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# Spectrum Sensing Techniques
# for
# Cognitive Radios

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# Τεχνικές Αίσθησης Φάσματος για Ευφυή Ραδιόφωνα

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# Abstract

The tremendous ongoing growth of wireless digital communications has raised spectrum shortage and security issues. In particular, the need for new spectrum is the main obstacle in continuing this growth. Recent studies on radio spectrum usage have shown that pre-allocation of spectrum bands to specific wireless communication applications leads to poor utilization of those allocated bands. Therefore, research into new techniques for efficient spectrum utilization is being aggressively pursued by academia, industry and government. Such research efforts have given birth to Cognitive Radio (CR). CR is the new key enabling technology that is presented as a solution to the spectrum scarcity. CRs are unlicensed devices that, through their most important functionality, i.e. spectrum sensing, sense the spectrum and they transmit without interfering with the licensed users. In order to do that, they use several spectrum sensing techniques. These techniques are used to detect the presence or absence of the primary user's signal. Spectrum sensing for one CR user has many challenges to overcome, such as multipath fading or shadowing. Thus, in that occasion we can utilize cooperative spectrum sensing. This type of sensing is realized in a CR network and the presence or absence of the primary user's signal is decided by many users or a base station. In this thesis, we are giving important background information about CRs and how we were lead to that technology. Moreover, we are going to describe the problem of spectrum sensing, what are the spectrum holes and the challenges that a CR must face in order to sense the RF spectrum efficiently. A big part of this thesis is the profound study of the most important techniques for sensing the spectrum and the comparison among them. Finally, we are discussing Cooperative Spectrum Sensing; the way it can be implemented and the problems that it can solve.

# Περίληψη

Η τεράστια συνεχιζόμενη ανάπτυξη των ασύρματων ψηφιακών επικοινωνιών έχει προκαλέσει έλλειψη στις ελεύθερες συχνότητες του ραδιοφάσματος αλλά επίσης και σε θέματα ασφαλείας. Ειδικότερα, η ανάγκη για νέες ζώνες συχνοτήτων στο ραδιοφάσμα είναι το κύριο εμπόδιο στην συνέχιση αυτής της ανάπτυξης. Πρόσφατες μελέτες σχετικά με τη χρήση του ραδιοφάσματος έχουν δείξει ότι η εκ των προτέρων κατανομή των ζωνών του φάσματος σε συγκεκριμένες εφαρμογές ασύρματης επικοινωνίας οδηγεί σε κακή χρήση αυτών των κατανεμημένων ζωνών. Ως εκ τούτου, η ακαδημαϊκή κοινότητα, η βιομηχανία και οι κυβερνήσεις επιδιώκουν την έρευνα για νέες τεχνικές για την αποτελεσματικότερη χρήση του φάσματος. Τέτοιες ερευνητικές προσπάθειες έχουν γεννήσει την τεχνολογία των Cognitive Radios (CR). Με τον όρο CR εννοούμε την νέα κύρια τεχνολογία που παρουσιάζεται ως λύση στην έλλειψη φάσματος. Τα CRs είναι συσκευές οι οποίες δεν έχουν άδεια για χρήση της συγκεκριμένης ζώνης συχνοτήτων στην οποία επιθυμούν να εκπέμψουν, ωστόσω μέσω της πιο σημαντικής λειτουργίας τους, της αίσθησης του ραδιοφάσματος, μεταδίδουν χωρίς να παρεμβάλλουν τους χρήστες που έχουν πληρώσει και έχουν άδεια να χρησιμοποιήσουν αυτή τη ζώνη συχνοτήτων. Για να το κάνουν αυτό, χρησιμοποιούν διάφορες τεχνικές ανίχνευσης φάσματος. Αυτές οι τεχνικές χρησιμοποιούνται για την ανίχνευση της ύπαρξης ή της απουσίας του σήματος του εξουσιοδοτημένου χρήστη. Η αίσθηση του φάσματος έχει πολλές προκλήσεις να ξεπεράσει, όπως η πολλαπλή όδευση του σήματος ή η επισκίαση ενός χρήστη. Έτσι, με την ευκαιρία αυτή μπορούμε να χρησιμοποιήσουμε τη συνεργατική αίσθηση φάσματος. Αυτό το είδος της αίσθησης πραγματοποιείται σε ένα δίκτυο με πολλούς χρήστες CRs και η ύπαρξη ή η απουσία του σήματος του εξουσιοδοτημένου χρήστη αποφασίζεται από πολλούς χρήστες ή έναν σταθμό βάσης με τον οποίο συνεργάζονται οι δευτερεύοντες χρήστες. Στην παρούσα εργασία, δίνουμε σημαντικές πληροφορίες σχετικά με τα CRs και πώς έχουμε οδηγηθεί σε αυτή την τεχνολογία. Επιπλέον, πρόκειται να περιγράψουμε το πρόβλημα της ανίχνευσης φάσματος, τι είναι και πως δημιουργούνται οι *τρύπες* του φάσματος και οι προκλήσεις που πρέπει να αντιμετωπίσει το CR προκειμένου να γίνει η λειτουργία της αίσθησης του φάσματος ραδιοσυχνοτήτων αποτελεσματικά. Ένα μεγάλο μέρος αυτής της διπλωματικής εργασίας είναι η εις βάθος μελέτη των πιο σημαντικών τεχνικών για την ανίχνευση του φάσματος και η σύγκριση μεταξύ τους. Τέλος, συζητάμε τη συνεργατική αίσθηση φάσματος, τον τρόπο με τον οποίο μπορεί να εφαρμοστεί και τα προβλήματα που μπορεί να επιλύσει.

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# Chapter 1

# Introduction

As wireless digital communications continue to grow driven by consumers' interest in wireless services, more and more spectrum resources will be needed. On the one hand, the increased diversity (voice, short message, Web, multimedia etc) and demand of high *quality-of-service* (QoS) applications have resulted in overcrowding of the officially allocated spectrum bands which leads to poor user satisfaction. On the other hand, major licensed bands, such as those allocated for television broadcasting, amateur radio and telemetry data, have been found to be largely underutilized, resulting in spectrum wastage. The above were derived by a survey of spectrum utilization made by the Federal Communications Commission (FCC) and published in November 2002 [1]. FCC is the main regulatory body for distributing spectrum bands to licensed users in USA. To overcome these problems, the FCC has been considering more flexible and comprehensive uses of the available spectrum, through the use of the *Cognitive Radio* (CR) technology.

CRs are wireless devices that are used for the improvement of spectrum utilization. They achieve that by letting a secondary user (SU), also referred as an *unlicensed user*, to exploit a spectrum band when it is not used by a primary user (PU), also referred as a *licensed user*. PUs have higher priority than SUs or legacy rights on the usage of a specific part of the spectrum. The spectrum bands that are not used by the PUs are called *spectrum holes*. CRs have the ability to sense and adapt to the environment continuously in order to detect the presence of the PUs' signal. Once they detect the PUs' signal, they stop transmitting in that spectrum band and they continue to sense the spectrum in order to find another spectrum hole for their transmission.

Among the many functionalities of a CR (they will be discussed later in more details), the most important is *spectrum sensing*, as mentioned above. It is the most important functionality because if a CR senses well its environment, the spectrum will be utilized more efficiently, as well as there will be high QoS for the PUs (no collisions, interference etc). The problem of spectrum sensing is to decide whether there is PU's signal or not. The detection or not of the *primary signal* (the signal of the PU) can be realized from the CR by using the *spectrum sensing techniques*. There are several algorithms for the detection of the primary signal, but in this thesis we focus on "Matched Filter Detection" (MF), "Energy Detection" (ED) and, finally, "Covariance Based Detection" and a variation of it.

Traditional wireless networks have predominantly used direct point-to-point or point-to-multipoint (e.g., cellular) topologies. The difference between these traditional methods and cooperative spectrum sensing is that the latter method allows different users or nodes in a wireless network to share resources and to create collaboration through distributed transmission and processing, in which each user's information is sent out not only by the user but also by the collaborating users. This method promises significant capacity and multiplexing gain increase in wireless networks as well as a new form of space diversity to combat the detrimental effects of severe fading and shadowing.

## 1.1 Thesis Outline

The rest of the thesis is organized as follows: in Chapter 2 we are giving important background information about CRs and how we were lead to that technology. Furthermore, the different definitions, the applications, the functionalities of CR and a brief description of IEEE 802.22 are going to be discussed. In Chapter 3 we are going to describe the problem of spectrum sensing, what are the spectrum holes and the challenges that a CR must face in order to sense the RF spectrum efficiently. In Chapter 4 we are going to discuss in depth the most important techniques for sensing the spectrum. We are analyzing the model, the decision statistic and we are deriving the performance of these techniques. Moreover, we are giving in figures the performance of the detectors. In Chapter 5 we are going to compare the different spectrum sensing techniques and the findings are going to be discussed. In Chapter 6 Cooperative Spectrum Sensing, the way it can be implemented and the problems that it can solve are going to be briefly discussed. Chapter 7 serves as an epilogue to this thesis.

# Chapter 2

# Cognitive Radios

## 2.1 Introduction

In this chapter we shall give some background information about the Cognitive Radios. In section 2.2, we discuss the background of CRs and the reasons which lead to the capturing of that idea. In section 2.3, we show the different definitions for CRs and in section 2.4 we are discussing the main functionalities of a CR. In section 2.5, we point out the most important applications of the CRs. Finally, the working group that has been formed by IEEE (802.22 WRAN) is going to be discussed briefly in section 2.6.

## 2.2 The vision of Cognitive Radios

The need for higher data rates is increasing as a result of the transition from voice-only communications to multimedia type applications. The requirements for this heavy load of data are large and it is obvious that the current *static* frequency allocation schemes cannot accommodate them. As a result, we must find new techniques for exploiting the available spectrum more efficiently.

Cognitive radio is the new key enabling technology that enables next generation communication networks to utilize the spectrum more efficiently in an opportunistic way without interfering with the PUs. In a report by the *Shared Spectrum Company (SSC)* in 2007 it was shown that the spectrum was not used

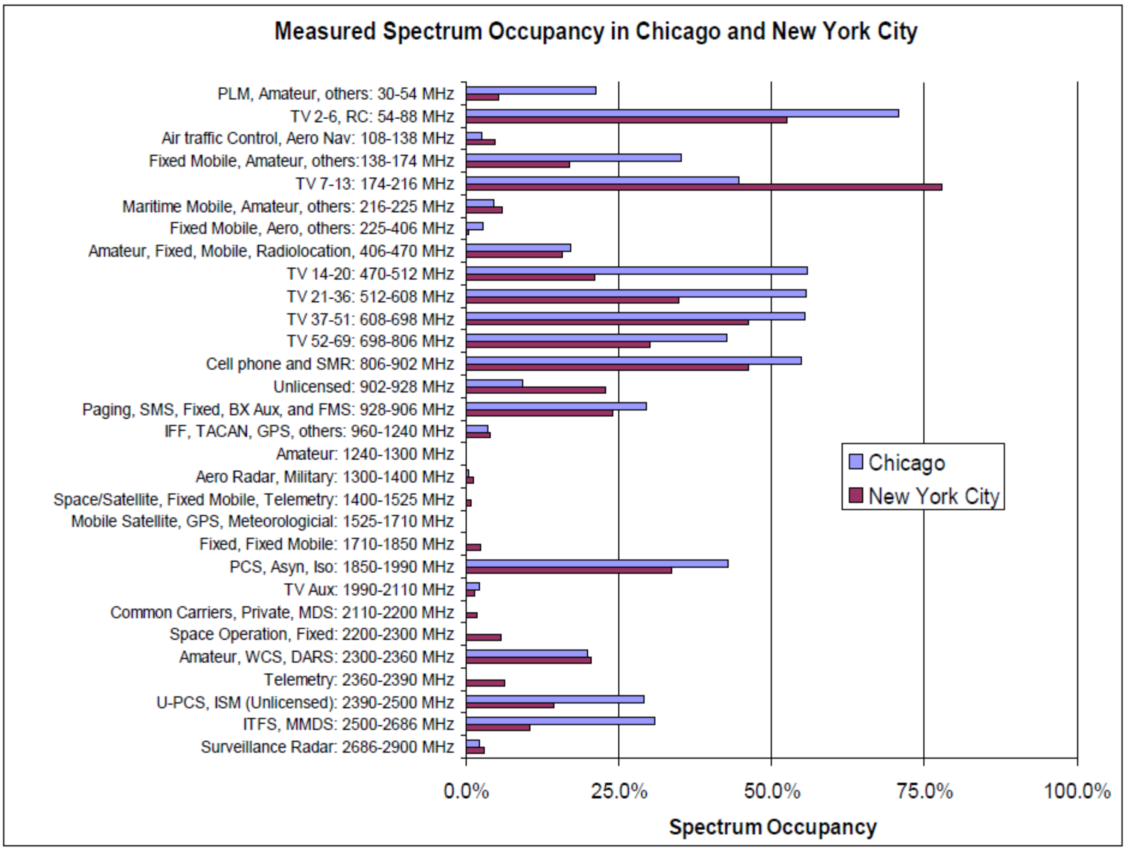


Figure 2.1: Bar Graph of the Spectrum Occupancy in Each Band in New York City and Chicago, USA.

effectively in almost all currently deployed frequency bands in USA (the same results were derived from measurements in other countries as well). Figures 2.1 and 2.2 show the spectrum occupancy for the region of bands in the 30 MHz to 3 GHz with the measurements taken in New York City and Chicago (USA) and in Dublin, Ireland (EU) for the period 16-18 April 2007; these results are from the report of SSC. The spectrum occupancy in Dublin, Ireland is similar to the ones in Chicago and New York. This proves that the inefficient usage of frequency spectrum is a problem not only in USA, but also in European countries. Thus, CRs is a solution to spectrum scarcity.

The term Cognitive Radio was first introduced in the pioneering work of

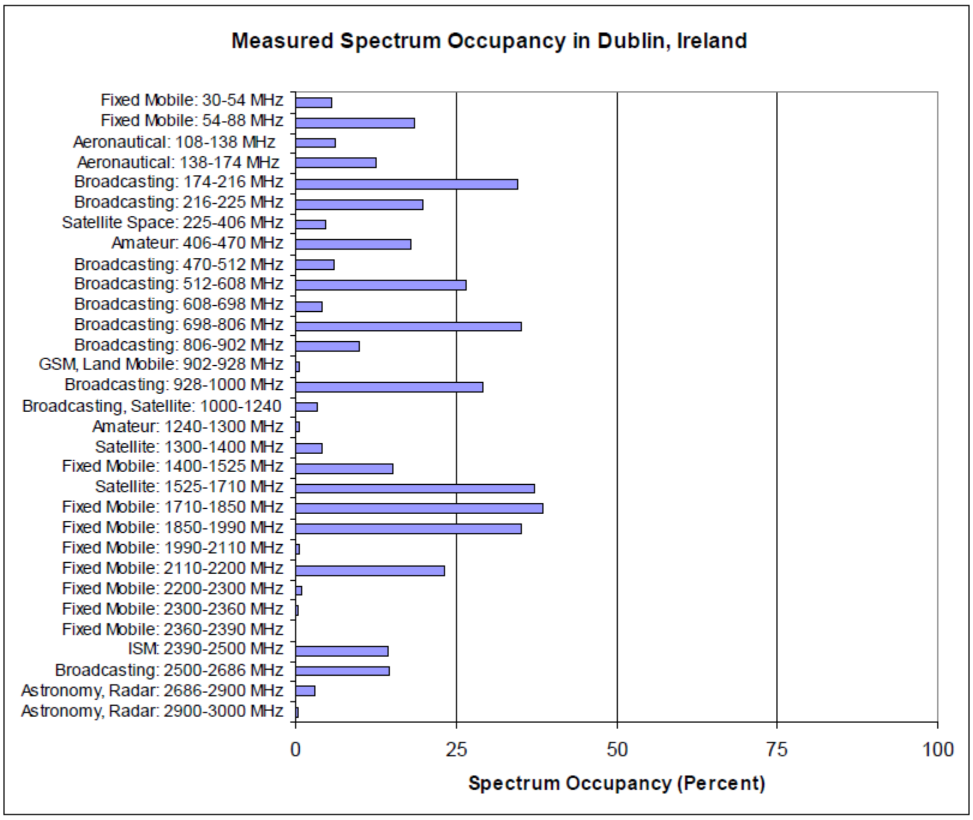


Figure 2.2: Spectrum Occupancy Measured in Each Band at Commission for Communications Regulation Building, Dublin, Ireland.

Joseph Mitola III [2]. In Mitola's dissertation (*KTH Royal Institute of Technology, Stockholm, Sweden, 2000*) and a number of publications [3], he envisioned such a self-reconfiguring radio and dubbed the term Cognitive Radio for it. According to Mitola's early vision, a CR would be realized through the integration of model-based reasoning with software radio and would be trainable in a broad sense, instead of just programmable. In analogy with the mental process of cognition, Mitola also outlined a cognitive cycle through which such radio can reconfigure itself through an ongoing process of awareness (both of itself and the outside world), perception, reasoning, and decision making (Fig. 2.3). The concept of CR emphasizes enhanced quality of information and experience for the user, with cognition and reconfiguration capabilities as a means to this end. Today, however, CR has become an all-encompassing term for a wide variety of technologies that enable radios to achieve various levels of self-configuration, and with an emphasis on different functionalities, ranging from ubiquitous wireless access, to automated radio resource optimization, to dynamic spectrum access for a future device-centric interference management, to the vision of an ideal CR.

The main characteristics of CRs are reconfigurability and intelligent adaptive behavior. Here by intelligent adaptive behavior we mean the ability to adapt without being a priori programmed to do this; that is, via some form of learning. From this it follows that cognitive radio functionality requires at least the following capabilities:

- *Flexibility and agility*, the ability to change the waveform and other radio operational parameters on the fly. In contrast, there is a very limited extent that the current multichannel multiradio (MC-MR) can do this. Full flexibility becomes possible when CRs are built on top of SDRs (2.3.1). Another important requirement to achieve flexibility, which is less discussed, is reconfigurable or wideband antenna technology.

- *Sensing*, the ability to observe and measure the state of the environment, including spectral occupancy. Sensing is necessary if the device is to change its operation based on its current knowledge of RF environment.

- *Learning and adaptability*, the ability to analyze sensory input, to recognize patterns, and modify internal operational behavior based on the analysis of a new situation, not only based on precoded algorithms but also as a result of a learning mechanism.

## 2.3 Definitions of Cognitive Radios

CR has drawn great attention due to its potential for solving current spectrum shortage problems and enhancing radio communication performance. These result in many academic institutions and industries generating various definitions for CR, according to their own needs, based on the original definition by Mitola in 1999. In this section we are going to point out the most popular definitions for CR:

**By Joseph Mitola** *"A radio that employs model based reasoning to achieve a specified level of competence in radio-related domains."*

**By Simon Haykin** *"Cognitive Radio is an intelligent wireless communication system that is aware of its surrounding environment and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g. transmit power, carrier-frequency and modulation strategy) in real time, with two primary objectives in mind*

- *highly reliable communications whenever and wherever needed;*
- *efficient utilization of the radio spectrum".*

**By FCC** *"A cognitive radio is a radio that can change its transmitter parameters based on interaction with the environment in which it operates".*

From the first and the second definition six words stand out: awareness, intelligence, learning, adaptability, reliability and efficiency. These are the cognitive capabilities that a CR must have and thanks to the advances of digital signal processing (DSP), networking, machine learning, computer software (SW) and computer hardware (HW). Except of these cognitive capabilities, a CR has another one which is borrowed from by a platform known as *Software-Defined Radio (SDR)*. On this platform the CR is built.

In the subsection 2.3.1 we give a brief description of what an SDR is.

### 2.3.1 Software-Defined Radio

A SDR is a radio in which the properties of carrier frequency, signal bandwidth, modulation and network access are defined by SW. It is a general-purpose device in which the same radio tuner and processors are used to implement many waveforms at many frequencies. The advantage of this approach is that the equipment is more versatile and cost-effective. Additionally, it can be upgraded with new SW for new waveforms and new applications after sale, delivery and installation.

## 2.4 Functions of Cognitive Radios

A typical duty cycle of CR, as illustrated in Figure 2.3, includes detecting spectrum white space, selecting the best frequency bands, coordinating spectrum access with other users and vacating the frequency when a primary user appears. Such a cognitive cycle is supported by the following functions:

- spectrum sensing and analysis,
- spectrum management and handoff,
- spectrum allocation and sharing.

Through spectrum sensing and analysis, CR can detect the spectrum white space, i.e. a portion of frequency band that is not being used by the primary users, and utilize the spectrum. On the other hand, when primary users start using the licensed spectrum again, CR can detect their activity through sensing, so that no harmful interference is generated due to SUs' transmission. After recognizing the spectrum white space by sensing, spectrum management and handoff function of CR enables SUs to choose the best frequency band and hop among multiple bands according to the time varying channel characteristics to meet various QoS

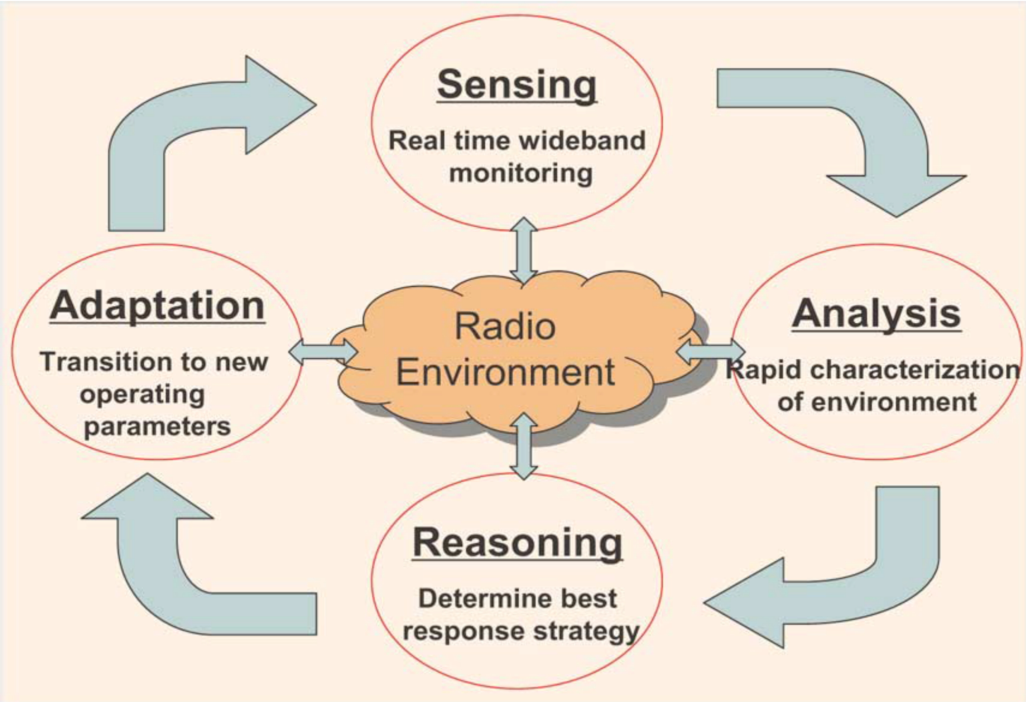


Figure 2.3: Cognitive Radio duty cycle [*"Advances in CR Networks: A survey"*, Beibei Wang, K.J. Ray Liu]

requirements. For instance, when a PU reclaims his/her frequency band, the SU that is using the licensed band can direct his/her transmission to other available frequencies, according to the channel capacity determined by the noise and interference levels, path loss, channel error rate, holding time, and etc. In dynamic spectrum access, a SU may share the spectrum resources with PUs, other SUs, or both. Hence, a good spectrum allocation and sharing mechanism is critical to achieve high spectrum efficiency. Since PUs own the spectrum rights, when SUs co-exist in a licensed band with PUs, the interference level due to secondary spectrum usage should be limited by a certain threshold. When multiple SUs share a frequency band, their access should be coordinated to alleviate collisions and interference.

## 2.5 Applications of Cognitive Radios

Because CRs are able to sense, detect and monitor the surrounding RF environment such as interference and access availability and reconfigure their own operating characteristics to best match outside situations, cognitive communications can increase spectrum efficiency and support higher bandwidth service. Thus, there are many application in which a CR can be employed. The most popular and useful are discussed:

**For military communications** The capacity of military communications in limited by radio spectrum scarcity because static frequency assignments freeze bandwidth into unproductive applications, where a large amount of spectrum is idle. CR using dynamic spectrum access can relieve the spectrum congestion through efficient allocation of bandwidth and flexible spectrum access. Therefore, CR can provide military with adaptive, seamless and secure communication.

**Public safety** A CR can be implemented to enhance public safety and homeland security. A natural disaster or terrorist attack can destroy existing communication infrastructure, so an emergency network becomes indispensable to aid the search and rescue. As a CR can recognize spectrum availability and reconfigure itself for much more efficient communication, this provides public safety staff with dynamic spectrum selectivity and reliable broadband communication to minimize information delay. Moreover, CR supports interoperability between various communication systems. By adaptation to the different network, CR can sustain multiple service types.

In Figure 2.4, an example of public safety teams is shown. Members of Team A employ a communications standard operating on a carrier frequency that is different from the communication equipment employed by both Teams B and C. Thus, unless these teams are coordinated with respect to operating parameters and communication standards, effective communications between them would be nearly impossible.

**Commercial purposes** Finally, another very promising application of CR is in the commercial markets for wireless technologies. Since CR can intelligently determine which communication channels are in use and automatically switches to an unoccupied channel, it provides additional bandwidth and versatility for rapidly growing data applications. Moreover, the adaptive and dynamic channel switching can help avoid spectrum conflict and expensive redeployment. As CR can utilize a wide range of frequencies, some of which has excellent propagation characteristics, CR devices are less susceptible to fading related to growing foliage, buildings, terrain and weather. When frequency changes are needed due to conflict or interference, the CR frequency management software will change the operating frequency automatically even without human intervention. Additionally, the radio software can change the service bandwidth remotely to accommodate new applications. As long as no end-user hardware needs to be updated, product upgrades or configuration changes can be completed simply by downloading newly released radio management software. Thus, CR is viewed as the key enabling technology for future mobile wireless services anywhere, anytime and with any device.

## 2.6 IEEE 802.22

IEEE 802.22 standard is known as cognitive radio standard because of the cognitive features it contains. The standard is still in the development stage. One of the most distinctive features of the IEEE 802.22 standard is its spectrum sensing requirement. IEEE 802.22 based wireless regional area network (WRAN) devices sense TV channels and identify transmission opportunities. The functional requirements of the standard require at least 90% probability of detection and at most 10% probability of false alarm for TV signals with - 116 dBm power level (approximately 0.001 $pW$) or above. The sensing is envisioned to be based on two stages: fast and fine sensing. In the fast sensing stage, a coarse sensing algorithm is employed, e.g. energy detector. The fine sensing stage is initiated based on the fast sensing results. Fine sensing involves a more detailed sensing where

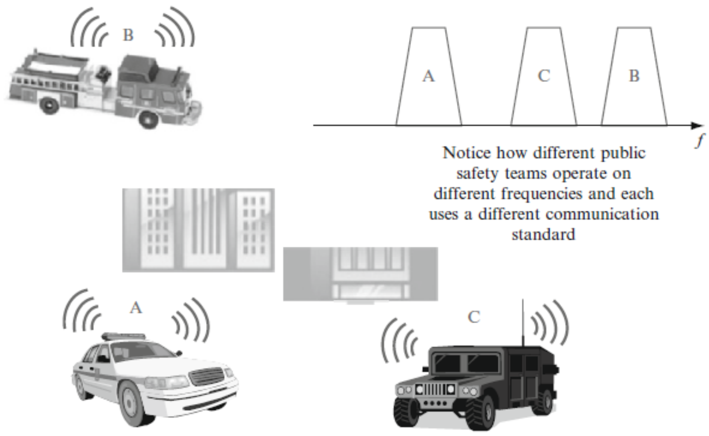


Figure 2.4: Example of public safety and emergency responder teams within the same geographical area operating on different center frequencies and potentially using different communication standards. ["Cognitive Radios Communications and Networks, p.10"]

more powerful methods are used. Several techniques that have been proposed and included in the draft standard include energy detection, waveform-based sensing (PN511 or PN63 sequence detection and/or segment sync detection), cyclostationary feature detection, and matched filtering. A base station (BS) can distribute the sensing load among subscriber stations (SSs). The results are returned to the BS which uses these results for managing the transmissions. Hence, it is a practical example of centralized collaborative sensing. Another approach for managing the spectrum in IEEE 802.22 devices is based on a centralized method for available spectrum discovery. The BSs would be equipped with a global positioning system (GPS) receiver which would allow its position to be reported. The location information would then be used to obtain the information about available TV channels through a central server. For low-power devices operating in the TV bands, e.g. wireless microphone and wireless camera, external sensing is proposed as an alternative technique. These devices periodically transmit beacons with a higher power level. These beacons are monitored by IEEE 802.22 devices to detect the presence of such low-power devices which are otherwise difficult to detect due to the low-power transmission. Figure 2.5 shows

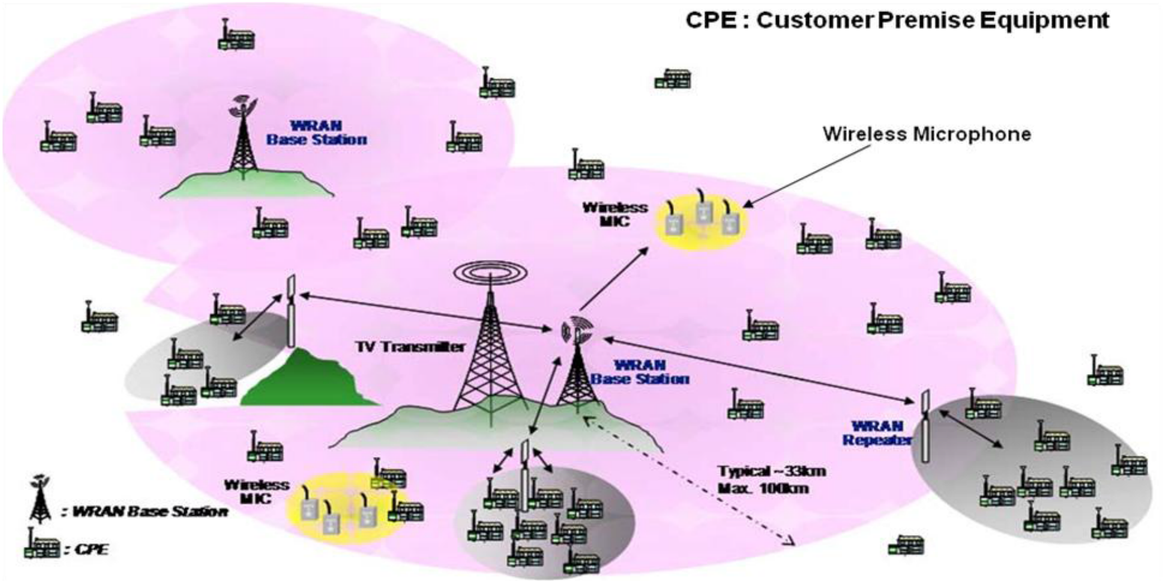


Figure 2.5: IEEE 802.22 WRAN service topology

the service topology for the IEEE 802.22 WRAN.

# Chapter 3

# Spectrum Sensing and Analysis

## 3.1 Introduction

Through spectrum sensing, CRs can obtain useful information about their surrounding radio environment, such as the presence of PUs and appearance of spectrum holes. Only with this information a CR can adapt its transmitting and receiving parameters, like transmission power, frequency, modulation schemes etc., in order to achieve efficient spectrum utilization and avoid interference to the PUs' signals. Therefore, spectrum sensing and analysis is a critical step towards dynamic spectrum management.

## 3.2 Spectrum Sensing

Spectrum sensing enables the capability of a CR to measure, learn and be aware of the radio's operating environment, such as the spectrum availability and power, noise temperature, interference status etc. When a certain frequency band is detected as not being used by the primary licensed user of the band at a particular time in a particular position (spectrum hole), SUs can utilize the spectrum, i.e. there exists a spectrum opportunity. Therefore, spectrum sensing can be performed in the time, frequency, space and code dimensions. With the recent development of transmit beamforming, multiple users can utilize the same channel/frequency at the same time in the same geographical location. Thus, in the case that a PU does not transmit in all directions, extra spectrum opportunities can be created for SUs in the directions where the PU is not operating.

Spectrum sensing helps CRs to gain awareness of their radio environment, in a manner that they know if a band is used by a PU in a geographical area. This awareness can be obtained by using beacons, by using geolocation and databases or by performing local spectrum sensing at cognitive radios. Recently, the latter method is used more than the others because of its broader application and lower infrastructure requirement.

Figure 3.1 shows the various aspects of spectrum sensing for CRs. In this chapter, we are going to analyze the *phenomenon* of spectrum holes in section 3.3, the challenges of spectrum sensing for CRs in section 3.4 and, finally, a classification according to the requirements that each method needs in order to be implemented will be discussed in section 3.5.

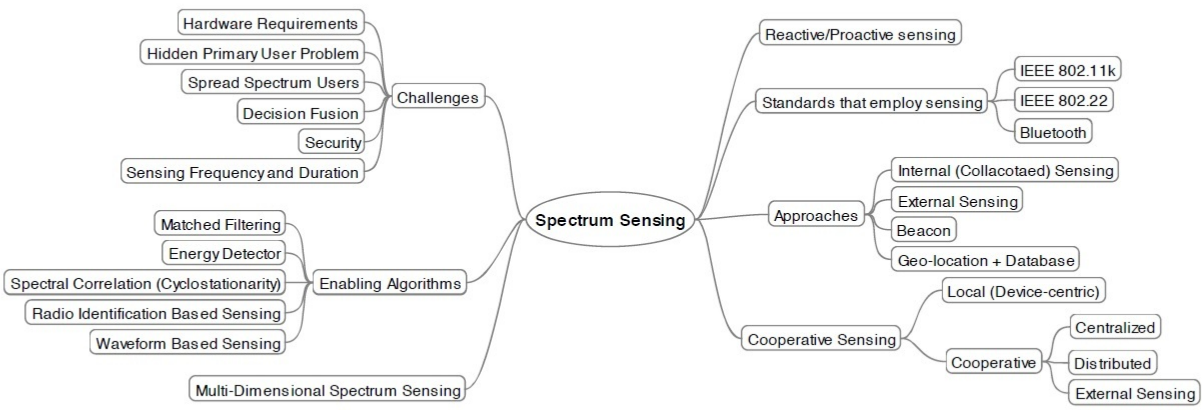


Figure 3.1: Various aspects of spectrum sensing for Cognitive Radio. [Yucek and Arslan: "A survey of spectrum sensing algorithms for cognitive radio applications"]

## 3.3 Spectrum Holes

**Spectrum Hole** *is defined as a licensed spectrum band that can be used by Cognitive Radio users without interfering the primary users.*

In general, spectrum holes can be divided into two categories: *temporal* and *spatial* spectrum holes. A further analysis is following and Figure 3.2 shows temporal (a) and spatial (b) spectrum holes.

### 3.3.1 Temporal Spectrum Holes

A temporal spectrum hole means that there is no transmission over the spectrum band of interest during the time of sensing. Thus, this band can be utilized by CR in the current time slot. The PUs and the SUs are located in the same area, in the sense that there can be interference between them. The CR avoids that by exploiting the spectrum holes in time, in order not to interfere the licensed user. Consequently, it is relatively easy to detect the presence or absence of the primary user activity since CRs only need to have a similar detection sensitivity as regular primary receivers and the only thing that is mandatory to do is to identify the presence of the primary signal, rather than demodulating and decoding it. So, there is no need for high complexity in signal processing.

### 3.3.2 Spatial Spectrum Holes

A spatial spectrum hole exists when the spectrum band of interest is occupied by the primary transmission only in a restricted geographical area. Thus, this band can be utilized by CRs only when they appear outside of this area. The difference between temporal and spatial holes is that for the CRs to be able to use the latter they must be outside of the transmission coverage area of the PUs. Since there are no PUs outside the coverage area, secondary communication over the licensed band is allowed if and only if the CR does not interfere with the operation of the PU inside the coverage area. In this case, the detection of the PU's signal from the SU is a difficult task, because the SU falls out of the coverage area of the PU's transmission. Therefore, it is comprehensible that the CR needs high complexity in signal processing, because is it obligatory that the PU's transmission will be detected at any location where there would be interference.

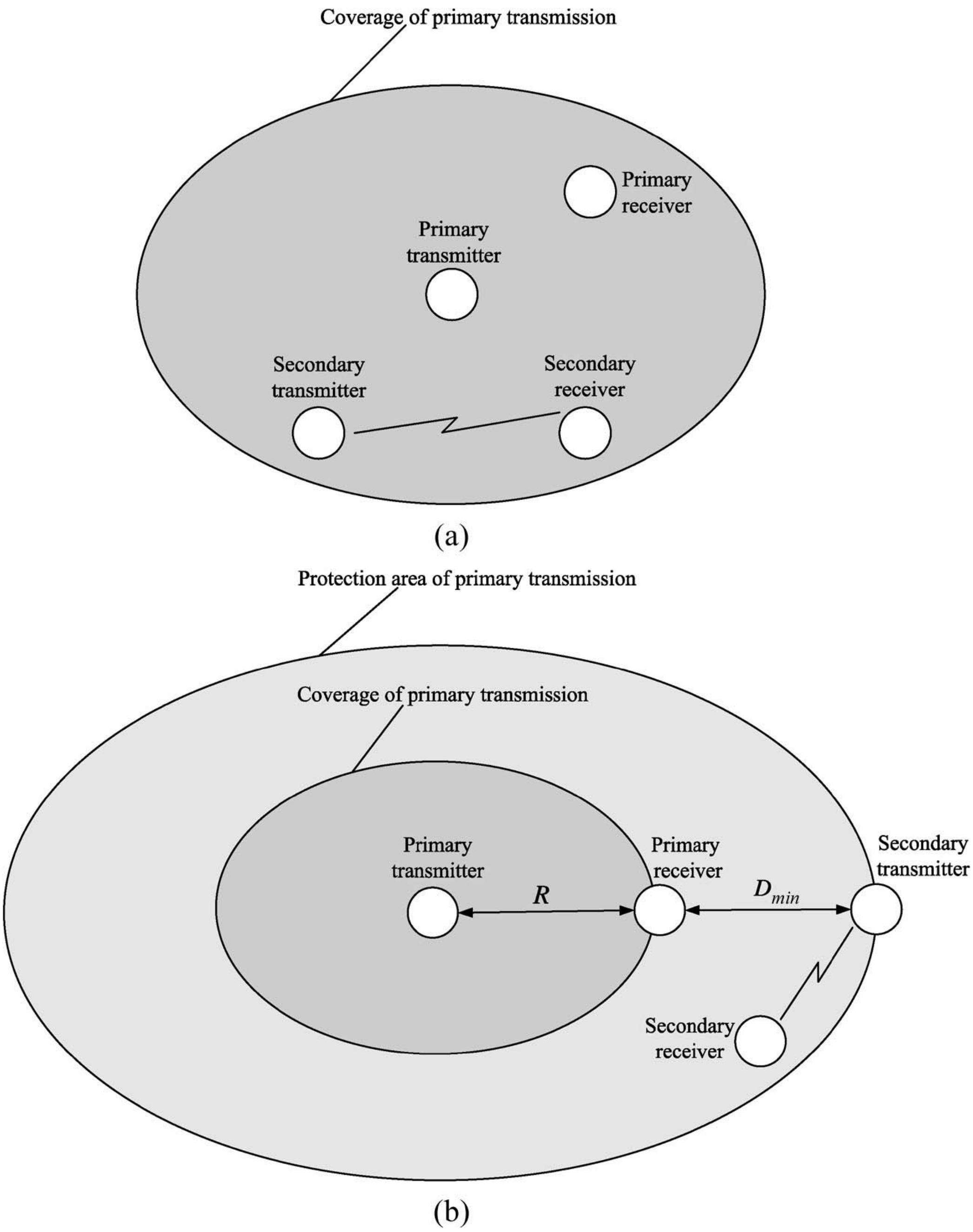


Figure 3.2: Spectrum holes for secondary communication. (a) Temporal spectrum holes and (b) spatial spectrum holes. ["Signal Processing in Cognitive Radio", J. Ma, G.Y. Li, B.H. Juang]

## 3.4 Challenges of Spectrum Sensing

In this section we are about to point out some challenges and other issues that spectrum sensing must face so as the CR to have a proper operation.

**Hardware Requirements** Spectrum sensing for CR applications requires high sampling rate, high resolution analog-to-digital converters (ADC) with large dynamic range and high speed signal processors. On the one hand, the noise interference problem is easier for these purposes as receivers are tuned to receive signals that are transmitted over a desired bandwidth. Moreover, simple receivers are capable of processing narrowband baseband signals with low complexity and power consumption. On the other hand, CR terminals are required to process transmission over a much wider band for utilizing any opportunity. Hence, CR should be able to capture and analyze a relatively larger band for identifying spectrum opportunities. Thus, additional requirements on the components in radio frequency (RF) bands, such as antennas and power amplifiers, are needed and they must operate in a wide range of frequencies. Also, high speed processors (DSPs or FPGAs) with low computationally complexity are necessary.

**Hidden Primary User Problem** This is a very serious problem for a CR user and it can be caused by many factors including severe multipath fading and shadowing observed by secondary users while scanning for primary users' transmissions. Figure 3.3 shows an illustration of a hidden node problem where the dashed circles show the operating ranges of the primary user and the cognitive radio device. In this example, the CR causes unwanted interference to the PU because the CR is outside of the transmission coverage area of the PU. We can tackle this problem by applying *Cooperative Spectrum Sensing*. In Chapter 6 we discuss the Cooperative Spectrum Sensing.

**Sensing Periodicity** While utilizing a white space, the SU should continue to periodically sense the desired band (e.g. every $T_p$) in case a PU starts to transmit. The sensing period, $T_p$, determines the maximum time during which the CR will not be aware of a reappearing PU and may interfere with it. Therefore, $T_p$ plays a key role for the QoS of the licensed user.

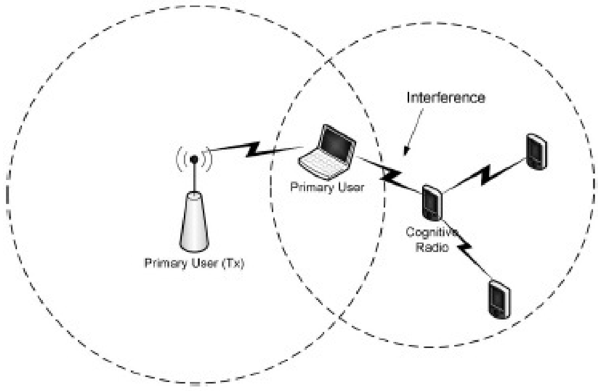


Figure 3.3: The hidden licensed user problem in cognitive radio systems. [Yucek and Arslan: "A survey of spectrum sensing algorithms for cognitive radio applications"]

The CR cannot simultaneously sense the band and transmit, so secondary transmission and sensing of the band must be combined properly. While from the regulator's perspective it suffices for the SU to monitor the band and make a decision whether there is or not a PU signal once every $T_p$, for the CR it is desired to maintain sensing time well below $T_p$, in order to have time for its transmission.

**Noise Uncertainty** It is not always available for a CR to know *a priori* the noise power, so the receiver must estimate it by itself. Unfortunately, calibration errors as well as changes in thermal noise caused by temperature variations limit the accuracy with which noise power can be estimated. Thus, the detection sensitivity, defined as the minimum $SNR$ at which the PU's signal can be accurately detected, must be calculated with the worst case noise assumption which leads to a more sensitive detector.

## 3.5 Classification of Spectrum Sensing Techniques

Several techniques have been proposed for a CR to detect the primary signal in order to utilize in an efficient way the spectrum and each one has different requirements so as to be implemented. These methods can be classified into three general categories: (a) methods requiring both primary signal and noise power information, (b) methods requiring only noise power information (*semiblind detection*) and (c) methods requiring no information on primary signal or noise power (*blind detection*). For example, *Likelihood Ratio Test (LRT), Matched Filter (MF)* and *Cyclostationary Detection (CSD)* belong to category (a); *Energy Detection (ED)* and *Wavelet-Based Detection* are semiblind methods and belong to category (b) and finally blind methods are the *Eigenvalue-Based Detection, Covariance-Based Detection* and *Blindly Combined ED* and belong to category (c).

In chapter 4 we shall show the characteristics as well as the performance of some of the above methods; for the MF detection and a variation of it, the ED and finally the Covariance-Based detection and a variation of that method.

# Chapter 4

# Spectrum Sensing Techniques

## 4.1 Introduction

In this section we are going to present the most important and widely used sensing methods for the CRs. The presentation is relative to the information that each method is needed so as to be implemented, i.e. first the method that needs both PU's signal and noise information (4.3), then the semiblind detection (4.4) and finally the blind detection (4.5). But first of all we are discussing the Neyman-Pearson theorem (4.2) which is the basis for the design of detectors of signals in noise.

## 4.2 Neyman-Pearson Theorem

A common approach to *simple hypothesis* testing is based on the *Neyman-Pearson (NP) theorem*. The simple hypothesis testing arises when the Probability Density Function (PDF) of each assumed hypothesis is completely known. NP theorem is used typically in sonar and radar systems.

**The NP theorem** Before continuing to the spectrum sensing techniques, it is mandatory to explain how the NP theorem works. An example will give us a good explanation.

Assume that we have a random variable (RV) whose PDF is either $\mathcal{N}(0, 1)$ or $\mathcal{N}(1, 1)$. By the notation $\mathcal{N}(\mu, \sigma^2)$ we mean that this random variable

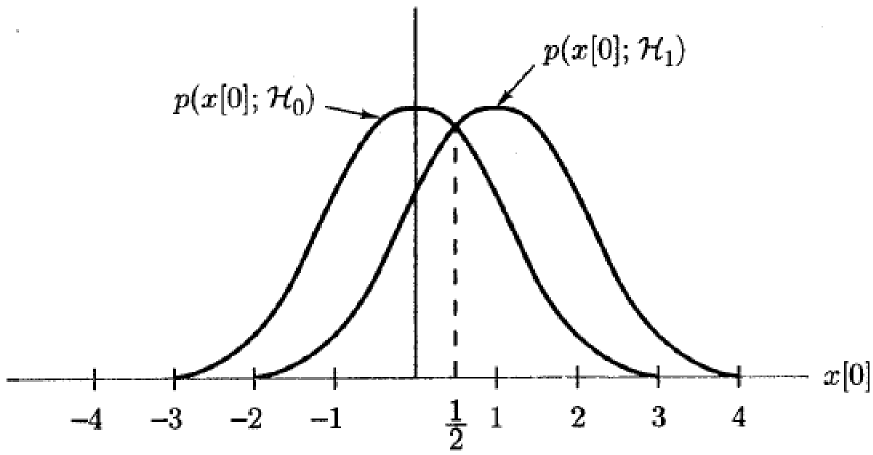


Figure 4.1: PDFs for hypothesis testing problem.

has a Gaussian (Normal) distribution with mean $\mu$ and variance $\sigma^2$. So, we have only one observation of that RV, i.e. $x[0]$ and we must determine if its mean is 0 or 1. Thus, we have to choose among two hypothesis:

$$\begin{aligned} \mathcal{H}_0 &: \mu = 0 \\ \mathcal{H}_1 &: \mu = 1 \end{aligned} \tag{4.1}$$

where $\mathcal{H}_0$ is the *null hypothesis* and $\mathcal{H}_1$ is the *alternative hypothesis*. This problem is known as the *binary hypothesis test* and in detection theory for signals is a key problem. The PDFs under each hypothesis are shown in Figure 4.1, with the difference in means causing the PDF under $\mathcal{H}_1$ to be shifted to the right.

Now, we must decide one in favor of the two hypotheses. It is difficult to decide based in only one sample but a good approach would be to decide $\mathcal{H}_1$ if $x[0] > 1/2$ because if this is happening then the observed sample is more likely if $\mathcal{H}_1$ is true. We call the value $1/2$ as our *threshold* (usually referred as $\gamma$) in this example with which we compare our observed data in order to decide one of the two hypothesis. We can make two types of errors. If we decide $\mathcal{H}_1$ but $\mathcal{H}_0$ is true we make a *false alarm* error. In the other hand, if we decide $\mathcal{H}_0$ while $\mathcal{H}_1$ is true we make a *miss detection* error. The threshold is a very important feature of the detection theory as it determines the performance of the detection method.

We can convert the binary hypothesis problem (4.1) to the signal detection problem, which will occupy us in the next sections:

$$\begin{aligned} \mathcal{H}_0 : &\quad x[0] = w[0] \\ \mathcal{H}_1 : &\quad x[0] = s[0] + w[0], \end{aligned} \tag{4.2}$$

Deciding $\mathcal{H}_1$ when $\mathcal{H}_0$ is true can be thought of as a false-alarm. Generally, in the implementation of the detectors we want very small values of *probability of false-alarm* ($P_{FA}$) or $Pr\{\mathcal{H}_1|\mathcal{H}_0\}$. On the other hand, we wish to maximize the *probability of detection* ($P_D$) or $Pr\{\mathcal{H}_1|\mathcal{H}_1\}$. NP approach maximizes the $P_D$ for a fixed $P_{FA}$. By writing $Pr\{\mathcal{H}_i|\mathcal{H}_j\}$ we mean that we choose the hypothesis $\mathcal{H}_i$ when the hypothesis $\mathcal{H}_j$ is true.

To return to the signal detection problem (4.2) we can constrain $P_{FA}$ by choosing the threshold $\gamma$ since

$$\begin{aligned} P_{FA} &= Pr\{\mathcal{H}_1|\mathcal{H}_0\} \\ &= Pr\{x[0] > \gamma|\mathcal{H}_0\} \\ &= \int_{\gamma}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}t^2\right) \mathrm{d}t \\ &= Q\left(\frac{\gamma - \mu}{\sqrt{\sigma^2}}\right) \\ &= Q(\gamma), \end{aligned} \tag{4.3}$$

because $x$ is a Gaussian RV and in the case of $\mathcal{H}_0$ $\mu = 0$ and $\sigma^2 = 1$. As an example, if $P_{FA} = 10^{-3}$ then $\gamma = 3$, because $Q^{-1}(P_{FA}) = 3$. We therefore decide $\mathcal{H}_1$ if $x[0] > 3$. Furthermore, with this choice we have

$$\begin{aligned} P_D &= Pr\{\mathcal{H}_1|\mathcal{H}_1\} \\ &= Pr\{x[0] > \gamma|\mathcal{H}_1\} \\ &= \int_{\gamma}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(t-1)^2\right] \mathrm{d}t \\ &= Q\left(\frac{\gamma-\mu}{\sqrt{\sigma^2}}\right) \\ &= Q(\gamma - 1) = Q(2) = 0.023, \end{aligned} \tag{4.4}$$

because $x$ is a Gaussian RV and in the case of $\mathcal{H}_1$ $\mu = 1$ and $\sigma^2 = 1$.

## 4.3 Matched Filter Detection

If SUs know information about a PU's signal a priori, then the optimal detection method is the matched filter since it maximizes the SNR of the received signal. The MF correlates the already known primary signal with the received signal to detect the presence of the PU and thus maximizes the SNR in the presence of additive noise. The advantage of MF detection is the short time that it needs in order to achieve a good detection performance compared to the other techniques, such as a low probability of false alarm and missed detection, since the MF needs less received samples. MF implementation complexity and power consumption is too high, because that detector needs receivers for all types of signals and corresponding receiver algorithms to be executed.

Matched filtering requires perfect knowledge of the PU's signal, e.g. the operating frequency, bandwidth, modulation type and order, pulse shape, packet format etc. If wrong information is used for matched filtering the detection performance will be degraded, which leads to malfunction of the CR concept and from the PU's perspective, leads to low QoS for the licensed users.

The development of the detector follows.

**Model** The detection problem is to distinguish between the two hypotheses:

$$\begin{aligned} \mathcal{H}_0 &: \quad x[n] = w[n], \qquad\qquad n = 0, 1, \ldots, N-1 \\ \mathcal{H}_1 &: \quad x[n] = s[n] + w[n], \quad n = 0, 1, \ldots, N-1 \end{aligned} \tag{4.5}$$

where $w[n]$ is White Gaussian Noise (WGN) with variance $\sigma^2$ and the source signal $s[n]$ is assumed a known deterministic one and Gaussian distributed. $x[n]$ is the received signal. WGN is defined as a zero-mean Gaussian process with constant spectral density.

**Decision Statistic** The NP detector decides $\mathcal{H}_1$ if the likelihood ratio exceeds a threshold $\gamma$ (we are going to analyze later in this section how the threshold is calculated) or

$$L(\mathbf{x}) = \frac{p(\mathbf{x}|\mathcal{H}_1)}{p(\mathbf{x}|\mathcal{H}_0)} > \gamma \tag{4.6}$$

where $\mathbf{x} = [x[0]\ x[1]\ \dots\ x[N-1]]^T$

Taking the PDFs of the two hypotheses, putting them in eq. (4.6) and after some mathematical calculations we manage to evaluate the *decision statistic* $T(\mathbf{x})$ of the MF detector. Thus, the detector decides $\mathcal{H}_1$ if:

$$T(\mathbf{x}) = \sum_{n=0}^{N-1} x[n]s[n] > \gamma' \tag{4.7}$$

where $\gamma'$ is a new threshold. This means that in eq. (4.7) if $T(\mathbf{x})$ is greater than the threshold, then the detector has detected a PU's signal.

The detector in eq. (4.7) is referred to as a *correlator* or *replica-correlator* since we correlate the received signal with a replica of the signal. In Figure 4.2 the replica-correlator detector is shown.

**Performance** We now determine the detection performance. Specifically, we will derive $P_D$ for a given $P_{FA}$. Using the eq. (4.7) we decide $\mathcal{H}_1$ if

$$T(\mathbf{x}) = \sum_{n=0}^{N-1} x[n]s[n] > \gamma'$$

.

Under both hypotheses, $x[n]$ is Gaussian and $T(\mathbf{x})$ is also Gaussian as it is a linear combination of Gaussian random variables. By $E(T;\mathcal{H}_i)$ we

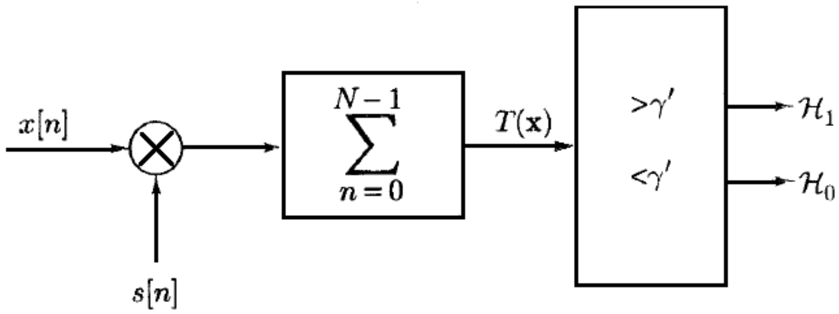


Figure 4.2: Neyman-Pearson detector for deterministic signals (replica correlator).

denote the expected value and by $var(T; \mathcal{H}_i)$ we denote the variance under hypothesis $\mathcal{H}_i$. Then we have:

$$E(T; \mathcal{H}_0) = E\left(\sum_{n=0}^{N-1} w[n]s[n]\right) = 0$$

$$var(T; \mathcal{H}_0) = \text{var}\left(\sum_{n=0}^{N-1} w[n]s[n]\right) = \sum_{n=0}^{N-1} \text{var}(w[n])s^2[n] = \sigma^2 \sum_{n=0}^{N-1} s^2[n] = \sigma^2 \mathcal{E}$$

where $\mathcal{E}$ is the energy of the source signal $s[n]$.

$$E(T; \mathcal{H}_1) = E\left(\sum_{n=0}^{N-1} (s[n] + w[n])s[n]\right) = \mathcal{E}$$

and finally the variance under hypothesis $\mathcal{H}_1$ is:

$$\text{var}(T; \mathcal{H}_1) = \text{var}\left(\sum_{n=0}^{N-1} (s[n] + w[n])s[n]\right) = \sigma^2 \mathcal{E}$$

Thus, the distributions of the test statistic under either hypotheses, $\mathcal{H}_0$ and $\mathcal{H}_1$ are, respectively:

$$T \sim \begin{cases} \mathcal{N}(0, \sigma^2 \mathcal{E}) & \text{under } \mathcal{H}_0, \\ \mathcal{N}(\mathcal{E}, \sigma^2 \mathcal{E}) & \text{under } \mathcal{H}_1 \end{cases}$$

Now, we are going to calculate the performance of the MF detector, by calculating the probability of false alarm and the probability of detection. As the probability of false alarm ($P_{FA}$) is defined when there is no signal, i.e. only noise, and we detect signal, from the distribution of the test statistic $T$ under hypothesis $\mathcal{H}_0$ we have:

$$P_{FA} = Pr\{\mathcal{H}_1|\mathcal{H}_0\} = Pr\{T > \gamma'|\mathcal{H}_0\} = Q\left(\frac{\gamma'}{\sqrt{\sigma^2\mathcal{E}}}\right). \tag{4.8}$$

The probability of detection ($P_D$) is defined when in the received signal there is source signal with noise and we detect the source signal. From the distribution of the test statistic $T$ under hypothesis $\mathcal{H}_1$ we have:

$$P_D = Pr\{\mathcal{H}_1|\mathcal{H}_1\} = Pr\{T > \gamma'|\mathcal{H}_1\} = Q\left(\frac{\gamma' - \mathcal{E}}{\sqrt{\sigma^2\mathcal{E}}}\right). \tag{4.9}$$

Thus, equations (4.8) and (4.9) give us the theoretical performance of the MF detector. Subsequently, we are going to calculate the threshold, which is a very important component of the detector as, in a way, it determines the performance of the detector.

Since we do not know if there is signal or not, it is difficult to set the threshold based on the $P_D$. So, we, usually, calculate it based on the $P_{FA}$. Hence, based on eq. (4.8) we have for the threshold $\gamma'$:

$$\gamma' = Q^{-1}(P_{FA})\sqrt{\sigma^2\mathcal{E}}. \tag{4.10}$$

We can do that because $Q(x) = 1 - \Phi(x)$ and $\Phi(x)$ is monotonically increasing, so $Q(x)$ is monotonically decreasing and has an inverse $Q^{-1}(\cdot)$. Figure 4.3 shows the values of the $Q(x)$ function.

Returning to the calculation of the performance of the MF detector, we have from combining the equations (4.9) and (4.10) the evaluation of the probability of detection of the MF detector. That is:

$$P_D = Q\left(\frac{\sqrt{\sigma^2\mathcal{E}}Q^{-1}(P_{FA})}{\sqrt{\sigma^2\mathcal{E}}} - \sqrt{\frac{\mathcal{E}}{\sigma^2}}\right) = Q\left(Q^{-1}(P_{FA}) - \sqrt{\frac{\mathcal{E}}{\sigma^2}}\right). \tag{4.11}$$

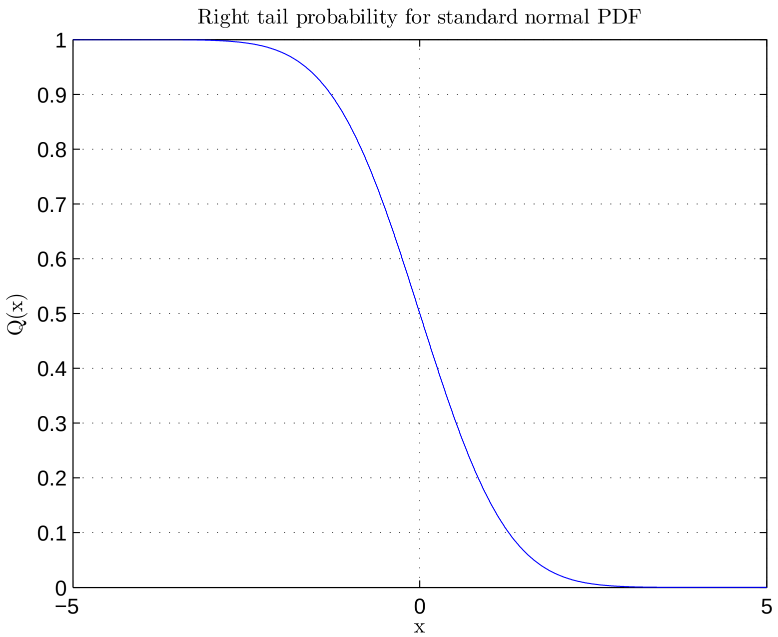


Figure 4.3: Right tail probability for standard normal PDF.

**Simulation** The detection performance and the Receiver Operating Characteristics (ROC) are shown in figures. In Figures 4.4 and 4.5 we can see the performance of the MF detector for different values of target $P_{FA}$, for $P_{FA} = 10^{-1}$ and $P_{FA} = 10^{-3}$ in the first case and for $P_{FA} = 10^{-5}$ and $P_{FA} = 10^{-7}$ in the second case. As we can observe from these figures, if we want to increase the detection performance we can always increase the $P_{FA}$ and/or increase the $ENR$, which is the energy-to-noise ratio, and we can do that by increasing the signal energy. We define $ENR$ as $10\log_{10}(\mathcal{E}/\sigma^2)$ and $\mathcal{E} = \sum_{n=0}^{N-1} s^2[n]$.

Another way to show the performance of a detector is the ROC in which the $P_D$ is plotted versus $P_{FA}$. Each point of the curve corresponds to a value of the set ($P_D$, $P_{FA}$) for a given threshold $\gamma$. As $\gamma$ increases, $P_D$ and $P_{FA}$ decrease and, as $\gamma$ decreases, $P_D$ and $P_{FA}$ increase. One characteristic of the ROC curve is that it should be always above the $45^o$ line. Figure 4.6 shows the ROC for the MF detector for different values of the $SNR$, where

$SNR_{dB} = 10\log_{10}\frac{\sigma_s^2}{\sigma^2}$.

### 4.3.1 Generalized Matched Filter

The MF is an optimal detector for a known signal in WGN. In this subsection we model the noise as *correlated noise*. Thus, we now assume that $\mathbf{w} \sim \mathcal{N}(\mathbf{0{,}C})$, where $\mathbf{C}$ is the covariance matrix.

**Model** The detection problem is to distinguish between the two hypotheses:

$$\begin{aligned} \mathcal{H}_0 : \quad & x[n] = w[n], & n = 0, 1, \ldots, N-1 \\ \mathcal{H}_1 : \quad & x[n] = s[n] + w[n], & n = 0, 1, \ldots, N-1 \end{aligned} \tag{4.12}$$

where s[n] is the source signal and is assumed known. The covariance matrix $\mathbf{C}$ is, also, assumed known.

**Decision Statistic** To determine the NP detector we again determine the likelihood ratio test (LRT) with

$$p(\mathbf{x}|\mathcal{H}_1) = \frac{1}{(2\pi)^{N/2}\det^{1/2}(\mathbf{C})}\exp\left[-\frac{1}{2}(\mathbf{x}-\mathbf{s})^T\ \mathbf{C}^{-1}(\mathbf{x}-\mathbf{s})\right] \tag{4.13}$$

$$p(\mathbf{x}|\mathcal{H}_0) = \frac{1}{(2\pi)^{N/2}\det^{1/2}(\mathbf{C})}\exp\left[-\frac{1}{2}\mathbf{x}^T\ \mathbf{C}^{-1}\mathbf{x}\right] \tag{4.14}$$

where we have noted that under $\mathcal{H}_0$, $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{C})$ and under $\mathcal{H}_1$, $\mathbf{x} \sim \mathcal{N}(\mathbf{s}, \mathbf{C})$.

We decide $\mathcal{H}_1$ if

$$l(\mathbf{x}) = \ln\frac{p(\mathbf{x}|\mathcal{H}_1)}{p(\mathbf{x}|\mathcal{H}_0)} > \ln\gamma. \tag{4.15}$$

But

$$\begin{aligned} l(\mathbf{x}) &= -\frac{1}{2}\left[(\mathbf{x}-\mathbf{s})^T\mathbf{C}^{-1}(\mathbf{x}-\mathbf{s}) - \mathbf{x}^T\mathbf{C}^{-1}\mathbf{x}\right] \\ &= -\frac{1}{2}\left[\mathbf{x}^T\mathbf{C}^{-1}\mathbf{x} - 2\mathbf{x}^T\mathbf{C}^{-1}\mathbf{s} + \mathbf{s}^T\mathbf{C}^{-1}\mathbf{s} - \mathbf{x}^T\mathbf{C}^{-1}\mathbf{x}\right] \\ &= \mathbf{x}^T\mathbf{C}^{-1}\mathbf{s} - \frac{1}{2}\mathbf{s}^T\mathbf{C}^{-1}\mathbf{s} \end{aligned} \tag{4.16}$$

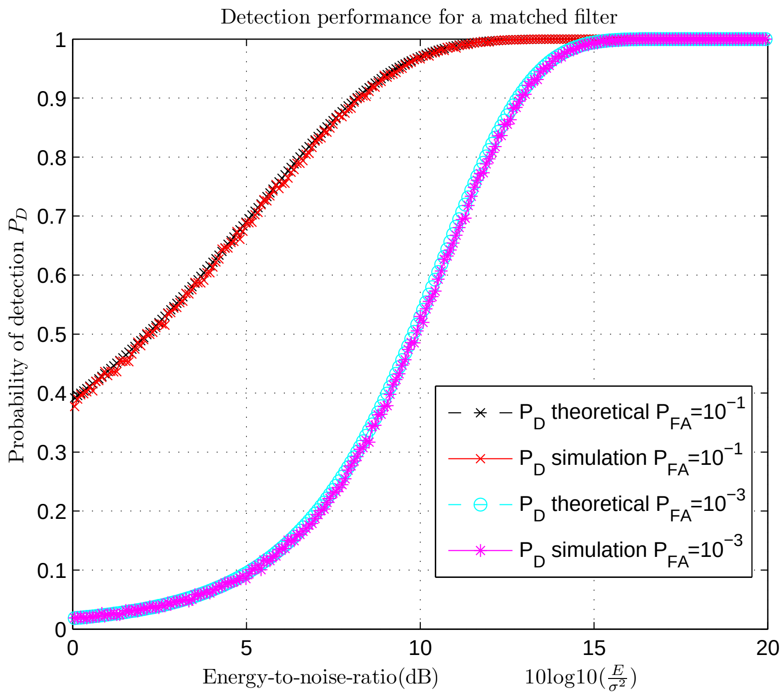


Figure 4.4: Detection performance of matched filter for target $P_{FA} = 10^{-1}$ and $P_{FA} = 10^{-3}$.

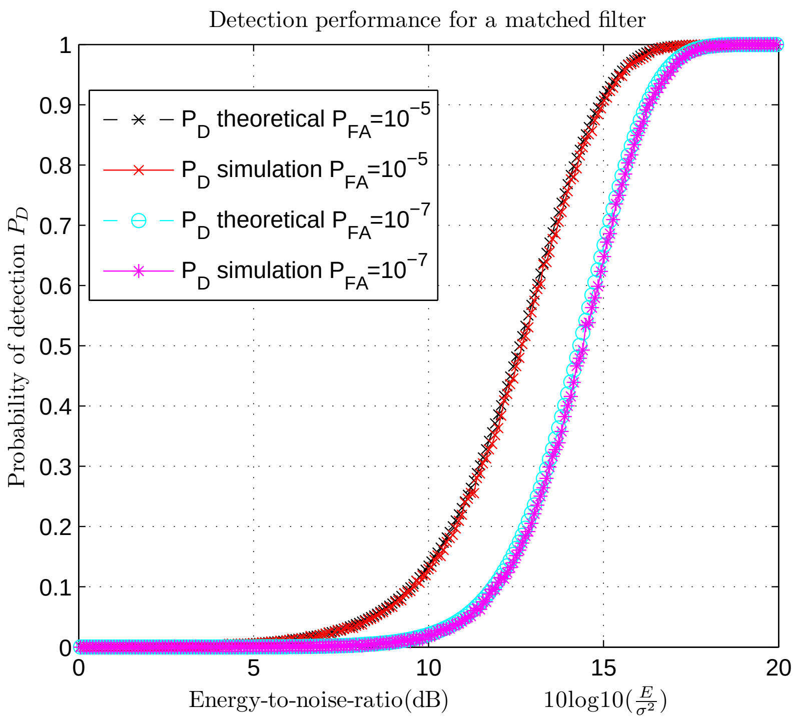


Figure 4.5: Detection performance of matched filter for target $P_{FA} = 10^{-5}$ and $P_{FA} = 10^{-7}$.

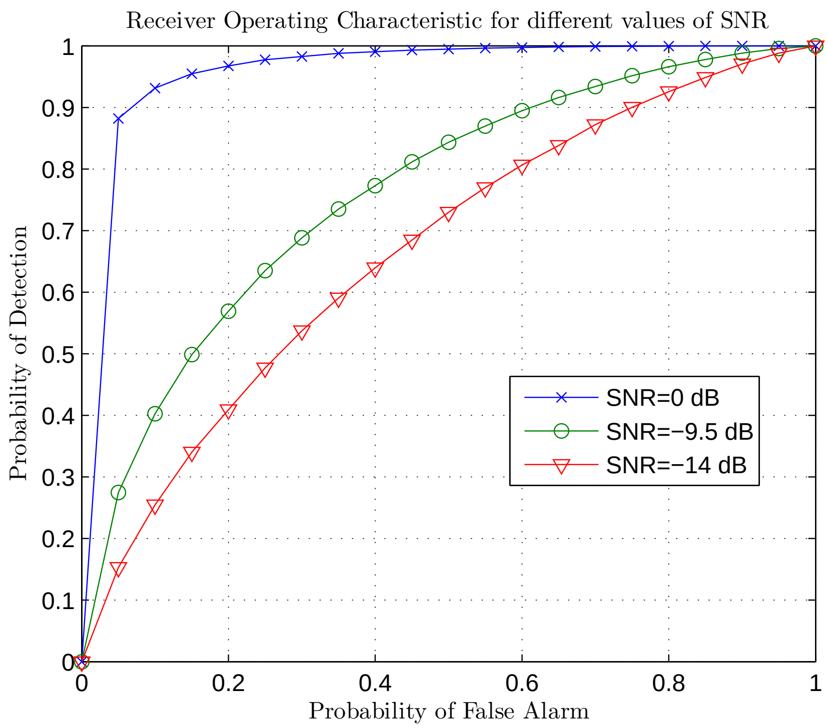


Figure 4.6: ROC curves for MF detector under different values of $SNR_{dB}$.

or by incorporating the non-data dependent term into the threshold we decide $\mathcal{H}_1$ if

$$T(\mathbf{x}) = \mathbf{x}^T \mathbf{C}^{-1} \mathbf{s} > \gamma. \tag{4.17}$$

The detector of eq. (4.17) is referred to as a *generalized replica-correlator*. The replica is the modified signal $\mathbf{s}' = \mathbf{C}^{-1}\mathbf{s}$.

**Performance** The generalized MF decides $\mathcal{H}_1$ if

$$T(\mathbf{x}) = \mathbf{x}^T \mathbf{C}^{-1} \mathbf{s} > \gamma'.$$

Under either hypotheses the test statistic is Gaussian, as it is a linear transformation of $\mathbf{x}$. Then, to derive the $P_D$ we do the same things as in MF detector. We have:

$$E(T|\mathcal{H}_0) = E(\mathbf{w}^T\mathbf{C}^{-1}\mathbf{s}) = 0$$

$$E(T|\mathcal{H}_1) = E\left[(\mathbf{s}+\mathbf{w})^T\mathbf{C}^{-1}\mathbf{s}\right] = \mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}$$

$$\mathrm{var}(T|\mathcal{H}_0) = E\left[(\mathbf{w}^T\mathbf{C}^{-1}\mathbf{s})^2\right] = E(\mathbf{s}^T\mathbf{C}^{-1}\mathbf{w}\mathbf{w}^T\mathbf{C}^{-1}\mathbf{s}) = \mathbf{s}^T\mathbf{C}^{-1}E(\mathbf{w}\mathbf{w}^T)\mathbf{C}^{-1}\mathbf{s} = \mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}$$

and finally,

$$\mathrm{var}(T|\mathcal{H}_1) = \mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}$$

This means that:

$$T \sim \begin{cases} \mathcal{N}(0,\ \mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}), & \text{under } \mathcal{H}_0 \\ \mathcal{N}(\mathbf{s}^T\mathbf{C}^{-1}\mathbf{s},\ \mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}), & \text{under } \mathcal{H}_1 \end{cases}$$

Thus, we have for the $P_{FA}$ and for the threshold $\gamma'$:

$$P_{FA} = Pr\{\mathcal{H}_1|\mathcal{H}_0\} = Q\left(\frac{\gamma'}{\sqrt{\mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}}}\right) \Rightarrow \gamma' = Q^{-1}\left(P_{FA}\right)\sqrt{\mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}}, \tag{4.18}$$

and the $P_D$ for a target $P_{FA}$ is

$$P_D = Pr\{\mathcal{H}_1|\mathcal{H}_1\} = Q\left(\frac{\gamma' - \mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}}{\sqrt{\mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}}}\right) \tag{4.19}$$

and with the help of eq. (4.18) we can transform the eq. (4.19) into:

$$P_D = Q\left(Q^{-1}(P_{FA}) - \sqrt{\mathbf{s}^T\mathbf{C}^{-1}\mathbf{s}}\right). \tag{4.20}$$

So, we derived the threshold and the $P_D$ for the generalized MF detector and now we are ready to show the detection performance of that detector based on the above equations and on simulations.

**Simulation** The detection performance of the generalized MF is summarized in Figure 4.7 and in Figure 4.8 the ROC is shown. In the first figure, we can see the curves that are created from the theoretical expressions of the $P_D$, i.e. from eq. (4.20) and the curves that are created via simulation. We plot the $P_D$ versus the $ENR_{dB}$ which is defined as $10\log_{10}(\mathbf{s}^T\mathbf{C}^{-1}\mathbf{s})$. We can see that the theoretical and the simulation are matched for both the values of $P_{FA}$. Also, we can observe that when the $P_{FA}$ increases, the detection probability increases as well. This happens because when a detector throws false alarm frequently this means that it will detect the signal properly more frequently. The first figure is derived for covariance matrix $\mathbf{C} = \begin{bmatrix} 4 & 0 \\ 0 & 9 \end{bmatrix}$ and the second figure is derived for covariance matrices $\mathbf{C}_{ENR_1} = \begin{bmatrix} 9 & 0 \\ 0 & 16 \end{bmatrix}$, $\mathbf{C}_{ENR_2} = \begin{bmatrix} 1 & 0 \\ 0 & 4 \end{bmatrix}$, $\mathbf{C}_{ENR_3} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

### 4.3.2 Pilot-Based Detection

Most wireless communication systems exhibit certain known patterns, such as pilot tones, preambles, midambles, spreading codes etc, which are used to assist control, equalization, synchronization, continuity or reference purposes. These pilot tones are transmitted periodically. Even though perfect information of a PU's signal may not be attainable, if a certain pattern is known from the received signals, *pilot-based detection* can be used to decide whether there is the signal of the licensed user or not. A brief description of pilot-based detection follows.

**Model** There are two hypotheses:

$$\begin{aligned} \mathcal{H}_0 :&\quad y(n) = w(n), && 0 \leq n \leq N-1 \\ \mathcal{H}_1 :&\quad y(n) = hp(n) + w(n), && 0 \leq n \leq N-1 \end{aligned} \tag{4.21}$$

where $p(n)$ is the *pilot sequence*, $w(n)$ is the white noise, $h$ is the unknown quasi-static block fading channel from the PU to the CR user. If we define

$$P_p = \frac{1}{N}\sum_{n=0}^{N-1} |p(n)|^2 \tag{4.22}$$

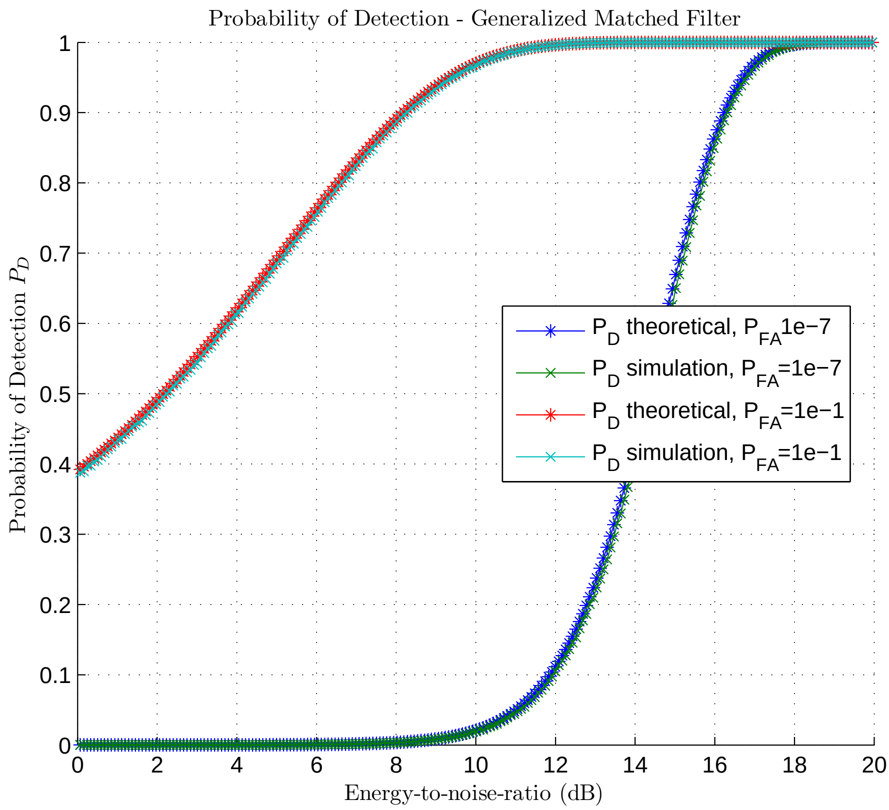


Figure 4.7: Performance of detection for the generalized MF for a variety of target $P_{FA}$.

as the average power of the pilot signal, then the instantaneous $SNR$ is given by

$$\gamma = \frac{|h|^2 P_p}{\sigma_n^2} \tag{4.23}$$

where $\sigma_n^2$ is the noise power.

**Decision Statistic** Using the Generalized Likelihood Ratio Test (GLRT) the NP detector decides $\mathcal{H}_1$ if the likelihood ratio exceeds a threshold $\gamma$ or

$$L(\mathbf{y}) = \frac{p(\mathbf{y}; \hat{h}_{ML}|\mathcal{H}_1)}{p(\mathbf{y}|\mathcal{H}_0)} > \gamma \tag{4.24}$$

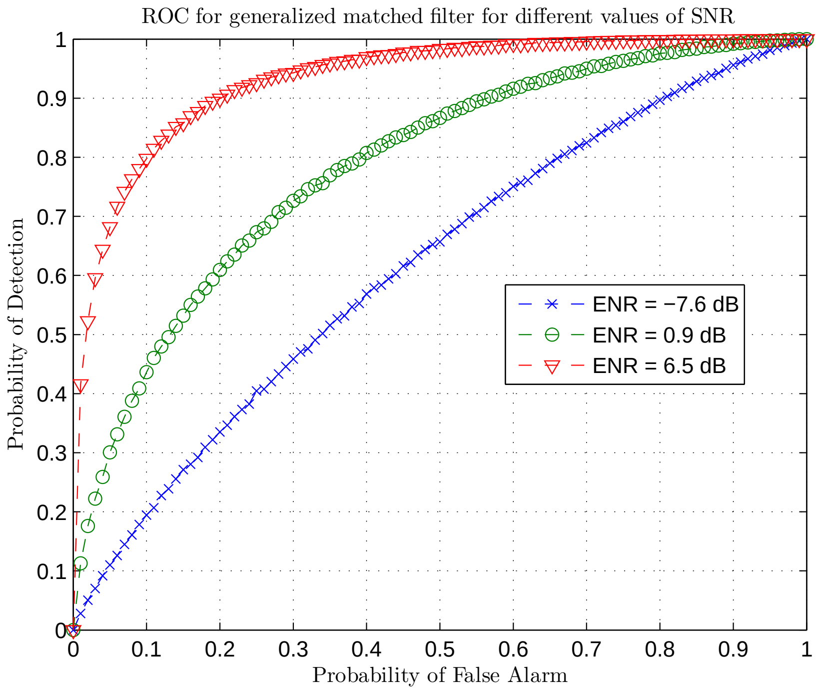


Figure 4.8: ROC for the generalized MF for a variety of values of $ENR_{dB}$.

We, then, take the logarithms of the two PDFs and after some mathematical calculations the test statistic of the coherent detection yields:

$$Y = \left| \sqrt{\frac{2}{NP_p\sigma_n^2}} \sum_{n=0}^{N-1} y(n)p^*(n) \right|^2 \tag{4.25}$$

which under $\mathcal{H}_0$ and $\mathcal{H}_1$ becomes:

$$Y = \begin{cases} \left| \sqrt{\frac{2}{NP_p\sigma_n^2}} \sum_{n=0}^{N-1} w(n)p^*(n) \right|^2, & \text{under } \mathcal{H}_0 \\ \left| \sqrt{\frac{2NP_p}{\sigma_n^2}} h + \sqrt{\frac{2}{NP_p\sigma_n^2}} \sum_{n=0}^{N-1} w(n)p^*(n) \right|^2, & \text{under } \mathcal{H}_1 \end{cases}$$

and we make the decision from the above test statistic by comparing it with a predetermined threshold $\gamma$, which is chosen that way to satisfy a target probability of false alarm.

Under $\mathcal{H}_0$, the test statistics $Y$ of that detector follows a *central chi-squared* distribution with two degrees of freedom. This happens because the expected value of $Y$ under $\mathcal{H}_0$ is 0 and its variance is 2 because it is a complex number squared, with real (Re) part and imaginary (Im) part. Re $\sim (0, 1)$ and Im $\sim (0, 1)$ are summed, thus the test statistic under $\mathcal{H}_0$ has expected value equal to 0 and variance equal to 2.

Under $\mathcal{H}_1$, $Y$ has a *noncentral chi-squared* distribution with two degrees of freedom and a non centrality parameter $\mu = 2N\gamma$. Summarizing the above, we have

$$f_Y(Y) = \begin{cases} \chi_2^2, & \text{under } \mathcal{H}_0 \\ \chi_2'^2(\mu), & \text{under } \mathcal{H}_1 \end{cases}$$

The central chi-squared distribution arises as the PDF of $x$ where $x = \sum_{i=1}^{\nu} x_i^2$ where $x_i \sim \mathcal{N}(0, 1)$ and the $x_i$s are independent and identically distributed. On the other hand, the noncentral chi-squared distribution arises as the PDF of $x$ where $x = \sum_{i=1}^{\nu} x_i^2$ where $x_i \sim \mathcal{N}(\mu_i, 1)$. Then $x$ has a noncentral chi-squared PDF with $\nu$ degrees of freedom and a noncentrality parameter $\lambda = \sum_{i=1}^{\nu} \mu_i^2$. Figures 4.9 and 4.10 show some examples of the PDFs for central and non central chi-squared RVs, respectively.

**Performance** The performance of the coherent detection is calculated experimentally.

**Simulation** The performance and the ROCs for a variety of values of instantaneous $SNR$ in db are shown in Figure 4.11 for different values of $SNR_{dB}$. As we can see from this figure when $SNR$ increases the detection performance of the coherent detection increases.

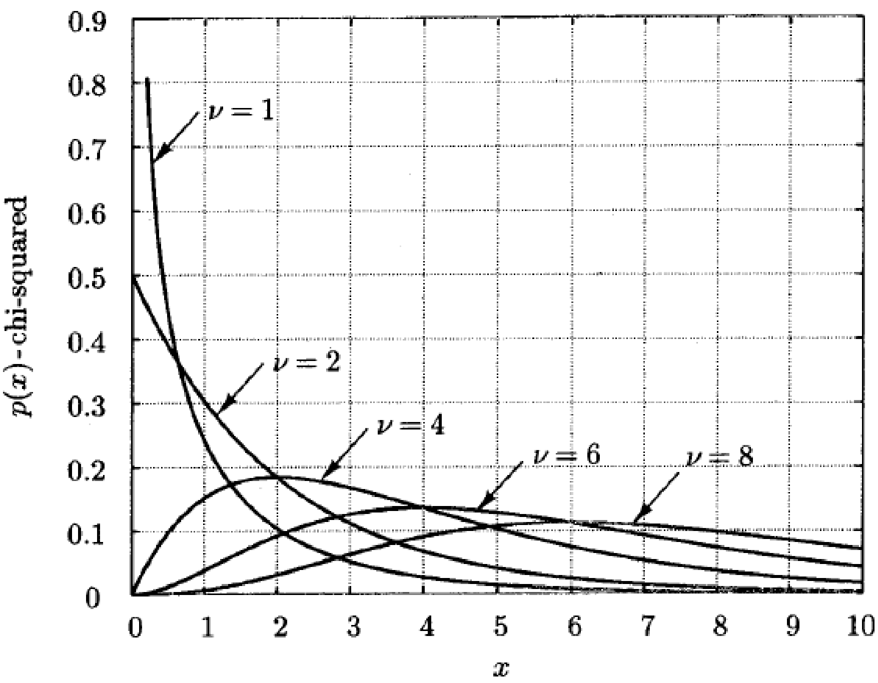


Figure 4.9: PDF for central chi-squared random variable.

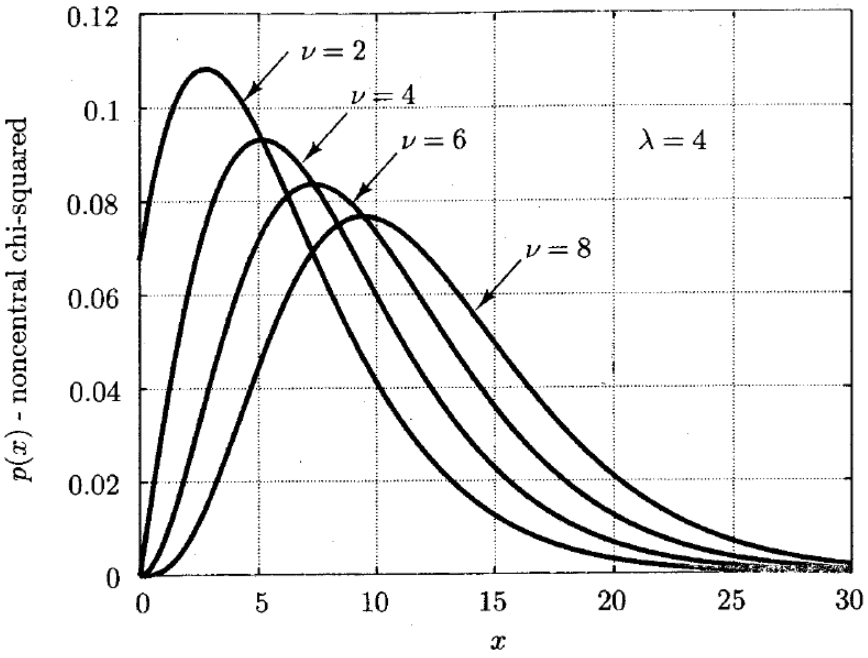


Figure 4.10: PDF for non central chi-squared random variable with varying degrees of freedom ($\nu$) and noncentrality parameter $\lambda = 4$.

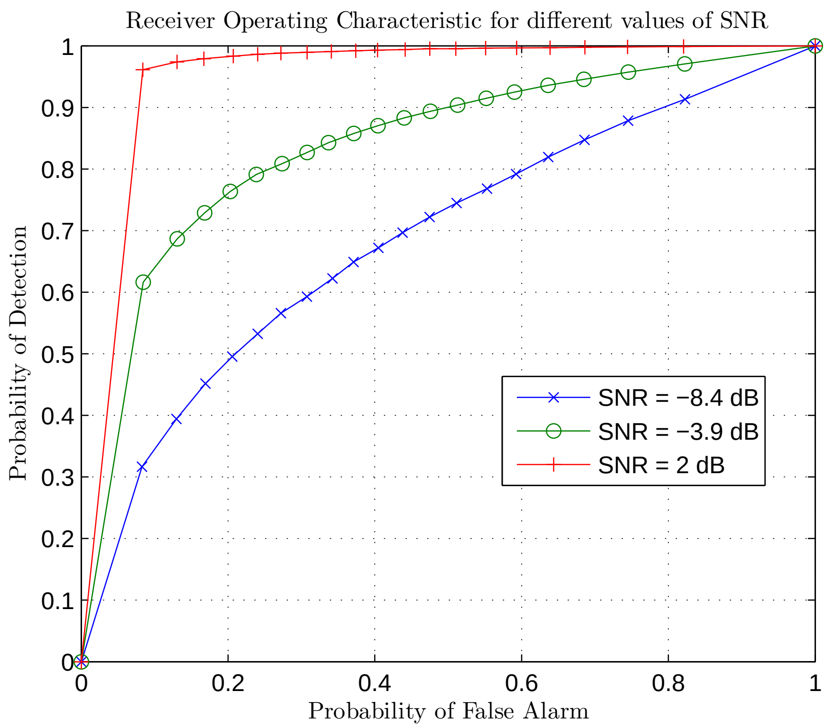


Figure 4.11: ROC curves for coherent detection for different values of $SNR_{dB}$.

## 4.4 Energy Detection

Energy Detection (also known as radiometry) is the simplest spectrum sensing technique and is widely used when there is no a priori information on the source signal. It simply treats the PU's signal as noise and decides on the presence or absence of the primary signal based on the energy of the observed signal. Since it does not need any a priori knowledge of the primary signal, the ED is robust to the variation of the primary signal. Two significant advantages of the ED is that it does not involve complicated signal processing and has low complexity.

Despite its advantages, ED has some drawbacks. It has not good performance under low $SNR$ conditions and there is an inability in differentiating the interference from other SUs sharing the same channel and the PU. This leads to frequently triggering false-alarm. Moreover, ED is not appropriate method for detecting spread spectrum signals.

In section 4.3 we assumed deterministic signals. In this section, we are going to analyze the ED assuming random signals. The analysis of the Energy Detector follows.

**Model** We model the source signal $s[n]$ as a zero mean, white, WSS Gaussian random process with variance $\sigma_s^2$ and the noise $w[n]$ is WGN with variance $\sigma^2$ and independent of the signal. That is, $s \sim \mathcal{N}(0, \sigma_s^2)$ and $w \sim \mathcal{N}(0, \sigma^2)$.

The detection problem is to distinguish between the two hypotheses:

$$\begin{aligned} \mathcal{H}_0 : \quad & x[n] = w[n], & n = 0, 1, \ldots, N-1 \\ \mathcal{H}_1 : \quad & x[n] = s[n] + w[n], & n = 0, 1, \ldots, N-1 \end{aligned} \tag{4.26}$$

**Decision Statistic** The NP detector decides $\mathcal{H}_1$ if the likelihood ratio exceeds a threshold $\gamma$ (we are going to analyze later in this section how the threshold is calculated) or

$$L(\mathbf{x}) = \frac{p(\mathbf{x}|\mathcal{H}_1)}{p(\mathbf{x}|\mathcal{H}_0)} > \gamma \tag{4.27}$$

From the above assumptions, we have for the received signal $\mathbf{x} = [x_0, \ x_1, \ , \ldots , \ , \ x_{N-1}]^T$ under $\mathcal{H}_0$ $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \sigma^2\mathbf{I})$ and under $\mathcal{H}_1$ $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, (\sigma_s^2 + \sigma^2)\mathbf{I})$. So, now, from eq. (4.27) we are going to evaluate the decision statistic for the ED taking the PDFs of the two hypotheses. Eq. (4.27) becomes:

$$L(\mathbf{x}) = \frac{\frac{1}{[2\pi(\sigma_s^2+\sigma^2)]^{\frac{N}{2}}} \exp\left[-\frac{1}{2(\sigma_s^2+\sigma^2)} \sum_{n=0}^{N-1} x^2[n]\right]}{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} x^2[n]\right]} \tag{4.28}$$

and after some mathematical calculations to the eq. (4.28) the decision statistic for the ED yields:

$$T(\mathbf{x}) = \sum_{n=0}^{N-1} x^2[n] > \gamma' \tag{4.29}$$

**Performance** We can observe from eq. (4.29) that the test statistic measures the energy of the received data and compares it to a threshold. If the signal is present, the energy of the received data increases. By dividing the test statistic $T(x)$ with $\sigma^2$ in the first case and with $\sigma^2 + \sigma_s^2$ in the second case, the distribution of the statistic becomes:

$$\frac{T(\mathbf{x})}{\sigma^2} \sim \chi_N^2 \qquad \text{under } \mathcal{H}_0 \tag{4.30}$$

$$\frac{T(\mathbf{x})}{\sigma_s^2 + \sigma^2} \sim \chi_N^2 \qquad \text{under } \mathcal{H}_1 \tag{4.31}$$

Hence, from (4.30), (4.31) and (4.29), for a given threshold $\gamma'$, we are able to compute the probability of false alarm and the probability of detection of the ED. The $P_{FA}$ is when there is only noise but the detector detects PU's signal and the $P_D$ is when there is PU's signal and noise and the detector detects it. Thus:

$$\begin{aligned} P_{FA} &= Pr\{\mathcal{H}_1 | \mathcal{H}_0\} \\ &= Pr\{T(\mathbf{x}) > \gamma' | \mathcal{H}_0\} \\ &= Pr\left\{\frac{T(\mathbf{x})}{\sigma^2} > \gamma'\right\} \\ &= Q_{\chi_N^2}\left(\frac{\gamma'}{\sigma^2}\right) \end{aligned} \tag{4.32}$$

and

$$\begin{aligned} P_D &= Pr\{\mathcal{H}_1 | \mathcal{H}_1\} \\ &= Pr\{T(\mathbf{x}) > \gamma' | \mathcal{H}_1\} \\ &= Pr\left\{\frac{T(\mathbf{x})}{\sigma_s^2 + \sigma^2} > \gamma'\right\} \\ &= Q_{\chi_N^2}\left(\frac{\gamma'}{\sigma_s^2 + \sigma^2}\right). \end{aligned} \tag{4.33}$$

If we define the $SNR$ as the ratio of the power of the source signal to the power of the noise, i.e. $\sigma_s^2/\sigma^2$, then from eq. (4.33) we can see that the detection performance increases as the $SNR$ increases. We show that:

$$P_D = Q_{\chi_N^2}\left(\frac{\gamma'/\sigma^2}{\sigma_s^2/\sigma^2 + 1}\right) \tag{4.34}$$

So, when $\sigma_s^2/\sigma^2$ increases, the argument of the $Q_{\chi_N^2}$ decreases and the probability of detection increases.

Now, we are going to evaluate the threshold. For its evaluation we use the recursive algorithm from the Problem 5.1 in p. 176 from the book *Fundamentals of Statistical Signal Processing-Detection Theory* by Steven Kay. Then, we have

$$P_{FA} = \exp\left(-\frac{\gamma'}{2\sigma^2}\right)\left[1 + \sum_{r=1}^{\frac{N}{2}-1} \frac{\left(\frac{\gamma'}{2\sigma^2}\right)^r}{r!}\right] \tag{4.35}$$

And then by letting $\gamma'' = \gamma'/2\sigma^2$ and rearranging terms we have:

$$\gamma'' = -\ln P_{FA} + \ln\left[1 + \sum_{r=1}^{\frac{N}{2}-1} \frac{(\gamma'')^r}{r!}\right] \tag{4.36}$$

Finally, we can evaluate the threshold $\gamma'$ by using the fixed point iteration:

$$\gamma''_{k+1} = -\ln P_{FA} + \ln\left[1 + \sum_{r=1}^{\frac{N}{2}-1} \frac{(\gamma''_k)^r}{r!}\right] \tag{4.37}$$

and begin the iteration with $\gamma''_0 = 1$.

**Simulation** The detection performance of the ED for two values of target $P_{FA}$ is shown in Figure 4.12. Also, in Figure 4.13 the Receiver Operating Characteristic for different values of $SNR$ in dB is shown. In the first figure we can see the curves that are created from the theoretical types of the $P_D$, i.e. from eq. (4.33) and the curves that are created via simulation. We can see that the theoretical and the simulation are matched for both values of $P_{FA}$.

## 4.5 Covariance-Based Detection

The key idea behind covariance-based detection is that the PU's signal received at the CR user is usually correlated because of the dispersive channels, the utility

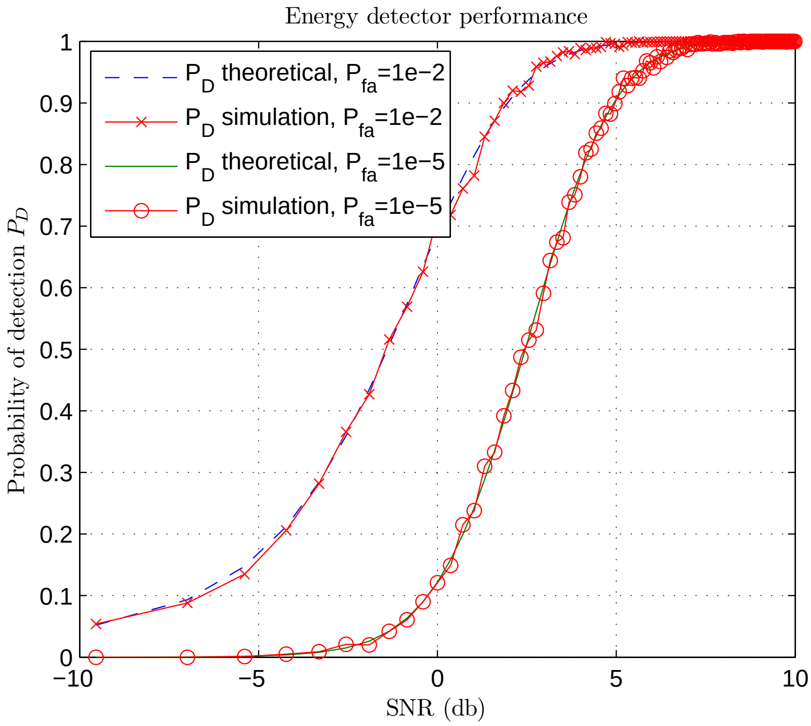


Figure 4.12: Performance of detection for the ED for a variety of target $P_{FA}$.

of multiple receive antennas or even over-sampling. Such correlation can be used by the CR user to differentiate the signal of the licensed user from white noise.

Covariance-based detector determines the presence or absence of the primary signal based on the covariance matrix of the received signal. Specifically, based on the ratio of maximum eigenvalue to minimum eigenvalue of the covariance matrix of the received signal we can detect the signal existence.

The analysis of the *maximum-minimum eigenvalue* (MME) detection follows.

**Model** The detection problem is to distinguish between the two hypotheses:

$$\begin{aligned} \mathcal{H}_0 : \quad & x[n] = w[n], & n = 0, 1, \ldots, N-1 \\ \mathcal{H}_1 : \quad & x[n] = \sum_{k=0}^{N} h[k]s[n-k] + w[n], & n = 0, 1, \ldots, N-1 \end{aligned} \tag{4.38}$$

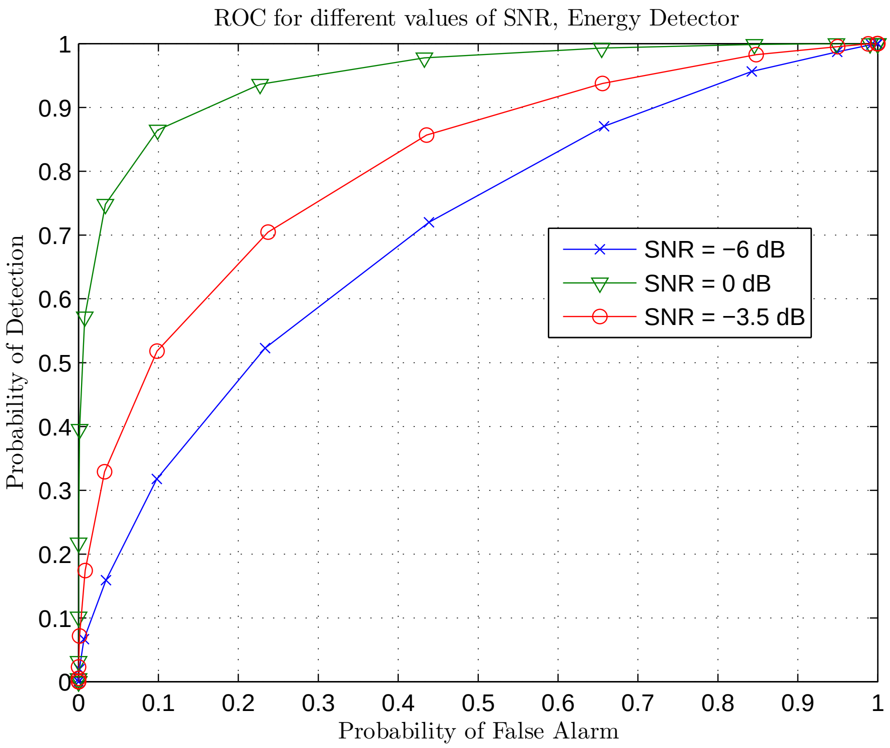


Figure 4.13: ROC for the ED for a variety of values of $SNR_{dB}$.

where $h$ is the channel response from source signal to the receiver, $s[n]$ is the PU's signal, $w[n]$ is the additive noise and $x[n]$ is the received signal in the CR receiver. Based on the received signals with little information on the source signals, noise power and channel responses a sensing algorithm should make a decision on the existence or the absence of the PU's signal. For a good detection algorithm (obviously for every algorithm discussed in this thesis) we want the $P_D$ to be high and the $P_{FA}$ to be low.

**Decision Statistic** The next step that we must do in this algorithm is to compute the covariance matrix of the received signal, that is:

$$\mathbf{R}(N_s) = \frac{1}{N_s} \sum_{n=L}^{L-1+N_s} x(n)x^{\dagger}(n) \tag{4.39}$$

where $N_s$ is the number of collected samples, $L$ is the number of consecutive outputs of the received signal and the superscript † denotes the transconjucate (or Hermitian) of the complex signal $x(n)$.

After the computation of $\mathbf{R}$ matrix from eq. (4.39) we must find its eigenvalues and obtain the maximum and the minimum eigenvalue of the matrix. Let $\lambda_{max}$ and $\lambda_{min}$ be the maximum and the minimum eigenvalue, respectively. Subsequently, we can make our decision from the two hypotheses of eq. (4.38) based on the ratio $\lambda_{max}/\lambda_{min}$.

Thus, if $\lambda_{max} > \gamma\lambda_{min}$ signal exists, i.e. hypothesis $\mathcal{H}_1$. Otherwise, signal does not exist, i.e. hypothesis $\mathcal{H}_0$. In the previous cases, $\gamma$ is the threshold and we are going to show later the way that is evaluated.

**Performance** The threshold, theoretically, is computed from the next equation for a given $P_{FA}$:

$$\gamma = \frac{(\sqrt{N_s}+\sqrt{L})^2}{(\sqrt{N_s}-\sqrt{L})^2}\left(1+\frac{(\sqrt{N_s}+\sqrt{L})^{-2/3}}{(N_sL)^{1/6}}F_2^{-1}(1-P_{FA})\right) \tag{4.40}$$

where $F_2(\cdot)$ is the CDF of the 2nd order Tracy-Widom distribution.

Generally, it is difficult to obtain a closed form expression of the detection probability $P_D = Pr\{\lambda_{max} > \gamma\lambda_{min}|\mathcal{H}_1\}$, so in the next figures the detection performance and the ROCs are computed experimentally.

**Simulation** The Receiver Operating Characteristic for the MME detector for two values of the $SNR$ in dB is shown in Figure 4.14. From that figure we can observe that when the $SNR$ increases, the detection performance increases as well. Furthermore, we can see that for low $SNR$ the red curve does not fall under the $45^o$ line, which means that, still, in this case the detection performance is satisfactory.

The values of the channel $h$ (with dimension $(N+1,1)$) for which the following ROC was produced are:

| Values of channel $h$ |
|---|
| $0.2321 + 0.1188i$ |
| $-1.7022 - 0.55962i$ |
| $-0.5913 + 0.7218i$ |
| $1.1470 - 0.5950i$ |
| $0.8434 - 1.0207i$ |
| $0.1451 + 1.7469i$ |

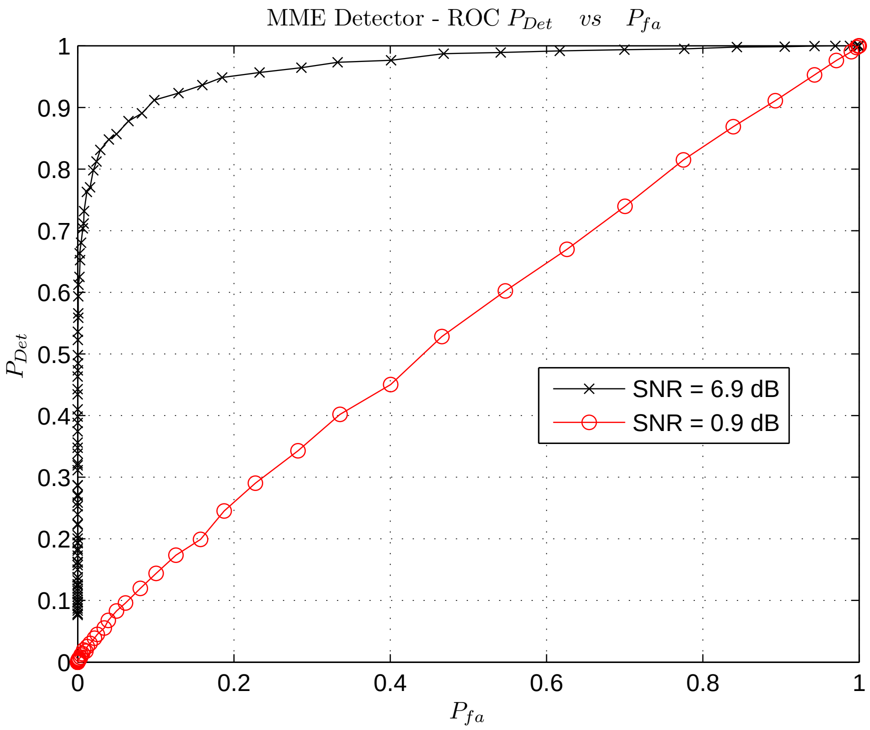


Figure 4.14: ROC for the MME detection for different values of the $SNR$ in dB.

# Chapter 5

# Comparison

## 5.1 Introduction

In this Chapter we are going to compare the different spectrum sensing techniques discussed in Chapter 4.

## 5.2 Energy Detection vs Matched Filter Detection

In this section we are comparing the performance of the ED to the one of the MF Detector. In the experiment we create a random signal and then we use it for the evaluation of the detection performance of each of these two methods. We compute the threshold and the test statistic of each of the methods (with the same signal we created before) and then we evaluate the $P_D$ and the $P_{FA}$ in the same way as in Chapter 4. Visually, the comparison of ED and MF is shown in Figure 5.1 for $SNR = -6$ dB, in Figure 5.2 for $SNR = 0$ dB and in Figure 5.3 for $SNR = 2$ dB.

From these figures we can observe that the MF has better detection performance than the ED for any $SNR$. This is reasonable, as in the MF detection we know information about the PU's signal *a priori* and the MF correlates the already known primary signal with the received signal to detect the presence of the PU. On the other hand, ED has no *a priori* information on the source signal.

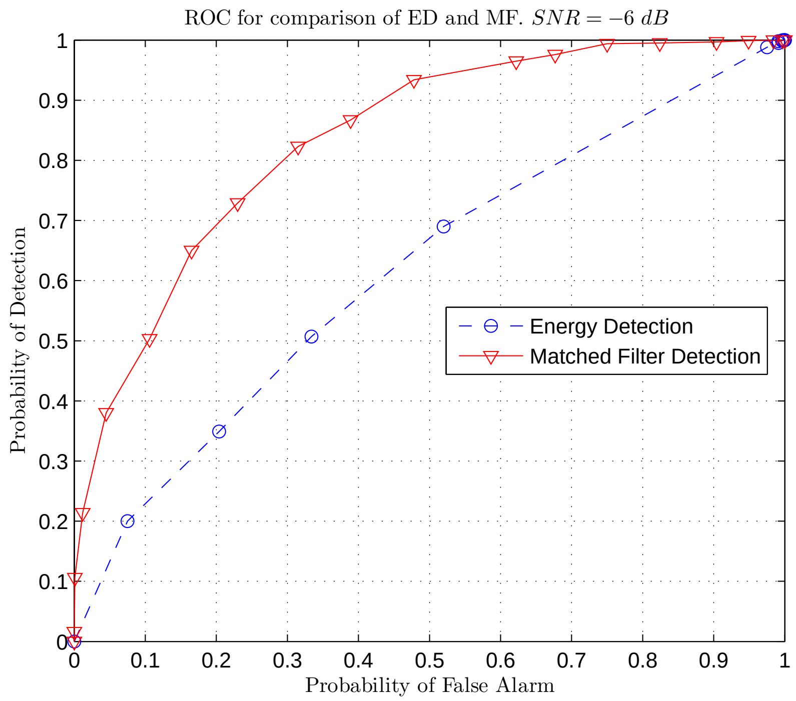


Figure 5.1: Comparison of Energy Detector and Matched Filter Detector for $SNR = -6\ dB$

It simply treats the PU's signal as noise and decides on the presence or absence of the primary signal based on the energy of the observed signal.

## 5.3 Energy Detection vs Matched Filter Detection vs Covariance Based Detection

In this section we compare the performances of the ED, the MF Detector and the Covariance-Based Detection. In the experiment we create a random signal and then we use it for the evaluation of the detection performance of each of these three techniques. Also, we have a channel, assumed known, and the useful signal is the result of the convolution of the signal we created with the values of the channel. The received signal is the summation of the useful signal plus the

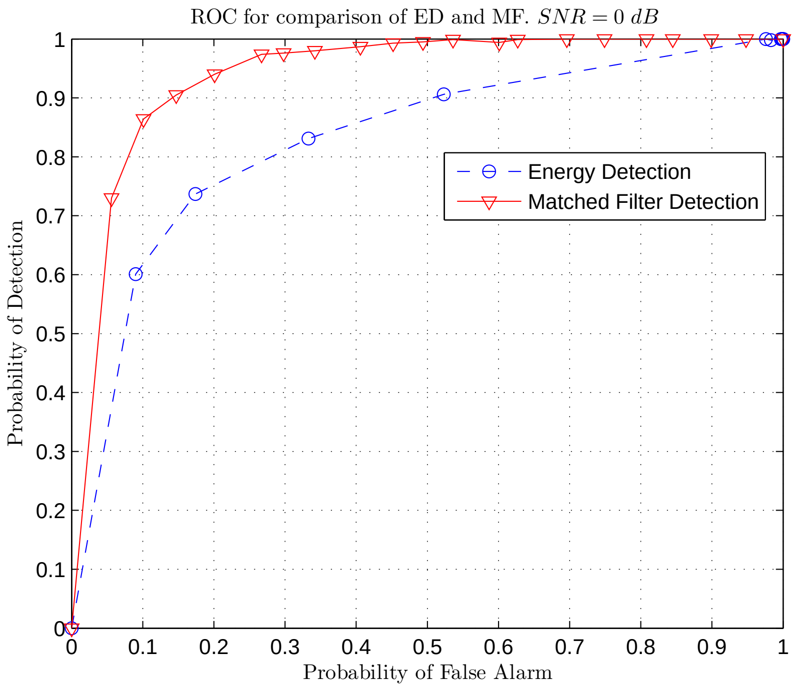


Figure 5.2: Comparison of Energy Detector and Matched Filter Detector for $SNR = 0\ dB$

noise. For the MF detection we assume the useful signal as known. In Figure 5.4 we show the ROCs for the three methods for $SNR = -2.4dB$ and in Figure 5.5 for $SNR = 3dB$. From these figures we can observe that the MF detection has almost excellent performance for low $SNR$ as well as for higher $SNR$. This is because we have perfect knowledge of the signal and the channel. Moreover, we can see that the ED has better performance than the MME detector. In this case we define $SNR$ as $10\log_{10}\left(\frac{||h||^2\sigma_s^2}{\sigma^2}\right)$.

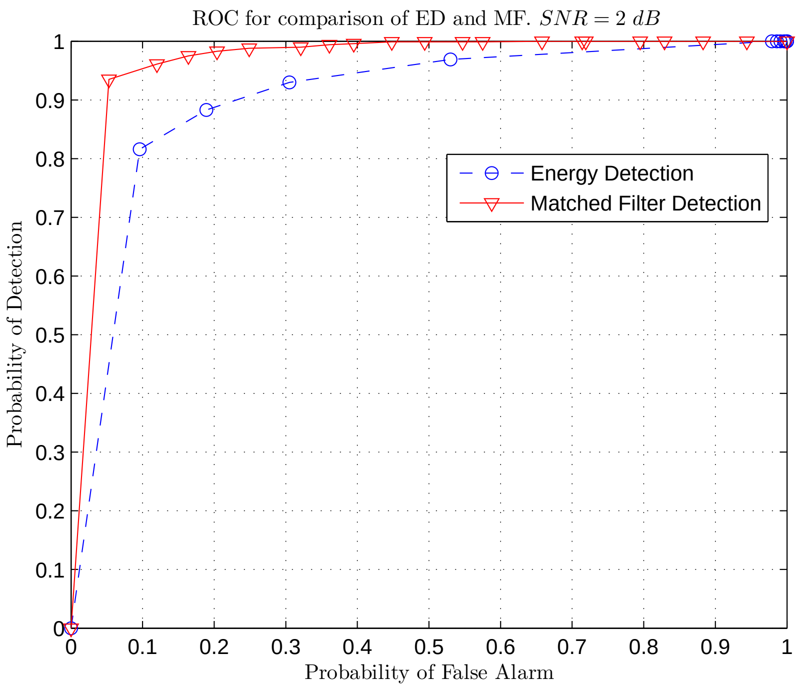


Figure 5.3: Comparison of Energy Detector and Matched Filter Detector for $SNR = 2\ dB$

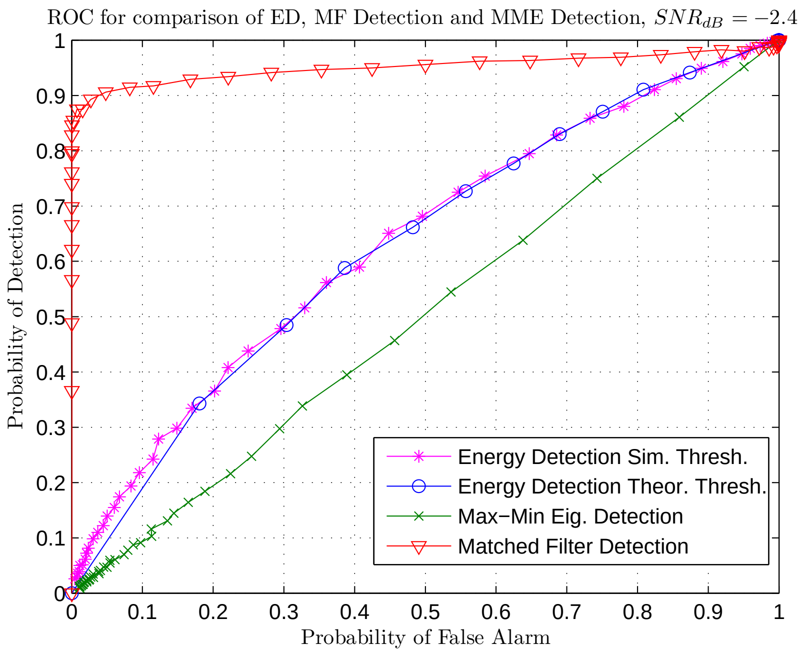


Figure 5.4: Comparison of Energy Detector, Matched Filter Detector and Max-Min Eigenvalue Detection for $SNR = -2.4\ dB$.

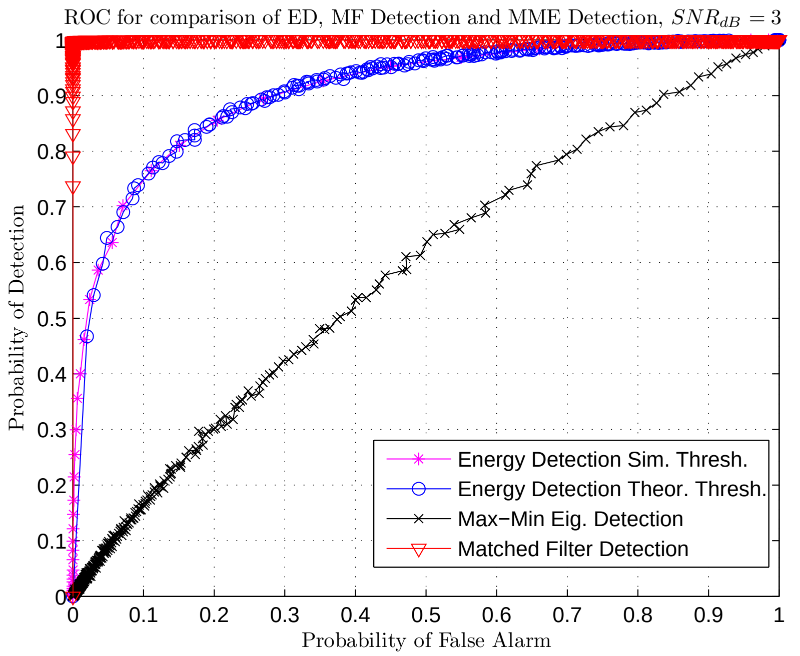


Figure 5.5: Comparison of Energy Detector, Matched Filter Detector and Max-Min Eigenvalue Detection $SNR = 3\ dB$.

# Chapter 6

# Cooperative Spectrum Sensing

## 6.1 Introduction

Spectrum sensing using a single CR has a number of limitations. First of all, the sensitivity of a single sensing device might be limited because of energy constraints. Furthermore, the CR might be located in a deep fade of the PU signal, and as such might miss the detection of this PU. Moreover, although the CR might be blocked from the PU's transmitter, this does not mean it is also blocked from the PU's receiver, i.e. the hidden terminal problem which was described in section 3.4. As a result, the PU is not detected but the secondary transmission could still significantly interfere at the PU's receiver. Figure 6.1 shows that CR3 is shadowed by a high building over the sensing channel (PU to the CR) and that CR1 is shadowed over the reporting channel (CR to Base Station).

## 6.2 General Concept

By taking advantage of the independent fading channels (i.e., spatial diversity) and multiuser diversity, cooperative spectrum sensing is proposed to improve the reliability of spectrum sensing, increase the detection probability to better protect a PU and reduce false alarm to utilize the idle spectrum more efficiently. The concept of cooperative spectrum sensing is to use multiple sensors and combine their measurements into one common decision.

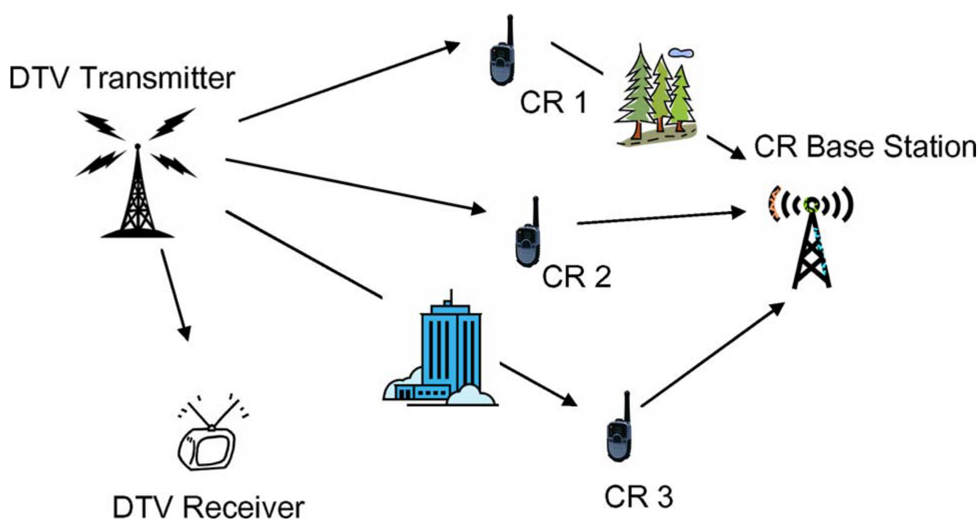


Figure 6.1: Cooperative spectrum sensing in CR networks. CR1 is shadowed over the reporting channel and CR3 is shadowed over the sensing channel. [Letaief and Zhang: "Cooperative Communications for Cognitive Radio Networks"]

The merit of cooperative spectrum sensing primarily lies in the achievable space diversity brought by the sensing channels, namely, sensing diversity gain, provided by the multiple CRs. Even though one CR may fail to detect the signal of the PU, there are still many chances for other CRs to detect it. With the increase of the number of cooperative CRs, the probability of missed detection for all the users will be extremely small. Another merit of cooperative spectrum sensing is the mutual benefit brought forward by communicating with each other to improve the sensing performance. When one CR is far away from the primary user, the received signal may be too weak to be detected by this CR. However, by employing a CR that is located nearby the PU as a relay, the signal of the PU can be detected reliably by the far user. There are mainly three relaying protocols:

- *Amplify-and-forward* (AF). In AF, the received signal is amplified and retransmitted to the destination. The advantage of this protocol is its simplicity and low cost implementation. But the noise is also amplified at the relay.

- *Decode-and-forward* (DF). In DF, the relay attempts to decode the received signals. If successful, it reencodes the information and retransmits it.

- *Compress-and-forward* (CF). CF attempts to generate an estimate of the received signal. This is then compressed, encoded, and transmitted in the hope that the estimated value may assist in decoding the original codeword at the destination.

### 6.2.1 Challenges

There also exist several challenges on cooperative spectrum sensing. For instance, secondary users can be low-cost devices only equipped with a limit of amount of power, so they can not afford very complicated detection hardware and high computational complexity. In wideband cooperative sensing, multiple secondary users have to scan a wide range of spectrum channels and share their detection results. This results in a large amount of sensory data exchange, high energy consumption, and an inefficient data throughput. If the spectrum environment is highly dynamic, the sensed information may even be stale due to user mobility, channel fading, etc. Furthermore, another challenge in the implementation of cooperative sensing is the issue of user reliability. For instance, a single malicious user may prevent a cognitive radio network (CRN) from accessing a white space by sending false reports to the band manager.

## 6.3 Methods of Cooperative Spectrum Sensing

Cooperation can be among cognitive radios or external sensors can be used to build a cooperative sensing network. In the former case, cooperation can be implemented in two fashions: centralized or distributed. These two methods and external sensing are discussed in the following sections.

### 6.3.1 Centralized Sensing

In centralized sensing, cooperative spectrum sensing consists of a base station (BS) or an access point (AP). The BS or AP collects sensing information from cognitive devices, identifies the available spectrum and broadcasts this information to other CR (i.e., the presence or absence of the PU's signal) or directly controls the cognitive radio traffic. The goal is to mitigate the fading effects of the channel and increase detection performance. In the case of a large number of users, the bandwidth required for reporting becomes huge. In order to reduce the sharing bandwidth, local observations of cognitive radios are quantized to one bit (hard decisions). Furthermore, only the cognitive radios with reliable information are allowed to report their decisions to the central unit. Hence, some sensors are censored. Censoring can be implemented by simply using more threshold values instead of one.

Generally, the sensing information combination at the BS can be categorized by soft combination and hard combination techniques.

**Soft Combination** In soft combination, also known as *data fusion*, the CR users send their original sensing data (measurements) to the base station without quantization. While soft combination requires large overhead to feedback the sensing data, it has excellent detection performance. Soft combination can be performed as described above:

1. Every CR performs its own local spectrum sensing measurements independently.
2. All of the CRs forward their measurements (data) to AP.
3. The common receiver fuses the CR decisions and makes a final decision to infer the absence or presence of the PU.

**Hard Combination** In order to minimize the communication overhead and hence the bandwidth required for the transmission of the data from the CRs to the AP, users may only report their final 1-bit decisions rather than the actual measurements. In hard combination schemes, also called *decision fusion*, the CR users send quantized sensing information to the BS and the

BS deploys a fusion rule to make the final decision, i.e. whether there is or not the PU's signal. While local hard decision at the CR users causes information loss and performance degradation, it greatly reduces the amount of feedback.

The simplest hard combination scheme is the one-bit counting scheme, in which each CR user sends one-bit information to the base station regarding its *observed energy* is above a predetermined threshold. Specifically, if each user only sends one-bit decision ("1" for signal present and "0" for signal absent) and no other information is available at the central processor, some commonly adopted decision fusion rules are described as follows.

1. "Logical-OR (LO)" Rule: If one of the decisions is "1" the final decision is "1". Assuming that all decisions are independent, then the probability of detection and probability of false alarm of the final decision are $P_D = 1-\prod_{i=1}^{M}(1-P_{D,i})$ and $P_{FA} = 1-\prod_{i=1}^{M}(1-P_{FA,i})$ respectively, where $P_{D,i}$ and $P_{FA,i}$ are the probability of detection and probability of false alarm for user $i$, respectively.
2. "Logical-AND (LA)" Rule: If and only if all decisions are "1", the final decision is "1". The probability of detection and probability of false alarm of the final decision are $P_D = \prod_{i=1}^{M} P_{D,i}$ and $P_{FA} = \prod_{i=1}^{M} P_{FA,i}$ respectively.
3. "K out of M" Rule: If and only if K decisions or more are "1", the final decision is "1". This includes "Logical-OR (LO)" (K = 1), "Logical-AND (LA)" (K = M), and "Majority" (K =$\lceil M/2 \rceil$) as special cases. The probability of detection and probability of false alarm of the final decision are

$$P_D = \sum_{i=0}^{M-K} \binom{M}{K+i} (1-P_{D,i})^{M-K-i}(1-P_{D,i})^{K+i}$$

and

$$P_{FA} = \sum_{i=0}^{M-K} \binom{M}{K+i} (1-P_{FA,i})^{M-K-i}(1-P_{FA,i})^{K+i}$$

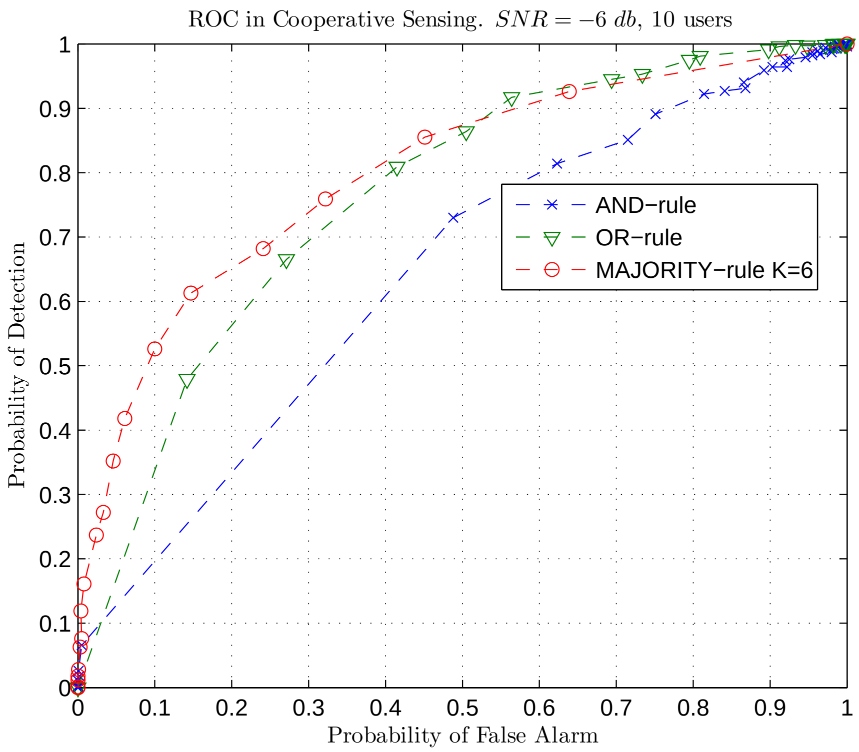


Figure 6.2: ROC curves for fusion rules in centralized cooperative spectrum sensing.

respectively.

In the following figures we show the ROCs for the three above rules. In Figure 6.2 we plot the probability of detection versus the probability of false alarm and in Figure 6.3 we plot the probability of missed detection ($P_{MISS}$) versus the probability of false alarm. The probability of missed detection is defined as $P_{MISS} = 1 - P_D$. Our experiment is implemented for 10 CR users in the Cognitive Radio Network (CRN) and a fusion center that collects the binary decisions from these CRs. We choose for the Majority-Rule the value of the factor $K = 6$.

In the literature, a new two bit hard combination scheme has been proposed [16]. With this scheme a better detection performance can be achieved.

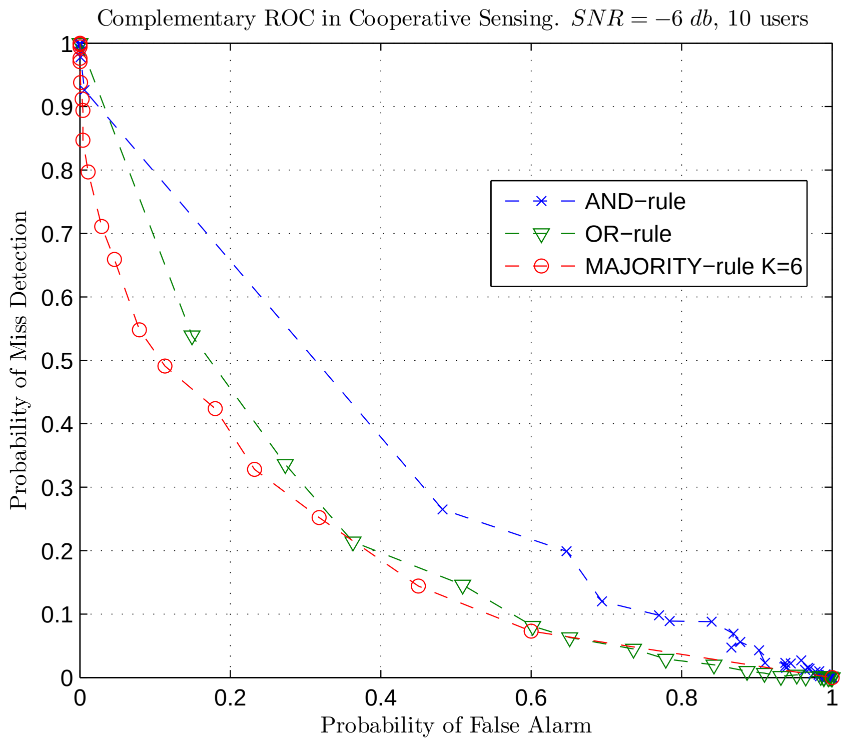


Figure 6.3: Complementary ROC curves for fusion rules in centralized cooperative spectrum sensing.

Figure 6.4 shows the one-bit and two-bit hard combination schemes. We can see that in the second case the observed energy is divided into four regions by three thresholds $\lambda_1, \lambda_2, \lambda_3$.

### 6.3.2 Distributed Sensing

In the case of distributed sensing, cognitive nodes share information among each other but they make their own decisions as to which part of the spectrum they can use. Distributed sensing is more advantageous than centralized sensing in the sense that there is no need for a backbone infrastructure and it has reduced cost.

Figure 6.5 shows a schematic representation of the AF cooperation scheme in a decentralized CR network. In the figure, P denotes the primary user and CR

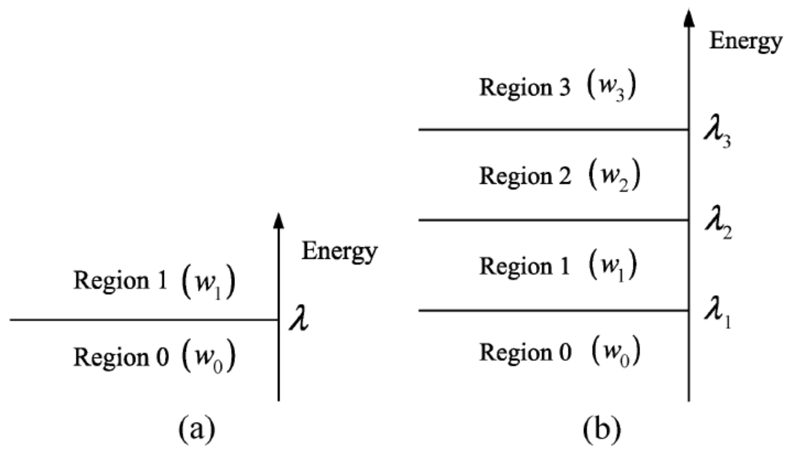


Figure 6.4: Principles of hard combination schemes (a) One-bit counting scheme and (b) two-bit hard combination scheme. [Ma et al.: "Signal Processing in Cognitive Radio"]

user U1 is sending data to CR user U3, while CR user U2 acts as an AF relay for U1. The AF cooperation scheme consists of two stages or time slots: in the first time slot U1 transmits while U2 listens; in the second time slot U2 transmits while U1 keeps silent. Thus orthogonal transmission of U1 and U2 is guaranteed. Since continuous spectrum sensing is required during the process of secondary communication between the CR users, actually U1 does not idle the second time slot away. Instead, U1 listens to its partner U2 and decides whether the received signal contains the primary signal in the second time slot.

### 6.3.3 External Sensing

Another technique for obtaining spectrum information is external sensing. In external sensing, an external agent performs the sensing and broadcasts the channel occupancy information to CRs. External sensing algorithms solve some problems associated with the internal sensing where sensing is performed by the cognitive transceivers internally. The main advantages of external sensing are overcoming hidden primary user problem and the uncertainty due to shadowing and fading.

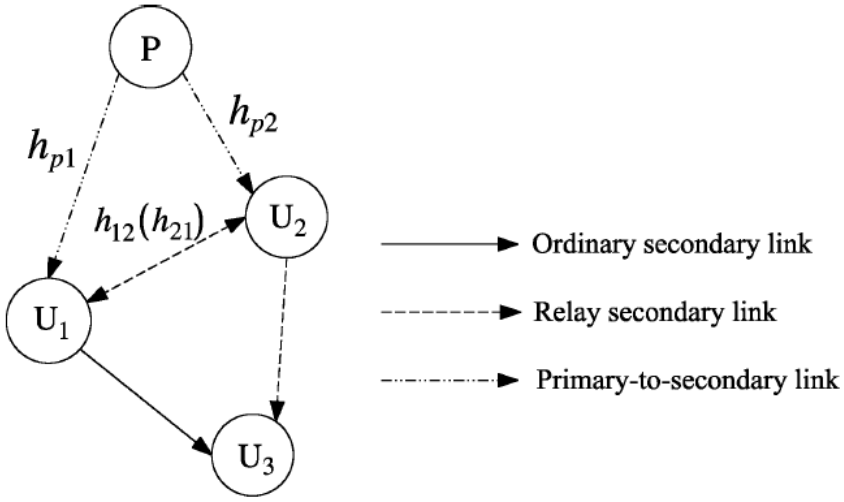


Figure 6.5: Schematic representation of the AF cooperation scheme in a decentralized CR network. [Ma et al.: "Signal Processing in Cognitive Radio"]

Furthermore, as the cognitive radios do not spend time for sensing, spectrum efficiency is increased. The sensing network does not need to be mobile and not necessarily powered by batteries. Hence, the power consumption problem of internal sensing can also be addressed. External sensing is one of the methods proposed for identifying primary users in IEEE 802.22 standard as well.

## 6.4 Practical Considerations about Cooperative Sensing

**Fading and Shadowing** In practice, the reporting channels between the CRs and the common receiver will also experience fading and shadowing (such as CR 1 in Figure 6.1). This will typically deteriorate the transmission reliability of the sensing results reported from the CRs to the BS. For example, when one CR reports a sensing result "1" (denoting the presence of the PU) to the BS through a realistic fading channel, the BS will likely detect it to be the opposite result "0" (denoting the absence of the PU) because of the disturbance from the random complex channel coefficient and random noise. Eventually, the performance of cooperative spectrum sensing will be degraded by the imperfect reporting channels.

**Trade-off Between Sensing Duration and Performance** Spectrum sensing is significant in CRs in avoiding a collision with the licensed user and improving the licensed spectrum utilization efficiency. The former is characterized by the $P_D$ and the latter is measured by the $P_{FA}$. The sensing duration $T$ is no doubt a key parameter to determine the sensing performance. A longer sensing duration $T$ can produce a better sensing performance but results in longer waiting time for cognitive users to access the channel. An extremely long sensing duration cannot be tolerated by an agile radio. From the perspective of the cognitive users, a lower false alarm probability implies that there will be more chances for the licensed channel to be reused. Assuming that the protection of the primary user is of the first priority in CR networks, we can maximize the throughput of the cognitive users in order to find an optimal sensing duration.

**Trade-off Between Cooperation and Sensing** In a CR network with a large number of CRs, cooperative spectrum sensing may become *impractical* because in a time slot only one CR should send its local decision to the BS so as to separate decisions easily at the receiver end. Hence, it may make the whole sensing time intolerantly long. Obviously the fewer CRs involved in cooperative spectrum sensing, the shorter the sensing duration. However, a small number of CRs in cooperative spectrum sensing results in a small sensing diversity order. This problem can be addressed by allowing the CRs to send the decisions *concurrently.* But this may complicate the receiver design when we try to identify the decisions from different CRs. Another potential solution is to send the decisions on orthogonal frequency bands, but this requires a large portion of the available bandwidth.

# Chapter 7

# Conclusion

Cognitive Radio is the new key technology that serves as a solution to the spectrum scarcity. It is necessary that the CRs are used in wireless communications in order to potentially improve the utilization efficiency of the radio spectrum. By tuning the frequency to the temporarily unused licensed band and adapting operating parameters to environment variations, CR technology provides future wireless devices with additional bandwidth, reliable broadband communications and versatility for rapidly growing data applications.

In this thesis we presented the fundamental concepts of CR technology and the idea that lead us to that technology. We presented the prerequisite requirement on deploying CR, i.e. spectrum sensing and we analyzed the basic detection techniques in order to realize the sensing of the RF spectrum. Furthermore, we presented cooperative spectrum sensing that serves as a solution to the challenges that one CR user can face, i.e. multipath fading and shadowing.

## 7.1 Future Work

Research on spectrum sensing thus far has mainly focused on meeting the regulatory requirements for reliable sensing. An important venue for further research is the interplay of spectrum sensing and higher-layer functionalities to enhance the end user's perceived QoS.

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