared} \end{cases} \tag{3.2}$$

Under H_1, detection and misdetection probabilities (P_d, P_{md}) can be defined as follows:

$$P(d_{ij}|H_1) = \begin{cases} P_{d(ij)}, & \text{if } D_{ij} = 1 \\ P_{md(ij)} = 1 - P_{d(ij)}, & \text{if } D_{ij} = -1 \end{cases} \tag{3.3}$$

Under H_0, detection of absent and false alarm probabilities can be defined as follows:

$$P(d_{ij}|H_0) = \begin{cases} P_{fa_(ij)}, & \text{if } D_{ij} = 1 \\ 1 - P_{fa(ij)}, & \text{if } D_{ij} = -1 \end{cases} \tag{3.4}$$

The sensing results of these techniques will be combined based on one of decision fusion models in the fusion unit. The inputs of this unit are the decision of each technique (D_{ij}) and its corresponding detection and false alarm probabilities ($P_{d(ij)}$ and $P_{fa(ij)}$). Let us consider the fused decision to be D_i and its detection and false alarm probabilities to be $P_{d(i)}$ and $P_{fa(i)}$. The output of fusion unit D_i is defined as follows:

$$D_i = f(D_{i1}, D_{i2}, ..., D_{iM}) \tag{3.5}$$

where D_{i1}, D_{i2}, D_{iM} are techniques decisions, and the function depends on the used fusion model.

The corresponding detection probability is

$$P_{d(i)} = f(P_{d(i1)}, P_{d(i2)}, ..., P_{d(iM)}) \tag{3.6}$$

, and the false alarm probability is

$$P_{fa(i)} = f(P_{fa(i1)}, P_{fa(i2)}, ..., P_{fa(iM)}) \tag{3.7}$$

To mitigate the effects of fading and shadowing, meta-fusion is performed to combine the local decisions of N independent users in a final decision D with detection probability P_d and false alarm probability P_{fa}. To perform this process, the N local fused decisions (D_i) combined with their probability of detection ($P_{d(i)}$) and false alarm ($P_{fa(i)}$) are sent to the meta-fusion unit to contribute to the final decision. The objective of this fusion process is to combine the local decisions D_i in a way that maximizes $P_{d(i)}$ and minimizes $P_{fa(i)}$. In other words, the target system performance is such that

$$P_{fa} \leq P_{fa(i)}, \text{ for i=1,2,...N} \tag{3.8}$$

and

$$P_d \geq P_{d(i)}, \text{ for i=1,2,...N} \tag{3.9}$$

The question here is which decision fusion model is the best for maximizing $P_{d(i)}$ and minimizing $P_{fa(i)}$. Chapter 5 demonstrates certain decision fusion models that can be used to achieve this goal.

3.6 Model Implementation

Implementation of the first three units can be done in either the user level or a central unit (CU). Designing the proposed model to be performed by each secondary user might be infeasible because of the added complexity and power consumption; most CR users are low-power, low-cost and small-sized devices. Therefore, the alternative solution is to implement this model to be performed only by a central unit, which is a powerful user such as a base station. If detection techniques are implemented at the user level, spectrum sensing is distributed. If all detection processes are performed in a central unit, spectrum sensing in this case is centralized. In this section, these approaches are discussed.

The first design option is to implement the detection methods and a decision fusion unit in each user. In this case, only the detection results are sent to a central unit. After the central unit receives the detection decisions of the N users, it combines them in a final decision and broadcasts the results to all secondary users. Figure 3.3 shows a flowchart of a distributed decision fusion model.

The other possible implementation option is to perform all detection stages only in a central unit. At the beginning of the sensing period, SUs stop transmission and start receiving a signal from their environment. Then each selected secondary user sends M samples of the received signal (y_i) to the central unit. The central unit manipulates the received signals from N sensor nodes to perform spectrum sensing, then sends the sensing results to the SUs. The minimum required number of samples (S_{min}) is proportional to $O(1/SNR_i)$. Therefore, if SNR is high enough, fewer samples are needed to perform spectrum sensing.

For the Matched filter, the minimum number of samples is [31]

$$S_{min} = [Q^{-1}(P_{fa}) - Q^{-1})(P_d)]^2 SNR^{-1} \tag{3.10}$$

The minimum number of samples required by the energy detection technique is [31]

$$S_{min} = 2[(Q^{-1}(P_{fa}) - Q^{-1}(P_d))SNR^{-1} - Q^{-1}(P_d)]^2 \tag{3.11}$$

To alleviate the data size problem, compressed sensing, which "is an emerging theory based on the fact that the salient information of a signal can be preserved in a relatively small

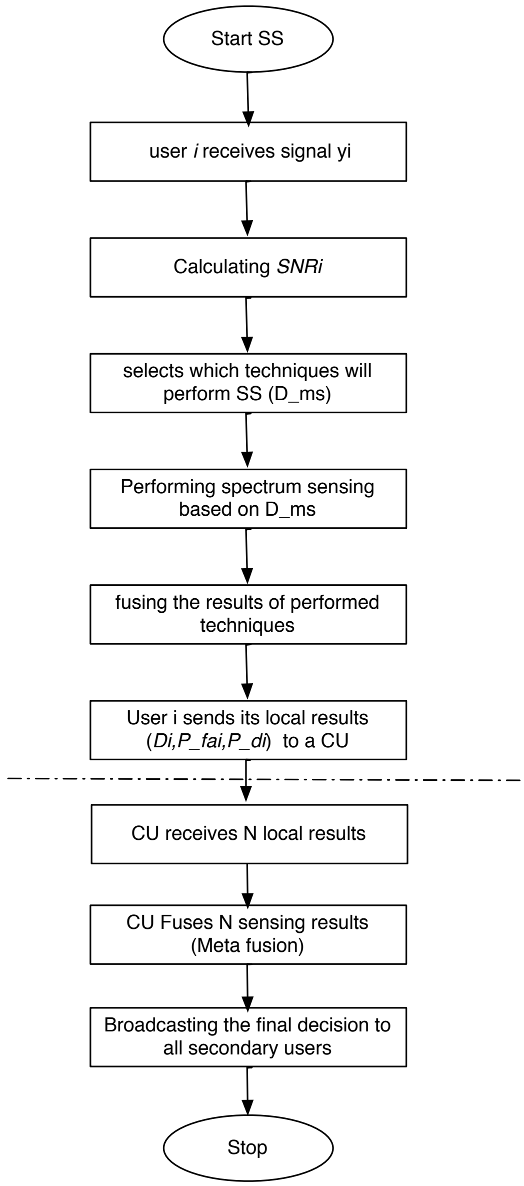

Figure 3.3: Flowchart of distributed-based model

number of linear projections" [56], can be used. Consequently, the communication between SUs and the central unit can use a low-bandwidth control channel.

Let us assume that the N users send their sensing data to the central unit; The central unit carries out the following steps, as shown in Figure 3.4:

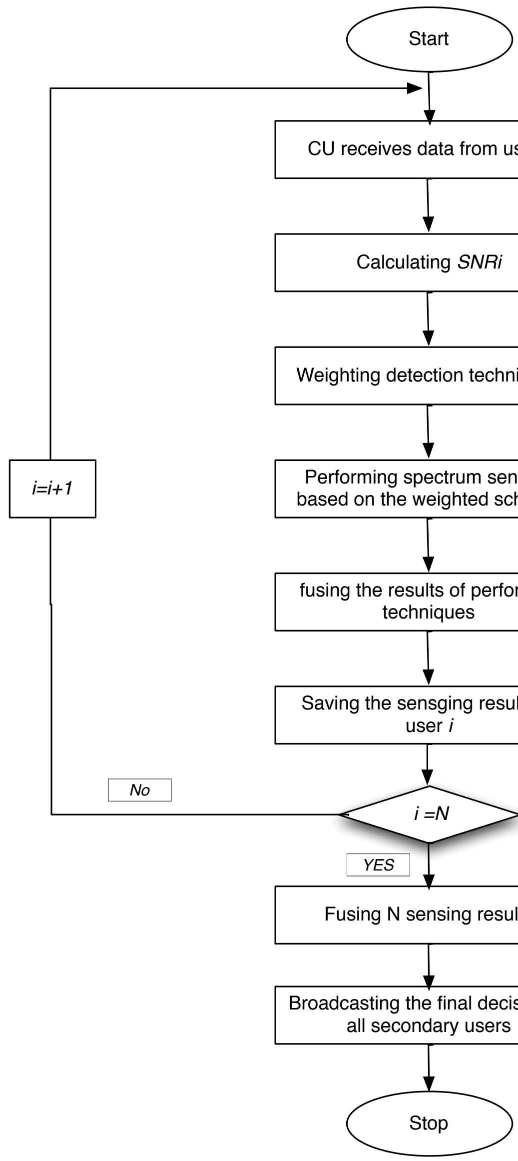

Figure 3.4: Flowchart of centralized-based model

1. The central unit receives sensing data from user i.

2. The central unit calculates SNR_i.

3. Based on the SNR_i and the available stored data, weights the detection techniques.

4. Executes the highest weighted detection technique for this specific user.

5. Saves the sensing result of user i (Decision (D_i), $P_{fa(i)}$, $P_{d(i)}$).

6. Repeats steps 1 to 4 for N users.

7. Performs decision fusion for the N decisions to obtain the final decision.

8. Reports the final decision D to the SUs.

3.7 Summary

This chapter proposes a spectrum sensing model based on a multi-detection techniques. The objective of the proposed model is to improve detection reliability. First, certain assumptions that the proposed model is based on were set. Second, the model's architecture were presented. After that, the model formulation was defined. Finally, different implementation approaches were proposed. The next two chapters present the implementation of the proposed model. Chapter 4 introduces the detection unit implementation, and chapter 5 presents the fusion unit implementation.

Chapter 4

Detection Unit Implementation

4.1 Introduction

The first step in implementing the proposed model is to choose the best candidate detection techniques. The most commonly used SS techniques are energy detector, matched filter, and cyclostationary feature detector. These techniques differ in their requirements and performance. For example, while energy detector cannot detect signals with low SNR, cyclostationary feature detector can do so at the cost of time and complexity. In contrast to matched filter detector and cyclostationary feature detector, energy detector does not require any prior knowledge of primary user signals. Table 4.1 summarizes a comparison among these techniques in terms of sensing time, complexity, required prior knowledge, sensitivity to a low SNR, and noise uncertainty. This comparison shows the complementary nature of certain combinations of these techniques. Collaboration among them could enhance sensing performance. Therefore, these techniques are selected to develop the detection unit of the proposed model and evaluate the model's performance. However, the selection is not limited to only these techniques; Other detection methods can be used.

This chapter introduces the implementation of the detection unit. First, it presents the

Detection technique	Sensing Time	computational process	Prior knowledge	low SNR
Matched Filter	short	simple	required	susceptible
Energy Detector	relatively short	simple	No	susceptible
Cyclostationary Feature Detector	long	complex	cyclic frequency	insensitive

Table 4.1: Comparison between sensing methods

system models for the selected detection techniques – the energy detector (ED), Matched filter (MF), and cyclostationary feature detector (CSFD). Second, it demonstrates and compares fixed and dynamic threshold setting methods. Finally, dynamic threshold settings for the three techniques are derived.

4.2 Energy Detection

The energy detection method measures the energy of a received signal and compares it with a predefined threshold. ED requires no prior knowledge of PU signals; consequently, it is the optimal detection method if a PU's information is unknown. Furthermore, its implementation is easy, and it requires no complex computational process. The energy detector consists of a low-pass filter, an analog-to-digital converter, and a square root device [57]. Figure 4.1 shows a block diagram of energy detector.

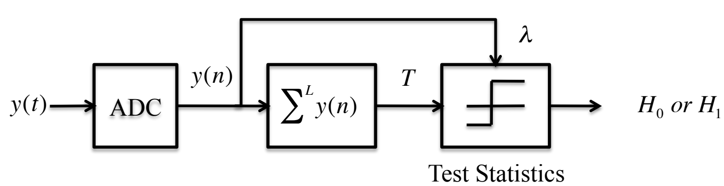

Figure 4.1: Block diagram of Energy Detector

The received signal at CR user is

$$y(t) = \begin{cases} s(t) + w(t), & \text{if PU is present} \\ w(t), & \text{if PU is absent} \end{cases} \tag{4.1}$$

where $y(t)$ is the received signal, $s(t)$ is the primary signal, which is assumed to be a Gaussian random process with variance σ_s^2, and $w(t)$ is the additive white Gaussian noise (AWGN) with zero mean and variance σ_n^2.

The energy of the received signal, which is the decision statistic, is given by [58]

$$T = \sum_{i=1}^{L} y^2(t) \tag{4.2}$$

where L is the number of samples.

The energy detector model for CR can be formulated as the following binary hypothesis problem [58]:

$$d_{ED} = \begin{cases} +1, & \text{if } H_1 \text{ is declared } (T \geq \lambda) \\ -1, & \text{if } H_0 \text{ is declared } (T < \lambda) \end{cases} \tag{4.3}$$

where H_0 indicates the absence of the PUs' signals, while H_1 indicates the presence of the PUs' signals. λ is the threshold value.

T is Chi-square distribution. The probability of false alarm (P_{fa}) and probability of detection (P_d) are given by [59]

$$\begin{aligned} P_{fa(ED)} &= P(T > \lambda/H_0) \\ &= \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)} \end{aligned} \tag{4.4}$$

and

$$\begin{aligned} P_{d(ED)} &= P(T > \lambda/H_1) \\ &= Q_u(\sqrt{2SNR}, \sqrt{\lambda}) \end{aligned} \tag{4.5}$$

where $\Gamma(,)$ is the incomplete gamma function, $Q_u(,)$ is the generalized Marcum Q-function and u is the time-bandwidth product.

For a large number of samples, T can be approximated to the Gaussian distribution using Central Limit Theorem, and the test statistics will be as follows [58]:

$$T \sim \begin{cases} \mathcal{N}(L\sigma_n^2, 2L\sigma_n^4), & \text{if } T \geq \lambda \\ \mathcal{N}(L\sigma_t^2, 2L\sigma_t^4), & \text{if } T < \lambda \end{cases} \tag{4.6}$$

where $\sigma_t^2 = \sigma_n^2 + \sigma_s^2$

The probability of false alarm (P_{fa}), probability of detection (P_d), and probability of misdetection are given, respectively, by [58]

$$\begin{aligned} P_{fa(ED)} &= P(T > \lambda/H_0) \\ &= Q(\tfrac{\lambda - \sigma_n^2}{\sqrt{2L\sigma_n^4}}), \end{aligned} \tag{4.7}$$

$$\begin{aligned} P_{d(ED)} &= P(T > \lambda/H_1) \\ &= Q(\tfrac{\lambda - \sigma_t^2}{\sqrt{2L\sigma_t^4}}), \end{aligned} \tag{4.8}$$

and

$$\begin{aligned} P_{md(ED)} &= P(T < \lambda/H_1) \\ &= 1 - P_d \end{aligned} \tag{4.9}$$

4.3 Matched Filter

Matched filter method detects a signal by calculating the correlation between the received signal and a known copy of the signal. It is the optimal detection technique, but it requires a priori knowledge about a PU's pilot signal, including modulation type, packet format, carrier frequency, and pulse shaping. Figure 4.2 shows a block diagram of matched filter.

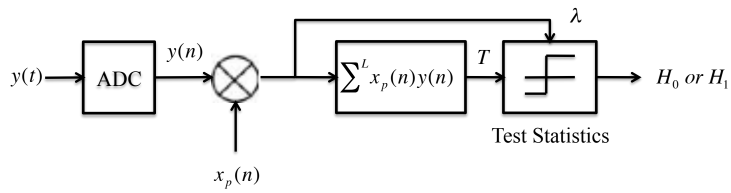

Figure 4.2: Block diagram of matched filter[31]

The received signal at CR user is [31]

$$y(t) = \begin{cases} w(t), & \text{if PU is absent} \\ x_p(t) + w(t)), & \text{if PU is present} \end{cases} \tag{4.10}$$

where $y(t)$ is the received signal, $x_p(t)$ is the pilot signal of the PU. $w(t)$ is the additive white Gaussian noise (AWGN) with zero mean and variance σ_w^2.

The decision statistic of matched filter is given by [31]

$$T = \sum_{i=1}^{L} y(t)X_p(t) \tag{4.11}$$

where L is the number of samples.

The matched filter can also be formulated as a binary hypotheses test as follows [31]:

$$d_{MF} = \begin{cases} +1, & \text{if } H_1 \text{ is declared } (T \geq \lambda) \\ -1, & \text{if } H_0 \text{ is declared } (T < \lambda) \end{cases} \tag{4.12}$$

The probability of false alarm, probability of detection and probability of misdetection are given by [31]

$$P_{fa(MF)} = Q(\frac{\lambda}{\sqrt{\varepsilon\sigma_n^2}}), \tag{4.13}$$

$$P_{d(MF)} = Q(\frac{\lambda - \varepsilon}{\sqrt{\varepsilon\sigma_n^2}}), \tag{4.14}$$

and

$$P_{md(MF)} = 1 - Q(\frac{\lambda - \varepsilon}{\sqrt{\varepsilon \sigma_n^2}}) \tag{4.15}$$

where $\varepsilon = \sum_1^L X_p^2$

4.4 Cyclostationary Feature Detection

Signal periodicity causes a cyclostationary feature in signal's mean and autocorrelation. If $x(t)$ is a signal and its mean and autocorrelation are M_x and R_x, the cyclostationary feature can be defined as follows [60]:

$$M_x(t + \tau) = M_x(t)$$

and

$$R_x(t + \tau, u + \tau) = R_x(t, u) \text{ for all } t \text{ and } u.$$

where τ is a periodic time. The cycle autocorrelation function (CAF) is presented as follows [60]:

$$R_x^\alpha(\tau) = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t + \frac{\tau}{2}) x(t - \frac{\tau}{2})^* e^{-j2\pi\alpha t} dt \tag{4.16}$$

where α is a frequency, called cyclic frequency, in which $R_x^\alpha(\tau)$ is nonzero. The Fourier transform of CAF is the spectral correlation density function (SCD), which is defined as follows [60]:

$$S_x^\alpha(f) = F\left\{R_x^\alpha(\tau)\right\} = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau \tag{4.17}$$

The noise does not have a cyclostationary feature; therefore, its autocorrelation is nonzero only when a cyclic frequency equals zero. Thus,

$$R_w^\alpha(\tau) = \begin{cases} \sigma_w^2 \delta(\tau), & \alpha = 0 \\ 0, & Otherwise \end{cases} \tag{4.18}$$

Knowing this feature, PU signals can be differentiated from noise by looking for peaks of a received signal's spectral correlation density (SCD) function at cyclic frequencies. Figure 4.3 the spectral correlation density function of AM signal with with a sampling frequency (f_s) of 4000 Hz, carrier frequency (f_c) of 1024Hz and (f_m) 32Hz. Several algorithms can be used to calculate SCD function, but these algorithms differ in their complexity and execution time. Since sensing time has to be as small as possible, a fast implementation of SCD must be used. Next, the FFT Accumulation Method (FAM), which estimates the SCD function, is presented.

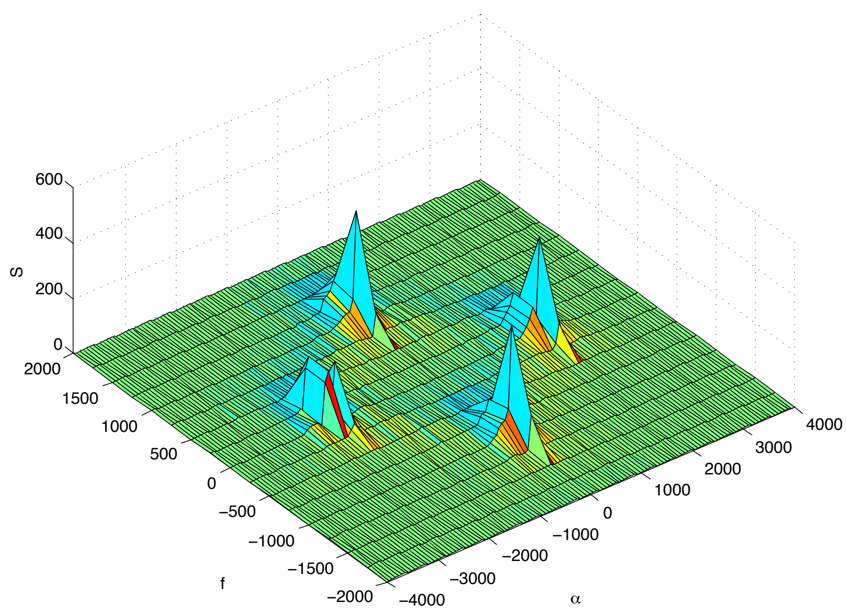

Figure 4.3: The spectral correlation density function

4.4.1 CSFD implementation using the FFT Accumulation Method (FAM)

This algorithm is a fast implementation of the cyclic autocorrelation function. In [60], the FFT Accumulation Method (FAM) for estimating the SCD is introduced. Figure 4.4 shows the implementation of FAM, and Figure 4.5 presents the FAM algorithm.

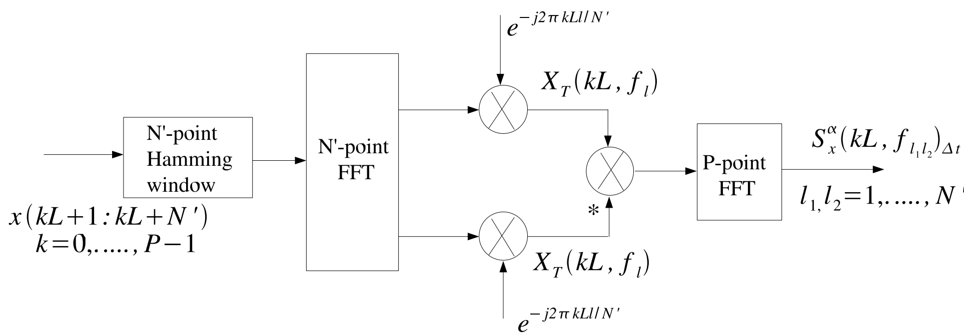

Figure 4.4: Block diagram of FFT Accumulation Method for estimating the SCD [61]

4.4.2 Detection model of CSFD

The spectral correlation density function (SCD) is defined as follows:

$$S_x^{\alpha}(f) = \begin{cases} S_w^{\alpha}(f), & \text{if PU is absent} \\ S_w^{\alpha}(f) + S_s^{\alpha}(f), & \text{if PU is present} \end{cases} \tag{4.19}$$

where $S_x^{\alpha}(f)$ is a SCD function of received signal $x(t)$, and $S_s^{\alpha}(f)$ is a SCD function of the PU signal. $S_w^{\alpha}(f)$ is the noise cyclic spectral density function.

The system model is formulated assuming cognitive users work in TV bands. CSFD detects the pilot tone of the TV signal. The AM signal s(t) is defined as follows [40]:

$$s(t) = 2\sqrt{P_s} cos(2\pi f_m t) cos(2\pi f_c t + \theta_0) \tag{4.20}$$

- The complex envelopes $X_T(k)$ are estimated efficiently by means of a sliding N'-point FFT, followed by a downshift in frequency to the baseband signal.
- For an even more efficient estimation, the N'-point FFT is applied to the data in blocks of L samples.
- The value of N' is determined according to the length of observation data T and sampling frequency f_s and given by $N' = f_s T$.
- The product sequence between complex envelopes and its conjugate are formed, then the cyclic spectrum is accomplished by means of a P-point FFT.
- The value of L is chosen to compromise between maintaining computational efficiency and minimizing cycle leakageand cycle aliasing, and is given by $L = N'/4$.
- The number of sampling points of second FFT P is determined according to the window size Δt , and in this simulation, it is chosen as $P = f_s/L\Delta t$.

Figure 4.5: FFT Accumulation Method (FAM) algorithm [61]

where P_s is the transmitted power of the pilot signal, f_m is the pilot signal's frequency, and f_c is the carrier frequency.

The estimated SCD of an AM signal using FAM is given by [40]

$$S^{\alpha}_{xN'}(n,k)_N = \frac{1}{P}\sum_{l=0}^{P-1}[\frac{1}{N'}X_{N'}(n+lK, k+\frac{\alpha}{2})X^*_{N'}(n+lK, k-\frac{\alpha}{2})] \tag{4.21}$$

where $K = \frac{N}{J}$, and $k = fN'/f_s$. Using central limit theorem, the distribution of $S^{\alpha}_{x}(n,k)_N$ is given by [40]

$$S^{\alpha_0}_{xN'}(n,k_0)_N \begin{cases} \mathcal{CN}(0, 2\sigma_0^2), & \text{if } H_0 \text{ is declared} \\ \mathcal{CN}(S^{\alpha_0}_{sN'}(n,k_0)_N, 2\sigma_1^2), & \text{if } H_1 \text{ is declared} \end{cases} \tag{4.22}$$

where "$\mathcal{CN}(0, 2\sigma_0^2)$ is circularly symmetric complex Gaussian noise with mean 0 and variance $2\sigma_0^2$. $\sigma_0^2 = \frac{\sigma_w^2}{2P_s}$, and $\sigma_1^2 = \frac{\sigma_w^4}{2P_s}(1 + \frac{S_{zN'}(k_0+\frac{\alpha_0}{2})+S_{zN'}(k_0-\frac{\alpha_0}{2})}{\sigma_w^2})$. $S_{sN'}(k)$ is the powers spectral density evaluated at discrete frequency k, and k_0 is the frequency bin of interest" [40].

The detection decision of CSFD is defined as the following hypothesis problem [40]:

$$D_{CSFD} = \begin{cases} 1, & \text{if } |S^{\alpha_0}_{xN'}(n, k_0)_N| > \lambda \\ -1, & \text{if } |S^{\alpha_0}_{xN'}(n, k_0)_N| < \lambda \end{cases}$$

or

$$D_{CSFD} = \begin{cases} 1, & \text{if } H_1 \text{ is declared} \\ -1, & \text{if } H_0 \text{ is declared} \end{cases} \tag{4.23}$$

The corresponding probability of false alarm, detection, and misdetection are given by [40]

$$P_{fa(CSFD)} = e^{\frac{-\lambda^2}{\sigma_0^2}}, \tag{4.24}$$

$$P_{d(CSFD)} = Q_1(\frac{S^{\alpha_0}_{xN'}(n, k_0)_N}{\sigma_1}, \frac{\lambda}{\sigma_1}), \tag{4.25}$$

and

$$P_{md(CSFD)} = 1 - Q_1(\frac{S^{\alpha_0}_{xN'}(n, k_0)_N}{\sigma_1}, \frac{\lambda}{\sigma_1}) \tag{4.26}$$

where Q_1 is the Marcum Q function.

4.5 Threshold Setting

One of the most important challenges in implementing detection techniques is setting an optimal threshold. The optimal threshold is the value that meets required detection performance. Optimally, the probability of false alarm must be as small as possible, and probability of detection as great as possible. A small probability of false alarm increases spectrum utilization, while a high probability of detection guarantees the absence of a primary user and reduces the probability of interference. Therefore, a trade off between these two probabilities is important.

The threshold can be set to be either fixed or dynamic. Two principles can be used to set a fixed threshold: the constant false alarm rate (CFAR) and constant detection rate (CDR) [62]. In CFAR, the threshold is set to meet a target P_{fa}, then the obtained threshold is used to calculate the corresponding P_d, while in CDR, a certain P_d is used to set the threshold. For example, for the energy detection, the threshold can be calculated based on these two principles as follows [62]:

$$\lambda_{fa} = \sigma_n^2(L + Q(P_{fa})\sqrt{(}2L)) \tag{4.27}$$

where λ_{fa} is the threshold based on CFAR.

$$\lambda_d = \sigma_t^2(L + Q(P_d)\sqrt{(}2L)) \tag{4.28}$$

where λ_d is the threshold based on CDR.

From Equations 4.27 and 4.28, in contrast to CDR, CFAR does not need the signal power of a PU to set the threshold. Therefore, CFAR is more commonly used. However, constantly setting P_{fa} to a small value such as 0.1, means the corresponding threshold will be high. Consequently, it will be hard to detect low power signals, and interference will occur. Therefore, a fixed threshold based on CFAR is not optimal. An optimal threshold setting can be archived if each secondary user dynamically sets its threshold according to its channel states. The next sections demonstrate a dynamic threshold setting method for the three detection techniques.

4.5.1 Dynamic Threshold Setting for Energy Detector

In most current cooperative spectrum sensing, local decisions are obtained by an energy detector based on CFAR. However, recent studies focus on setting dynamic thresholds using different approaches. In [13], Xuping et al. propose an optimal threshold method based on minimizing the total error rate, which is the summation of the probability of false alarm and mis-detection. This error can be expressed as follows:

$$P_e = P_{md} + P_{fa} \tag{4.29}$$

By substituting Equations 4.7 and 4.9 in Equation 4.29, the total error of ED is

$$P_{e(ED)} = 1 - Q(\frac{\lambda - \sigma_t^2}{\sqrt{2L\sigma_t^4}}) + Q(\frac{\lambda - \sigma_n^2}{\sqrt{2L\sigma_n^4}}) \tag{4.30}$$

The optimal threshold (λ_{opt}) is the value that gives the minimum total error rate, which can be obtained by solving the next optimization problem:

$$\lambda_{opt} = arg_{\lambda}\min\ P_e \tag{4.31}$$

The solution to this problem is as follows [13]:

$$\lambda_{opt} = \frac{-B - \sqrt{B^2 - 4AC}}{2A} \tag{4.32}$$

where $A = \frac{-1}{2L}(\frac{1}{\sigma_t^2} + \frac{1}{\sigma_n^2})$,$B = \frac{\sigma_s^2}{\sigma_t^2\sigma_n^2}$, and $C = -2ln\frac{\sigma_n^2}{\sigma_t^2}$

This setting approach was employed for ED in [13]. Next, this method is applied for both matched filter and cyclostationary feature detector.

4.5.2 Dynamic Threshold Setting for Matched Filter

The total error for matched filter is the summation of Equations 4.13 and 4.15; thus, the total error of MF is

$$P_{e(MF)} = 1 - Q(\frac{\lambda - \varepsilon}{\sqrt{\varepsilon\sigma_n^2}}) + Q(\frac{\lambda}{\sqrt{\varepsilon\sigma_n^2}}) \tag{4.33}$$

where $\varepsilon = \sum_1^L X_p^2$.

Using the dynamic threshold setting scheme, which is introduced in [13], the optimal threshold is:

$$\lambda_{opt(ED)} = arg_\lambda \text{min}\ [1 - Q(\frac{\lambda - \varepsilon}{\sqrt{\varepsilon\sigma_n^2}}) + Q(\frac{\lambda}{\sqrt{\varepsilon\sigma_n^2}})] \tag{4.34}$$

The solution of this minimization problem is the threshold value that makes the derivative of the total error equal zero. Thus,

$$\frac{\partial P_e}{\partial\lambda} = 0 \tag{4.35}$$

The derivative of Equation 4.33 is

$$\frac{\partial P_e}{\partial\lambda} = -\frac{\partial}{\partial\lambda}\int_{\frac{\lambda-\varepsilon}{\sqrt{\varepsilon\sigma_n^2}}}^{\infty} e^{-t^2/2}dt + \frac{\partial}{\partial\lambda}\int_{\frac{\lambda}{\sqrt{\varepsilon\sigma_n^2}}}^{\infty} e^{-t^2/2}dt = 0 \tag{4.36}$$

Using Leibniz's integral rule, Equation 4.36 becomes:

$$\frac{e^{-\frac{(\lambda-\varepsilon)^2}{\varepsilon\sigma_n^2}}}{\sqrt{\varepsilon\sigma_n^2}} - \frac{e^{-\frac{\lambda^2}{\varepsilon\sigma_n^2}}}{\sqrt{\varepsilon\sigma_n^2}} = 0 \tag{4.37}$$

$$e^{-\frac{(\lambda-\varepsilon)^2}{\varepsilon\sigma_n^2}} = e^{-\frac{\lambda^2}{\varepsilon\sigma_n^2}} \tag{4.38}$$

$$(\lambda - \varepsilon)^2 = \lambda^2 \tag{4.39}$$

The optimal threshold of MF is

$$\lambda_{opt(MF)} = \varepsilon/2 \tag{4.40}$$

4.5.3 Dynamic Threshold Setting for Cyclostationary Feature Detection

The total error for CSFD is the summation of Equations 4.24 and 4.26, thus, the total error rate of CSFD is given by

$$\begin{aligned} P_{e(CSFD)} &= 1 - Q_1(\tfrac{S}{\sigma_1}, \tfrac{\lambda}{\sigma_1}) + e^{\frac{-\lambda^2}{\sigma_0^2}} \\ &= 1 - \int_{\frac{\lambda}{\sigma_1}}^{\infty} x.e^{(-\frac{(x^2+\frac{S^2}{\sigma_1^2})}{2})} I_0(\tfrac{S.x}{\sigma_1}).dx + e^{\frac{-\lambda^2}{\sigma_0^2}} \end{aligned} \tag{4.41}$$

The objective function is to find the optimal threshold that minimizes $P_{e(SCFD)}$. This problem is defined as follows:

$$\lambda_{opt} = arg_{\lambda}\text{min } P_{e(CSFD)}$$

The solution of this minimization problem is the threshold value that makes the derivative of the total error equals zero; thus, the solution is to find the value of λ that solves the next equation.

$$\frac{\partial P_e}{\partial \lambda} = \lambda^2(\frac{1}{\sigma_0^2} - \frac{1}{2\sigma_1^2}) + ln(I_0(\frac{S_{xN'}^{\alpha_0}(n,k_0)_N\lambda}{\sigma_1^2}) - ln(2\sigma_1)) - \frac{(S_{xN'}^{\alpha_0}(n,k_0)_N)^2}{2\sigma_1^2} = 0 \tag{4.42}$$

Using one of the numerical methods such as the Newton-Raphson method, this equation can be solved with respect to λ.

4.6 Summary

This chapter presented the detection unit implementation. Three detection methods were chosen to perform SS, based on the diversity in their requirements and performance. Models of the selected techniques were demonstrated, and two threshold setting approaches were used and compared. The next chapter presents the fusion unit implementation in the proposed SS model.

Chapter 5

Fusion Unit Implementation

5.1 Introduction

In the previous chapter, the performance of candidate detection techniques was investigated, and two threshold setting methods were compared. The next step is to show how these techniques can collaborate using a decision fusion concept. This chapter focuses on implementing the fusion unit in the proposed model. In order to enhance detection performance, the fusion unit combines techniques' decisions based on a decision fusion strategy.

Several decision fusion models can be considered for implementing this unit. In order to maintain sensing process as simple as possible, simple decision fusion modelmust be applied. Based on the fusion results of different models, the best fusion model will be selected. The results of the fusion process comprise the local decision, the probability of false alarm and the probability of detection. D_i denotes a local decision of a secondary user i, and its corresponding false alarm and detection probabilities are $P_{fa(i)}$ and $P_{d(i)}$. D_i is defined as follows:

$$D_i = f(D_{i1}, D_{i2}, D_{i3}) \tag{5.1}$$

where D_{i1}, D_{i2}, D_{i3} are energy detector, matched filter and cyclostationary feature detector decisions respectively.

The detection probability of the fusion process is

$$P_{d(i)} = f(P_{d(i1)}, P_{d(i2)}, P_{d(i3)}) \tag{5.2}$$

where $P_{d(i1)}, P_{d(i2)}, P_{d(i3)}$ are detection probability of ED, MF and CSFD respectively.

The false alarm probability of the fusion process is

$$P_{fa(i)} = f(P_{fa(i1)}, P_{fa(i2)}, P_{fa(i3)}) \tag{5.3}$$

where $P_{fa(i1)}, P_{fa(i2)}, P_{fa(i3)}$ are detection probability of ED, MF and CSFD respectively.

The function in Equations 5.1, 5.2 and 5.3 is fusion model dependent. Figure 5.1 shows decision fusion unit structure. In this chapter, two decision fusion models are introduced. Section 5.2 presents voting model, and Section 5.3 introduces a maximum a posteriori probability (MAP) fusion rule (minimum error probability detection rule). Section 5.4 summarizes this chapter.

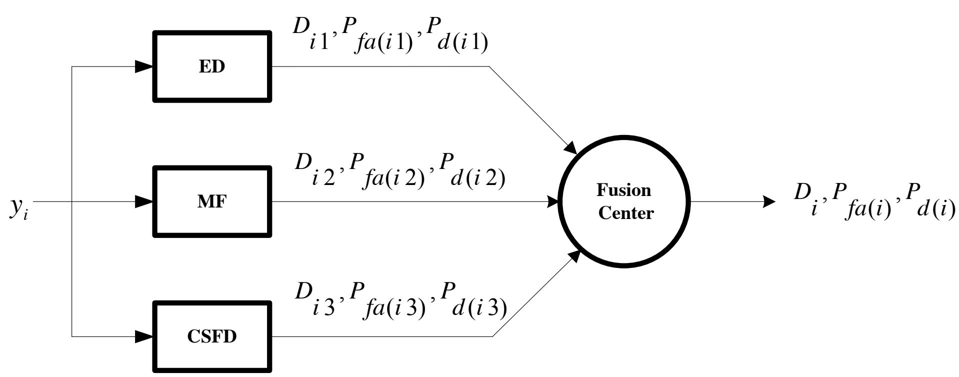

Figure 5.1: Fusion unit structure

5.2 Voting model

This fusion model is the simplest and most commonly used fusion model. The fusion centre reaches an agreement based on one of the voting rules, which include OR-rule, AND-rule, majority rule, and weighted-voting rule.

In the AND-rule, the final decision is 1 only and only if all techniques' decisions are 1. Otherwise, the fused decision is -1 (PU is absent). In this case, the detection decision is expressed as follows:

$$D_{And} = \begin{cases} 1, & \text{if } D_i = 1, \text{ for all } i \\ -1, & otherwise \end{cases} \tag{5.4}$$

The corresponding probability of false alarm and detection are given by [27]

$$P_{f(ai)} = \prod_{j=1}^{N} P_{fa(ij)} \tag{5.5}$$

and

$$P_{d(i)} = \prod_{j=1}^{N} P_{d(ij)} \tag{5.6}$$

where N is the number of techniques.

In the OR-rule, if at least one of the techniques' decisions indicates the presence of PU, the fused decision will be 1. Therefore, this voting rule ca be unreliable and imprecise. The detection decision based on OR-rule can be defined as follows:

$$D_{OR} = \begin{cases} -1, & \text{if } D_i = -1, \text{ for all } i \\ 1, & otherwise \end{cases} \tag{5.7}$$

The corresponding probability of false alarm and detection are given by [27]

$$P_{fa(i)} = 1 - \prod_{j=1}^{N} (1 - P_{fa(ij)}) \tag{5.8}$$

and

$$P_{d(i)} = 1 - \prod_{j=1}^{N}(1 - P_{d(ij)}) \tag{5.9}$$

In majority voting rule, if at least two techniques out of three reports the presence of PU, the final decision will be 1. This means

$$D_{Maj} = \begin{cases} 1, & \text{if } \sum_{i=1}^{3} D_i \geqslant 2 \\ -1, & otherwise \end{cases} \tag{5.10}$$

5.3 Maximum A-Posteriori Probability (MAP) Fusion Model

This rule is a Bayesian detection rule based on minimizing error probability. The decision fusion problem is represented as a binary hypothesis detection problem (H_1, denotes PU is present, and H_0, denotes PU is absent). These two hypotheses are assumed to have a priori probabilities $P(H_1)$ and $P(H0)$, respectively. The local decisions of N detectors are $D_1, D_2, ..., D_N$. The likelihood ratio test of this problem is [63]

$$\begin{aligned} LRT &= \Lambda(D_1, D_2, ...D_N) \\ &= \frac{P(D_1, D_2, ..., D_N|H_1)}{P(D_1, D_2, ..., D_3|H_0)} \\ &= \frac{P_1(D_1)P_1(D_2|D_1)......P_1(D_N|D_1D_2.....D_{N-1})}{P_0(D_1)P_0(D_2|D_1)......P_0(D_N|D_1D_2.....D_{N-1})} \end{aligned} \tag{5.11}$$

where $P_1(D_2|D_1)$ and $P_1(D_N|D_1D_2.....D_{N-1})$ are conditional probabilities under hypothesis H_1, and $P_0(D_2|D_1)$ and $P_0(D_N|D_1D_2.....D_{N-1})$ are conditional probabilities under hypothesis H_0.

The optimum decision rule is given by [64]

$$\frac{P(D_1, D_2, ...D_N|H_1)}{P(D_1, D_2, ...D_3|H_0)} \gtrless \frac{P(H_0)(C_{10} - C_{00})}{P(H_1)(C_{01} - C_{11})} \tag{5.12}$$

where C_{00} and C_{11} are the cost of correct decisions. C_{10} and C_{01} are the cost of errors. The probability of error decisions is assumed to be minimum. Therefor, $C_{00} = C_{00} = 0$, and $C_{10} = C_{10} = 1$ [64]. Hence, Equation 5.12 is equivalent to [63]

$$\text{MAP Detection Rule} = \begin{cases} H_1, & \text{if } LRT > \frac{P(H_0)}{P(H_1)} \\ H_0, & \text{if } LRT < \frac{P(H_0)}{P(H_1)} \end{cases} \tag{5.13}$$

In [63], the MAP decision (D_{MAP}) is defined as follows:

$$D_{MAP} = \begin{cases} 1, & \text{if } w_0 + \sum_{i=1}^{N} w_i D_i \geq 0 \\ -1, & \text{if } w_0 + \sum_{1}^{N} w_i D_i < 0 \end{cases} \tag{5.14}$$

The weights for correlated decisions are given by [63]

$$w_i = \begin{cases} log\frac{P(H_1)}{P(H_0)}, & \text{for i = 0} \\ \begin{cases} log\frac{P_1(D_1)}{P_0(D_1)}, & \text{if } D_1 = +1 \\ log\frac{P_0(D_1)}{P_1(D_1)}, & \text{if } D_1 = \text{-}1 \end{cases} & \text{for i = 1} \\ \begin{cases} log\frac{P_1(D_i|D_1,D_2,....,D_{i-1})}{P_0(D_i|D_1,D_2,....,D_{i-1})}, & \text{if } D_i = +1 \\ log\frac{P_0(D_i|D_1,D_2,....,D_{i-1})}{P_1(D_i|D_1,D_2,....,D_{i-1})}, & \text{if } D_i = \text{-}1 \end{cases} & \text{for i > 1} \end{cases} \tag{5.15}$$

For independent decisions, the weights are given by [64]

$$w_i = \begin{cases} log\frac{P(H_1)}{P(H_0)}, & \text{for i = 0} \\ \begin{cases} log\frac{P_{d(i)}}{P_{fa(i)}}, & \text{if } D_i = +1 \\ log\frac{1-P_{fa(i)}}{1-P_{d(i)}}, & \text{if } D_i = -1 \end{cases} & \text{for i > 0} \end{cases} \tag{5.16}$$

Three spectrum sensing techniques are used as sensors (detectors) in the proposal SS model. Hence, N=3. Figure 5.2 shows the structure of the MAP fusion rule for the proposed model.

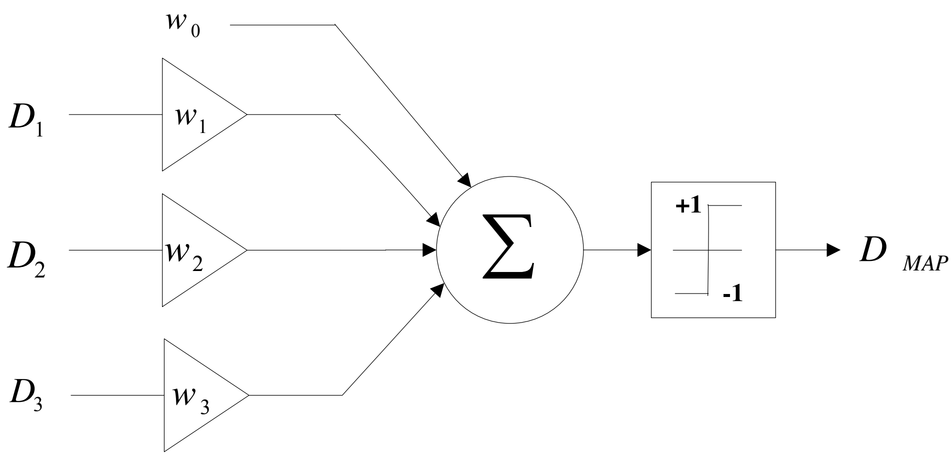

Figure 5.2: MAP fusion center structure

Using MAP rule, detection probability and false alarm probability can be calculated as follows:

$$P_d = \frac{\sum_{i=1}^{N} w_i P_{d(i)}}{\sum_{i=1}^{N} w_i} \tag{5.17}$$

and

$$P_{fa} = \frac{\sum_{i=1}^{N} w_i P_{fa(i)}}{\sum_{i=1}^{N} w_i} \tag{5.18}$$

5.4 Summary

Decision fusion is used to obtain the final local decision by combining techniques' decisions, which are the output of the detection unit. This chapter demonstrates two decision fusion methods that can be used to implement the fusion unit in the proposed SS model. First, a voting model based on And-rule, OR-rule and majority-rule are introduced. After that, a maximum a posteriori probability (MAP) fusion rule is presented. The next chapter presents simulation results of experimental work, including comparison among the selected detection techniques and evaluation of fusion results.

Chapter 6

Results

6.1 Experimental Setup

Several experiments were designed to detect the AM pilot signal in TV broadcast with a sampling frequency (f_s) of 4 kHz, carrier frequency (f_c) of 1024 Hz and (f_m) 32 Hz. Monte-Carlo simulation using MATLAB is used to evaluate the selected detection techniques and the proposed SS model under variable SNR. Simulation results are presented in the next sections.

6.2 Simulation Results

The results are divided into three sections. Section 6.2.1 shows performance evaluation of each technique under the fixed and dynamic threshold setting method. Section 6.2.2 presents performance comparison among ED, MF and CSFD. Section 6.2.3 shows the results of decision fusion.

6.2.1 Comparison between the dynamic and fixed threshold

The fixed and dynamic threshold setting methods introduced in Chapter 4 are employed to implement the three detectors. To set a fixed threshold, the constant false alarm rate principle (CFAR) is used, in which the probability of false alarm (P_{fa}) is set to 0.1. The simulation is done for a fixed number of samples $L = 5000$. First, the simulation results of the energy detector are presented. Figure 6.1 shows the threshold value corresponding to different SNR values using CFAR and dynamic threshold setting. Figure 6.3 and Figure 6.2 show ED performance using both setting methods in terms of P_{fa} and P_d, respectively. From Figure 6.1, the dynamic threshold value increases when the SNR increases. It reaches the fixed threshold value at SNR=-10 dB, then continues increasing. As a result of this increase, P_{fa} using dynamic threshold significantly decreases, as shown in Figure 6.2, and it approaches the fixed P_{fa} at SNR=-10 dB. After that, it saturates at zero.

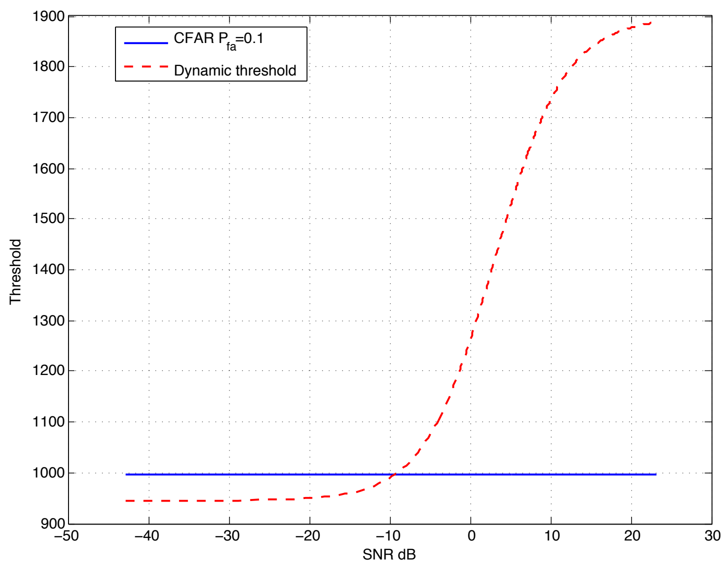

Figure 6.1: Energy Detector: Dynamic and fixed threshold for different values of SNR

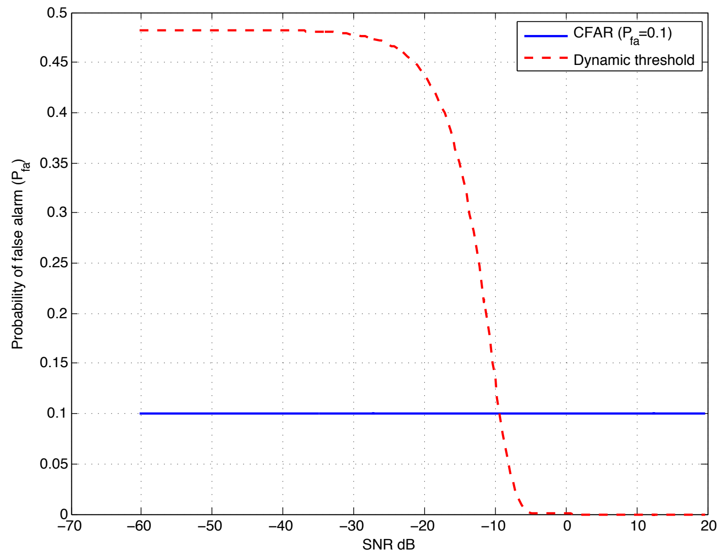

Figure 6.2: ED: P_{fa} for fixed and dynamic threshold under different SNR

Figure 6.3 shows the detection probability of ED under different SNR values. P_d of both methods increases with the increase of SNR values until it saturates at zero. However, the P_d of the dynamic threshold starts at a larger value. After SNR = -10 dB, the P_d of the fixed threshold becomes equal to the P_d of the dynamic threshold. The two setting techniques are also compared in terms of the total error rate, which is the summation of (P_{md}) and (P_{fa}). Figure 6.4 shows there is no significant difference between them in total error. However, the average error rate under the fixed threshold is equal to **0.12**, while it is only **0.02** for the dynamic threshold. These findings are consistent with those of Xuping et al. presented in [13].

The same experiments have been made for the matched filter and cyclostationary feature detector. Figure 6.5 and Figure 6.6 show a comparison between the fixed and dynamic threshold settings of MF in terms of P_d and P_{fa}, respectively. Figure 6.7 shows the total error rate of MF. Similar to ED's results, dynamic threshold enhances probability of

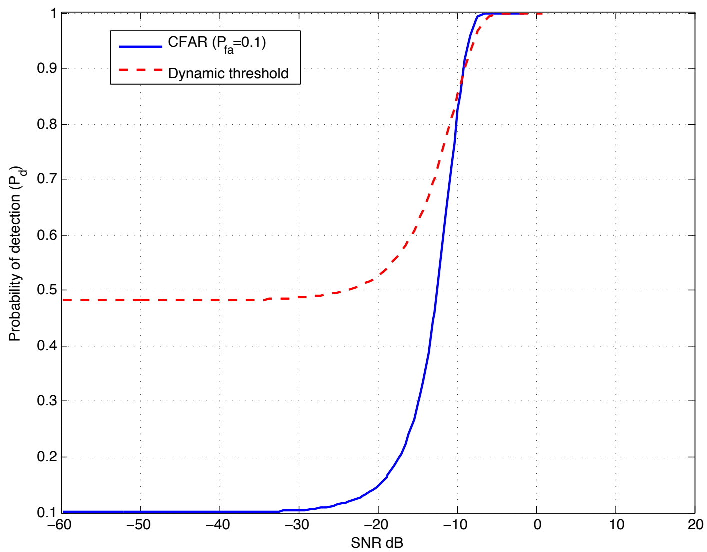

Figure 6.3: ED: P_d for fixed and dynamic threshold under different SNR

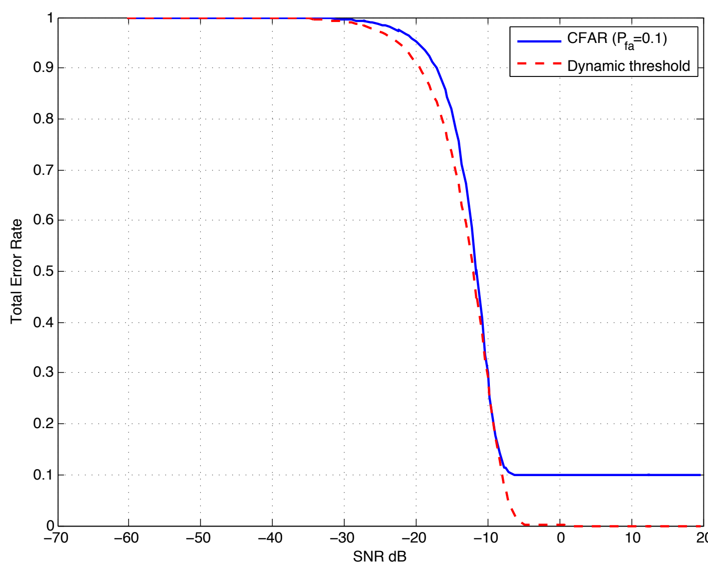

Figure 6.4: ED: Total error rate for fixed and dynamic threshold

detection in low SNR; on the other hand, it compromises probability of false alarm.

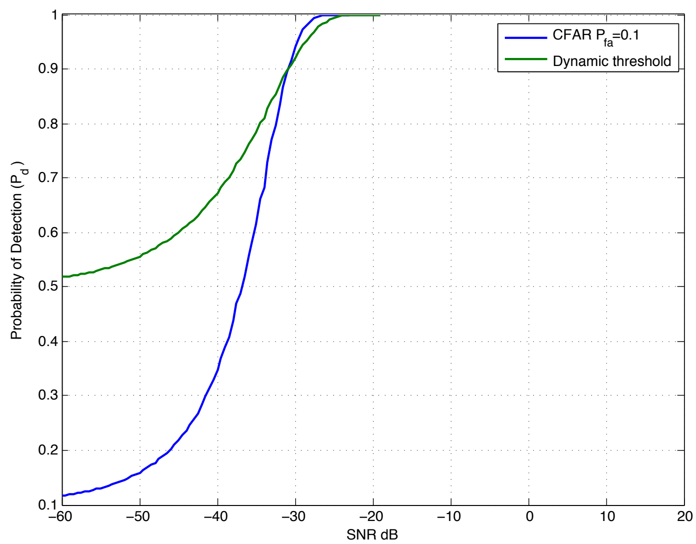

Figure 6.5: MF: P_d for fixed and dynamic threshold under different SNR

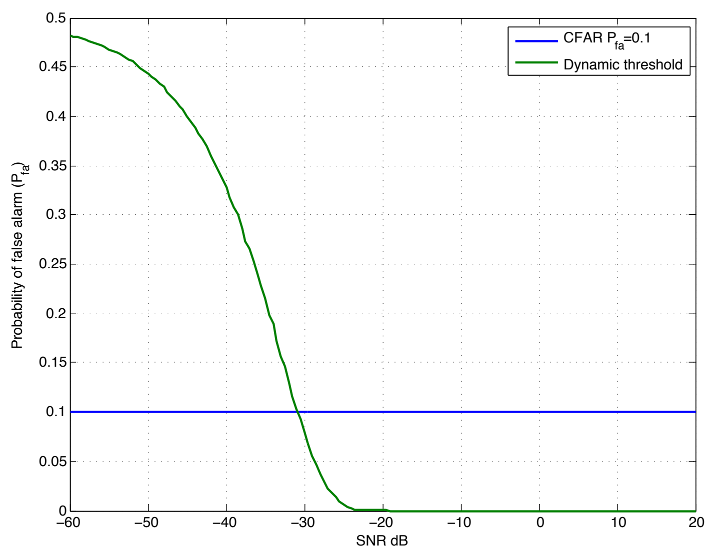

Figure 6.6: MF: P_{fa} for fixed and dynamic threshold under different SNR

Figure 6.8 and Figure 6.9 show a comparison between the fixed and dynamic threshold setting for CSFD in terms of P_d and P_{fa}, respectively. The findings from these results are

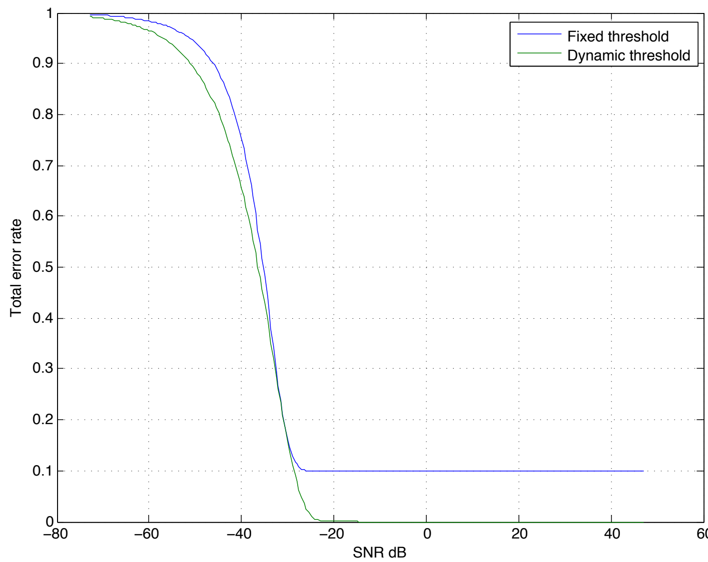

Figure 6.7: MF: Total error rate for fixed and dynamic threshold

also similar to the findings of ED.

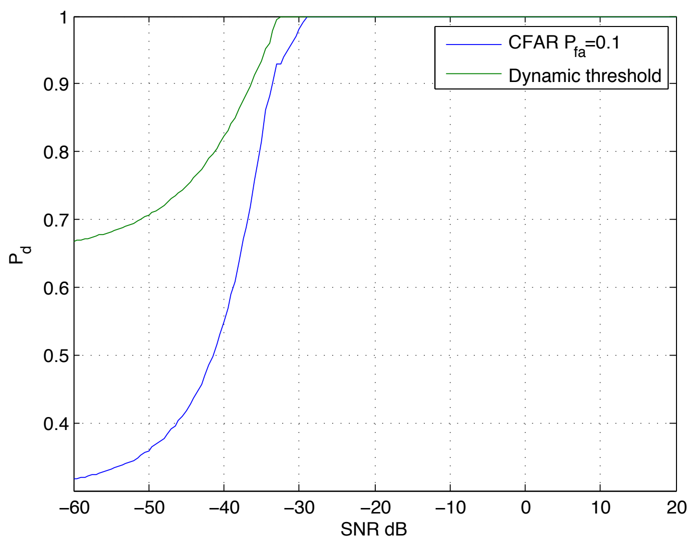

Figure 6.8: CSFD: P_d for fixed and dynamic threshold under different SNR

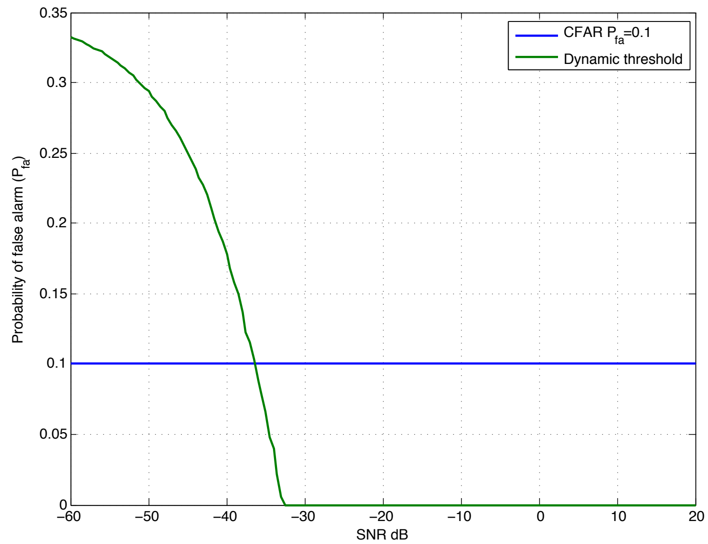

Figure 6.9: CSFD: P_{fa} for fixed and dynamic threshold under different SNR

These results show that the dynamic threshold decreases the misdetection probability and increases the false alarm probability. Therefore, it can be concluded that there is no way to improve one of these probabilities without compromising the other one. Determining which probability must be restricted depends on users preferences and CR's application. In other words, if it is very important to not miss any frequency opportunity, probability of false alarm must be constrained to be as small as possible to guarantee high spectrum utilization. However, avoiding interference with PUs must be the main concern in CR; consequently, the probability of detection must be constrained to be high (for example, $0.5 < P_d \leq 1$). By constraining both misdetection probability and false alarm probability to be as small as possible, the solution of the optimization problem that minimizes the total error is most likely to be infeasible in very low SNR environment.

6.2.2 Performance Comparison of the Detection Techniques

In the previous section the tow threshold setting methods were compared. This section presents and compares the performance of the three techniques. Their detection results were obtained using both the fixed and dynamic threshold setting approaches. Figure 6.10 shows the receiver operating characteristic (ROC) of the three techniques at SNR = -30 dB when the number of samples (L) is 1000. The results indicate that CSFD outperform ED and MF in low SNR. The present findings seem to be consistent with other studies such as [40]. In order to know the number of samples affects the detection techniques performance,

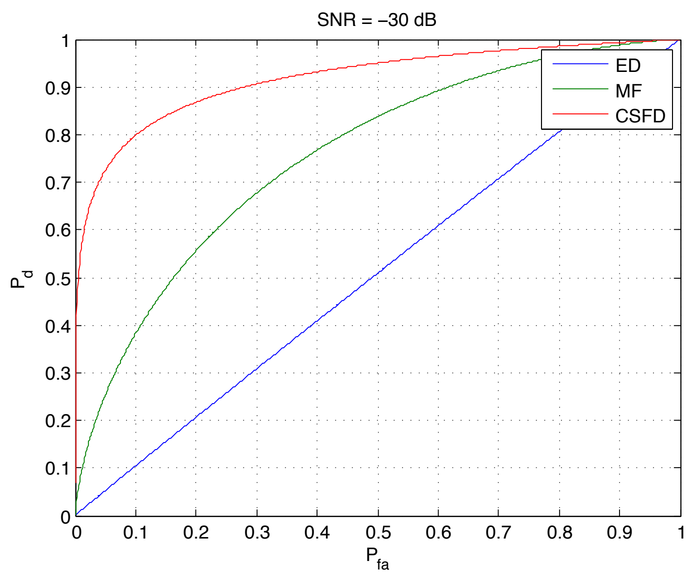

Figure 6.10: ROC of the three techniques at SNR= -30 dB and L=1000

different sample size have used to obtain the ROC of the three techniques at a specific SNR. Figure 6.11 shows the ROC of the three techniques at SNR = -40 dB when the number of samples (L) is 1000. Figure 6.12 shows ROC of the three techniques at SNR = -40 dB and L=5000. By comparing the results of these two figures, the performance of MF and CSFD

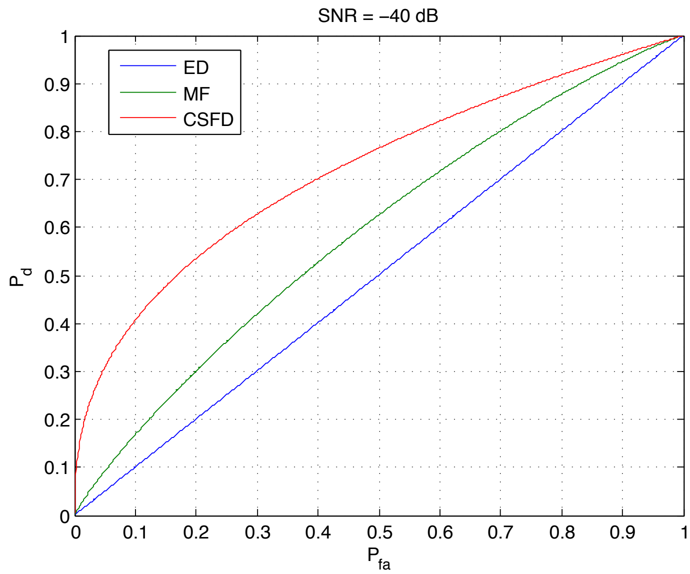

Figure 6.11: ROC of the three techniques at SNR= -40 dB and L=1000

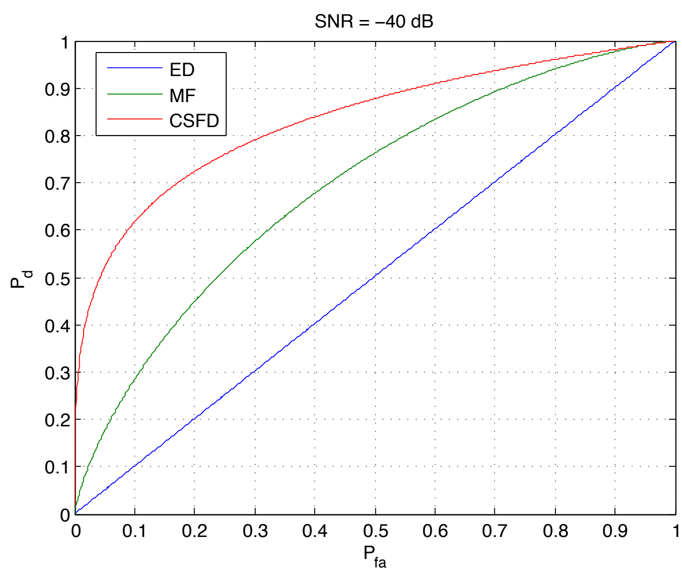

Figure 6.12: ROC of the three techniques at SNR= -40 dB and L=5000

enhances by increasing the number of samples from 1000 to 5000. However, the number of samples must be chosen carefully to be as small as possible in order to perform sensing in short time.

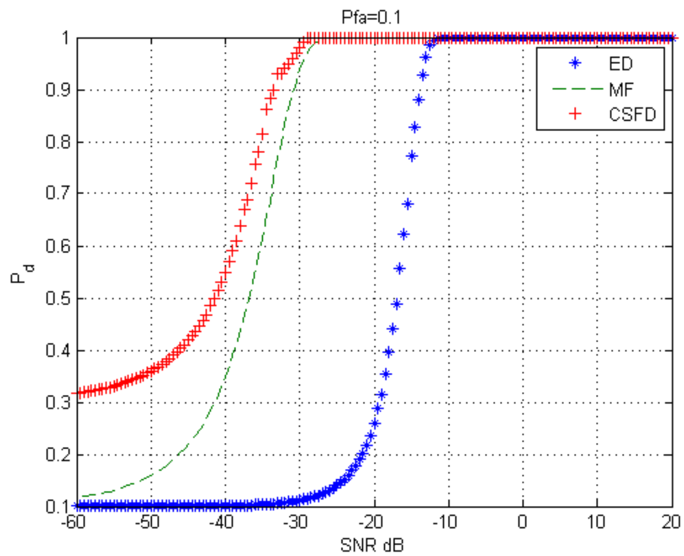

Figure 6.13: Probability of detection under different SNR using fixed threshold

Figure 6.13 shows the probability of detection under different SNR values using a fixed threshold (P_{fa}=0.1). The results show that in low SNR, the ED's detection probability is quite low compared to the MF and CSFD's. From Figure 6.13, at SNR ≈ -30 dB, $P_{d(ED)}$ starts increasing up till reaches 1 at SNR =-10 dB. Although MF's detection probability also starts at low value, at SNR= ≈ -50 dB, it increases faster than ED's detection probability does. On the other hand, in low SNR, CSFD's detection probability is relatively high compared to the other two techniques, and it rapidly increases and is saturated at SNR $= \approx -30$.

The results show that at SNR is almost -10 dB, P_d of the three techniques is equal to 1. This finding indicates that energy detector, matched filter, and cyclostationary feature detector can detect PU's signal when $SNR \geq -10$. Determining this SNR value is required to implement the technique selector unit in the proposed model. The technique selector can be designed to select which techniques perform spectrum sensing based on the value of SNR. If SNR is greater than -10 dB, sensing can be performed only by the energy detector. However, ED cannot differentiate between the noise and signals while MF and CSFD can do so. As a result, even in positive SNR values, combining detection results makes the detection decision more reliable and adds confidence to the results. Based on these facts, spectrum sensing can be performed by both the matched filter and energy detector when SNR is positive. In this case, the sensing time will be relatively small. For negative SNR, spectrum sensing is performed by the three techniques, and the sensing time is the summation of the CSFD detection time and the fusion process time.

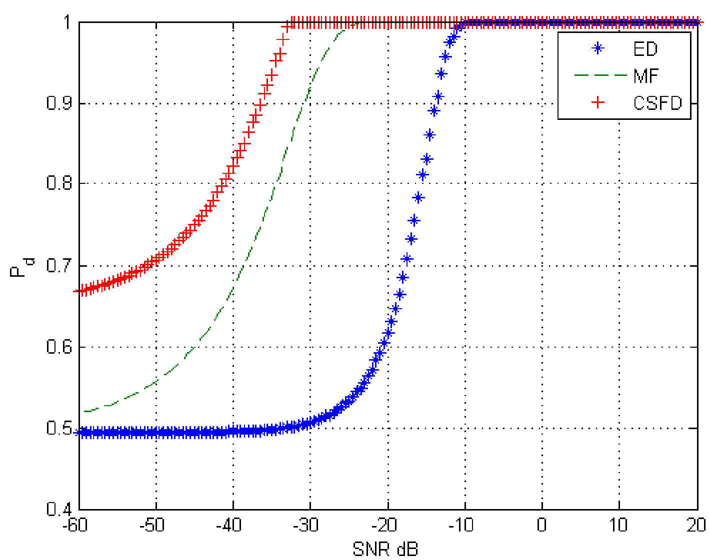

Figure 6.14: Probability of detection under different SNR using dynamic threshold

The performance of the three detection techniques is also compared using the dynamic threshold setting method. Figure 6.14 shows the probability of detection under different

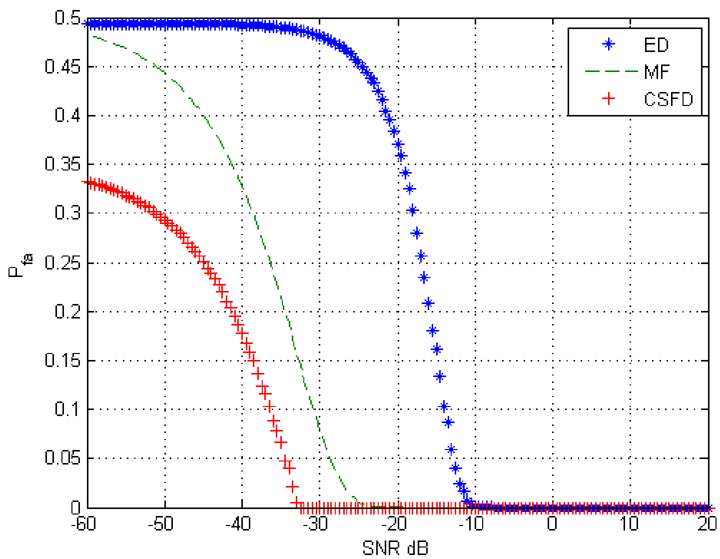

Figure 6.15: Probability of false alarm under different SNR using dynamic threshold

SNR values. Figure 6.15 shows the probability of false alarm under different SNR values. From the results, the dynamic threshold increases the detection probability in low SNR environment; on the other hand, it negatively affects the false alarm probability of the three techniques. However, CSFD is still the superior technique in low SNR situations.

Before combining techniques' results, the correlation among the detection techniques must be determined. To do so, the correlation matrix of techniques' results was calculated. The results of this matrix using fixed threshold ($P_{fa} = 0.1$) is as follows:

$$R_D = \begin{bmatrix} 1 & 0.5 & 0.34 \\ 0.5 & 1 & 0.7 \\ 0.34 & 0.7 & 1 \end{bmatrix}$$

where R_D is a decision's correlation matrix.

The diagonal of the correlation matrix indicates the correlation between each technique and itself, which is always one since the technique detection is perfectly correlated with itself. The correlation matrix is symmetric since the correlation between each two techniques is calculated twice. According to the results, the correlation between the decisions of the energy detector and matched filter is 0.5, and the correlation between the decisions of the energy detector and cyclostationary feature detector is 0.34. The correlation between the decisions of the matched filter and cyclostationary feature detector is 0.7. The results indicate that there is a significant correlation between the CSFD and MF as well as between the ED and MF. These findings are considered in implementing the MAP fusion model.

6.2.3 Fusion Results

The final stage of implementing the proposed model is to perform the decision fusion. Voting based on both AND-rule and OR-rule were used to perform the decision fusion. In addition, MAP decision fusion model was used, in which $P(H_0)$ is assumed to be 0.3, and $P(H_1)$ is assumed to be 0.7. The experiments have conducted for a fixed number of samples L=5000. Figure 6.16 shows the fusion results using the And-rule, Or-rule voting model, and MAP model and compares their probability of detection to techniques' under fixed P_{fa}. Figure 6.17 presents the fusion results and compares their probability of detection to techniques' using the dynamic threshold. Figure 6.18 shows the fusion results and compares their false alarm probability to techniques' using the dynamic threshold.

For the fixed threshold, using And-rule minimizes the overall probability of detection and makes it smaller than the detection probability of ED in low SNR, but using the dynamic threshold we can obtain $P_{fa} < 0.1$ while P_d value is raising. For example, from Figure 6.16 at SNR= -40, the detection probability of ED, MF, and CSFD are approximately equal to 0.1, 0.35 and 0.55, respectively. P_d after combining these probabilities using And-rule is 0.02, while false alarm probability decreases from 0.1 to 0.001. This

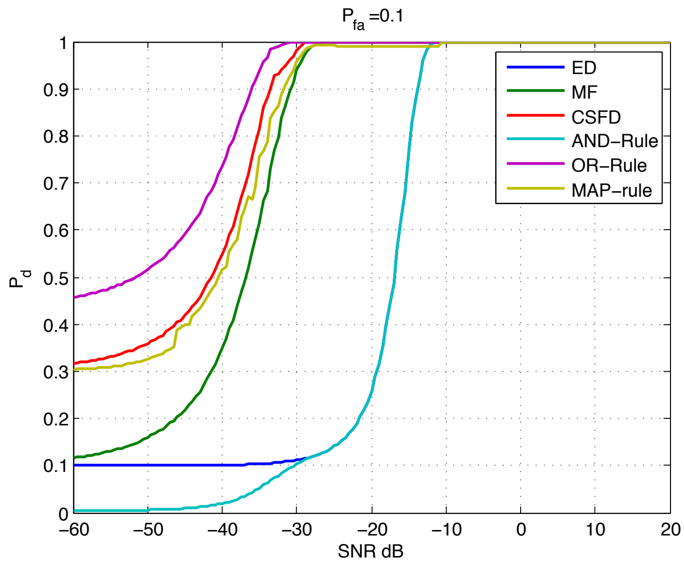

Figure 6.16: Detection probability of techniques and fusion under fixed P_{fa}

finding can be explained by the fact that ED is weak of detecting PUs in low SNR ; consequently, agreement among the three techniques of detecting the presence of PU is less likely to happen.

In contrast to the And-rule, in low SNR, the Or-rule improves P_d and makes the overall probability of detection higher than the one obtained by CSFD with both the fixed and dynamic threshold. However, OR-rule increases P_{fa}, as shown in Figure 6.18. Since Or-rule is based on detecting PUs by at least one of the techniques, its results reliability is affected by the reliability of techniques that report the presence of PU. Although using OR-rule guarantees no interference with PUs, it may cause missing available frequency. Consequently, spectrum will be underutilized.

From Figures 6.16, 6.17 and 6.18, the MAP-results are close to the results obtained by the cyclostationary feature detector, but P_d is smaller and P_{fa} is larger than CSFD's. From these findings, it can be concluded the MAP fusion model works just like the CSFD.

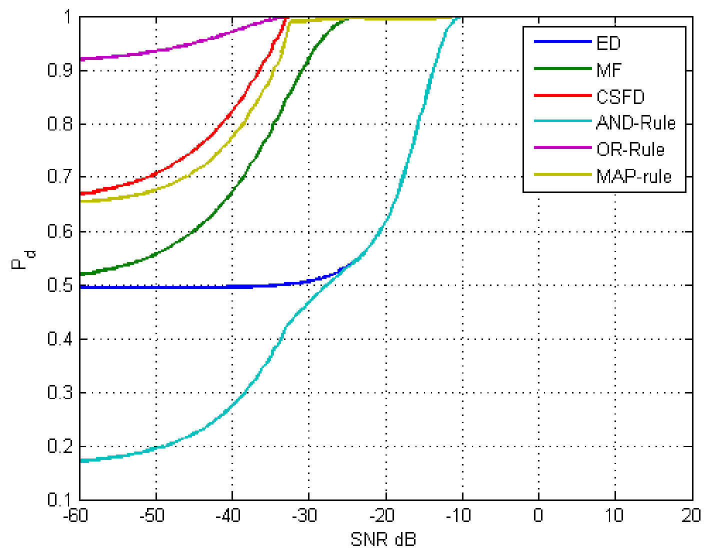

Figure 6.17: Detection probability of techniques and fusion using dynamic threshold

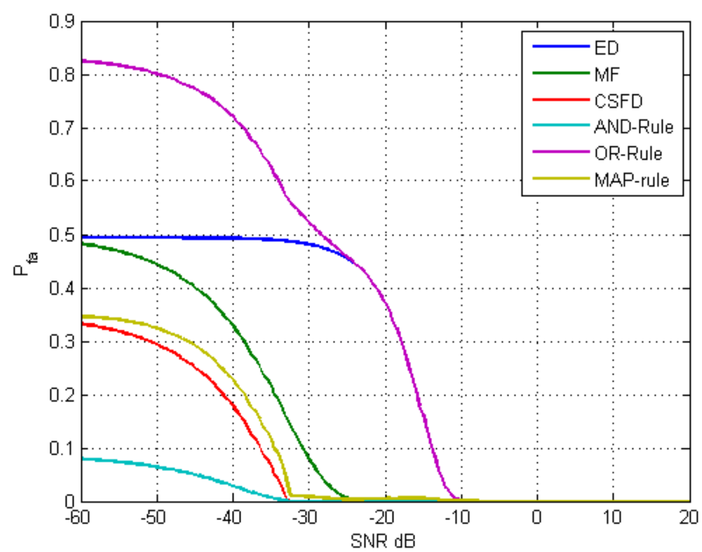

Figure 6.18: False alarm probability of techniques and fusion under dynamic threshold

This finding raises the question whether it is necessary to use more than one technique to perform local spectrum sensing and combine their results. The answer of this question is that the decision fusion makes local decision more reliable in low SNR.

Determining which fusion model is the best for combining the fusion results depends on the CR application and the sensed band. If it is essential not to miss any frequency opportunities, the And-rule is the best voting rule. In case that avoiding interference with PUs has the highest priority, the Or-rule is the most suitable rule. To achieve the best advantage of detection fusion, the MAP-rule is the optimal choice among the fusion models used in this study; however, other fusion models can be considered and may obtain better results. The reason why other fusion models such as neural networks is not employed in this study is to reduce the complexity of the fusion process so it can be implemented in CR devices. In addition, in the base station of cognitive radio network, another fusion model is employed to combine the spectrum sensing results of the different users (meta-fusion). In other words, there is no need to use a powerful fusion method at the user level. Therefore, the fusion method used in the CR users should be chosen to be as simple as possible.

6.3 Summary

This chapter presents the experimental work conducted to analyze the performance of the proposed spectrum sensing system. First, the experimental work evaluated the performance of the energy detector, the matched filter, and the cyclostationary feature detector under fixed and dynamic threshold settings. It is found that dynamic thresholding enhances the probability of detection in low SNR, while it compromises false alarm probability. Second, the performance of the three detection techniques were compared. The findings indicate that the cyclostationary detector outperforms the energy detector and the matched filter in low SNR. The correlation between the techniques results was examined. The results show that techniques results are correlated. Finally, the decision fusion was performed using the voting model (And-rule and Or-rule) and the MAP model. The results of the decision fusion methods were discussed and compared.

Chapter 7

Conclusion and Future Works

7.1 Conclusion

Cognitive radio is a new intelligent radio paradigm proposed to overcome spectrum scarcity and underutilization problems. This study has investigated spectrum sensing in cognitive radio. The importance and challenges of spectrum sensing have been demonstrated. In addition, current SS techniques, including local and cooperative sensing, have been presented and compared. This research was undertaken to design a reliable local SS model based on multi-detection techniques. In other words, the present study was designed to determine whether it is possible to enhance local sensing results in low SNR if more than one technique contributes in detection decision based on one of decision fusion method. In this study, the energy detector, matched filter, cyclostationary feature detector were selected. According to the techniques' evaluation, these techniques can collaborate to enhance SS reliability in low SNR.

In order to develop the proposed model, the performance of the selected techniques was examined and compared based on two threshold setting methods: the fixed false alarm rate and the minimum total error rate. The findings support previous studies which showed that the cyclostationray feature detector surpasses both the energy detector and matched filter in low SNR. The results also showed that the ED's performance is the worst among the three techniques in low SNR situations. It was also found that the dynamic thresholding setting method enhances the detection probability and compromises the false alarm probability in low SNR situations. Another important finding is that the three techniques can detect primary users when SNR is greater than -10 dB. According to this result, the technique selector unit in the proposed model can be designed to select two techniques to perform spectrum sensing when the SNR is within this range.

The important findings from the decision fusion results can be summarized as follows: the And-rule is the best voting rule to achieve high spectrum utilization in low SNR but with a significant risk of misdetecting the PUs. In contrast, Or-rule guarantees no interference with PUs in low SNR but at cost of missing possible spectrum opportunities. The MAP decision fusion model provides satisfying and reasonable performance with respect to the probability of detection and false alarm in low SNR. Other fusion methods can be used to perform the decision fusion. The optimal fusion model can be selected based on the CR application and the sensed band.

7.2 Future Work

The research work in this thesis focuses on spectrum sensing in cognitive radio. A number of possible future studies can be done in this area. First, further research might explore other threshold setting methods to determine the optimal threshold according to certain error probability constraints instead of only minimizing the total error. Since three detection methods perform spectrum sensing in the proposed model, power consumption significantly increases. Therefore, it is recommended that future studies attempt to adapt the proposed sensing model to be energy-aware.

Further experimental investigations are also needed to assess the effects of fading on the sensing results. It would be interesting to compare the results of this study to the results of two-stage spectrum sensing proposed in related literatures. More work can also be done to evaluate and compare the performance of the proposed model based on other decision fusion methods in order to find the optimal one. A further study should examine the overall performance of the proposed model after performing the meta-fusion in the CRN base station and compare it to current cooperative spectrum sensing techniques. Another possible related research topic is to assess the proposed model using real data.

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