Cooperative Spectrum Sensing based on 1-bit Quantization in Cognitive Radio Networks

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Abstract

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The wireless frequency spectrum is a very valuable resource in the field of communications. Over the years, different bands of the spectrum were licensed to various communications systems and standards. As a result, most of the easily accessible parts of it ended up being theoretically occupied. This made it somewhat difficult to accommodate new wireless technologies, especially with the rise of communications concepts such as the Machine to Machine (M2M) communications and the Internet of Things (IoT). It was necessary to find ways to make better use of wireless spectrum.

Cognitive Radio is one concept that came into light to tackle the problem of spectrum utilization. Various technical reports stated that the spectrum is in fact under-utilized. Many frequency bands are not heavily used over time, and some bands have low activity. Cognitive Radio (CR) Networks aim to exploit and opportunistically share the already licensed spectrum. The objective is to enable various kinds of communications while preserving the licensed parties' right to access the spectrum without interference.

Cognitive radio networks have more than one approach to spectrum sharing. In the interweave spectrum sharing scheme, cognitive radio devices look for opportunities in the spectrum, in frequency and over time. Therefore, and to find these opportunities, they employ what is known as spectrum sensing. In a spectrum sensing phase, the CR device scans certain parts of the spectrum to find the voids or white spaces in it. After that it exploits these voids to perform its data transmission, thus avoiding any interference with the licensed users.

Spectrum sensing has various classifications and approaches. In this thesis, we will present a general review of the main spectrum sensing categories. Furthermore, we will discuss some of the techniques employed in each category including their respective advantages and disadvantages, in addition to some of the research work associated with them.

Our focus will be on cooperative spectrum sensing, which is a popular research topic. In cooperative spectrum sensing, multiple CR devices collaborate in the spectrum sensing operation to enhance the performance in terms of detection accuracy. We will investigate the soft-information decision fusion approach in cooperative sensing. In this approach, the CR devices forward their spectrum sensing data to a central node, commonly known as a Fusion Center. At the fusion center, this data is combined to achieve a higher level of accuracy in determining the occupied parts and the empty parts of the spectrum while considering Rayleigh fading channels. Furthermore, we will address the issue of high power consumption due to the sampling process of a wide-band of frequencies at the Nyquist rate. We will apply the 1-bit Quantization technique in our work to tackle this issue. The simulation results show that the detection accuracy of a 1-bit quantized system is equivalent to a non-quantized system with only 2 dB less in Signal-to-Noise Ratio (SNR). Finally, we will shed some light on multiple antenna spectrum sensing, and compare its performance to the cooperative sensing.

To my mother, whose grace and kindness warm my life

my father, whose commitment and generosity ease my struggle

and my brother, whose joy and friendship fill my days with happiness

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All thanks go first and foremost to God, for granting me the strength and patience to successfully finish this work. May his light and grace follow me and aide me throughout my life.

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Finally, I would like to thank my research lab colleagues for providing some helpful remarks during my work, as well as my friends in the Space Concordia student society.

Contents

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Special Terms

3G Third Generation.

5G Fifth Generation.

ADC Analog-to-Digital.

AGC Automatic-Gain-Control.

AWGN Additive White Gaussian Noise.

CDF Cumulative Distribution Function.

CR Cognitive Radio.

CSCG Circularly Symmetric Complex Gaussian.

DFT Discrete Fourier Transform.

DSL Digital Subscriber Line.

DSP Digital Signal Processor.

EVB Eigenvalue-Based.

FC Fusion Center.

FFT Fast Fourier Transform.

GLR Generalized Likelihood Ratio.

GPRS General Packet Radio Service.

GSM Global System for Mobile Communications.

HSDPA High Speed Data Packet Access.

i.i.d Independent and Identically Distributed.

i.n.i.d Independent non-Identically Distributed.

IoT Internet of Things.

IP Internet Protocol.

IT Information Technology.

LNA Low Noise Amplifier.

LTE Long Term Evolution.

M2M Machine to Machine.

MAC Medium Access Control.

MF Matched Filter.

MIMO Multiple Input Multiple Output.

MRC Maximum Ratio Combining.

MTC Machine Type Communication.

NLOS Non-Line-of-Sight.

PDF Probability Distribution Function.

PLL Phase-Locked-Loop.

PSD Power Spectral Density.

PU Primary User.

QAM Quadrature Amplitude Modulation.

RF Radio Frequency.

ROC Receiver Operating Characteristics.

RSSI Received Signal Strength Indicator.

SDR Software Defined Radio.

SNR Signal-to-Noise Ratio.

SU Secondary User.

TWDP Two-Wave with Diffuse Power.

UE User Equipment.

Chapter 1

Introduction

1.1 Evolution of Communications Networks

About thirty years ago, communication networks began to spread around the globe. At first, networks' capabilities were rather humble. Internet connections were almost limited to universities and big Information Technology (IT) companies and did not wield high rates. Wireless communications were starting to gain presence, but included only voice calls and were quite costly and reliant on different standards between different regions.

After 1995, communications networks started to gain momentum, with the increase of networks operators. That resulted in a considerable decrease in call costs, even for intercontinental calls. It was around the time where a global standard of wireless communications took shape. It started with the introduction of the Global System for Mobile Communications (GSM), which offered reliable voice and messaging services. Home internet connections began to be more affordable and accessible as well, in the form of dial-up connections. Mobile internet, however, was still quite limited and GSM only offered small rates of data transfer.

After 2000, development in the field accelerated. Internet industry and telecommunication started to become more and more reliant and supportive of each other. Faster internet connections such as Digital Subscriber Line (DSL) became available and offered a considerable improvement over dial-up connections. In addition, there were attempts to provide services that enable voice calls over the internet, for example, Skype calling service [1]. General Packet Radio Service (GPRS) made mobile internet more accessible to the audience, with its packet switching technique.

It was by far better for different internet services than circuit switching.

From 2005 onward, mobile communications and internet accessibility experienced a rapid expansion. Faster DSL connections became available, and Third Generation (3G) communications networks came to light. 3G networks offered new and faster access protocols, such as the High Speed Data Packet Access (HSDPA). They provided faster mobile internet connections, suitable for easy web browsing and e-mail. Smartphone prices dropped considerably and cheaper data packages became available, increasing the number of the global population with access to these services. Not long after that, even higher data rates came to be, with the introduction of Long Term Evolution (LTE) networks, early this decade. LTE networks provide impressive rates, suitable for video streaming and video calls, with affordable prices. It will not be very long now before Fifth Generation (5G) networks see the light and will offer unprecedented data transfer rates. One thing to note here is that almost all forms of digital communications are heading towards packet switching. They are relying on the Internet Protocol (IP) to implement different services, to unify all sorts of communications under this standard.

With the continuous demand for higher rates, comes the demand for more frequency bandwidth. In mobile communications, this is a real challenge. The frequency spectrum is a shared resource between all communication devices in a certain region. Over the years, different parts of the frequency spectrum were assigned to different communication standards and protocols. As a result, most of the accessible spectrum got assigned, making it somewhat difficult for new wireless technologies. With the need to accommodate new wireless technologies and various other radio systems, along with new concepts like the IoT and M2M communications, some solutions were introduced. One of those solutions is the concept of Cognitive Radio (CR).

1.2 Cognitive Radio

1.2.1 The Need for Cognitive Radio

The main objective of CR is to achieve a dynamic and more efficient spectrum utilization. The assignment of frequency spectrum bands to conventional wireless systems rendered most of the easily accessible parts theoretically occupied. However, different measurements and technical reports conducted in different urban areas stated that the spectrum is under-utilized. It was found that on average only about 13% of it is being used at any given moment. Additionally, it was found that a number of bands have low spectrum occupancy [2]. As a result, it became a necessity to make more efficient use of the already assigned parts of the spectrum. It should be done in an opportunistic manner that saves the right of the owners of these parts to use them when needed without interference. Making better use of the bandwidth will go a long way in supporting the demand for more data rates which are needed for different wireless systems and services, especially with the rise of concepts like IoT and M2M, among others.

1.2.2 The Nature of Cognitive Radio

Generally speaking, a Cognitive Radio (CR) device can be aware of the environment around it. It detects occupied bands of the spectrum and has the agility to adjust its transmission frequency, technology, and protocols. The objective is to take advantage of certain free parts of the spectrum. Under the condition of reserving the bandwidth owners' right to use it, a cognitive radio device should also be able to quickly detect the presence of a Primary User (PU) signals. That is necessary to clear the channel and avoid causing interference to them. Cognitive Radio can be considered an extension of the Software Defined Radio (SDR) concept [2]. An SDR can be used to implement dynamic spectrum access algorithms needed to exploit potential chances in the spectrum, both temporally and spatially.

There are however some issues that need to be addressed. For example, determining the capacity of Cognitive Radio networks and employing effective spectrum sensing techniques. Additionally, in some cases, we need an accurate estimation of the channel between primary users themselves, and between primary and secondary users. A Secondary User (SU) is a usual term for Cognitive Radio devices.

1.3 Thesis Motivation

As cognitive radio networks achieve more proliferation, more and more CR devices will be around. This is quite useful to improve the performance of CR networks. Multiple CR devices can cooperate to achieve improved performance in the spectrum sensing phase, an important part of the operation of CR networks. Considering these facts, it is useful to study this spectrum sensing technique and find possible ways to optimize it. Additionally, it is of interest to address the power consumption in CR devices, especially in wide-band sensing, as it can be a pressing issue given that these devices are likely to be mobile and battery-powered. Furthermore, employing multiple antennas in the spectrum sensing operation is another approach that has some interest in the literature. Therefore, it is useful to study its performance and compare it to the performance of cooperative spectrum sensing.

The objectives of this thesis can be summarized as:

1. Study the performance of wide-band cooperative spectrum sensing using energy detection as a means to enable cognitive radio networks in interweave spectrum sharing paradigm;

2. investigate possible ways to optimize that performance;

3. address the power consumption issue in wide-band spectrum sensing, especially in the context of the aforementioned study point;

4. partially address multiple antennae as a spectrum sensing approach.

1.4 Contribution

Main contributions in this thesis are:

1. Discuss and simulate a soft-fusion cooperative spectrum sensing technique based on energy statistics accumulation, and provide accurate analysis of this approach, in a special case of SNR consideration.

2. Propose a performance optimization approach of the aforementioned technique based on minimizing the probabilities of undesirables error scenarios.

3. Extend the analysis of this problem to more general SNR consideration, and provide a good starting point for further research in that regard within this sensing technique.

4. Apply the 1-bit quantization sampling technique as proposed in [3] to the mentioned sensing technique in both special and general SNR considerations and analyze its effect on the performance, to address the power consumption issue.

5. Provide an overview of the multi antennae approach of spectrum sensing, simulate and analyze this approach in its ideal case and compare its performance to the previously mentioned cooperative spectrum sensing technique.

1.5 Thesis Organization

The thesis is organized as follows:

In chapter 2, we present some background in the field of cognitive radios networks, spectrum sharing schemes and give special attention to the study of the spectrum sensing operation. We review the main classifications of spectrum sensing techniques for single users, with a special focus on the ones related to our work. Next, we discuss the cooperative spectrum sensing while mainly focusing on the two distinct data-fusion approaches: hard-fusion and soft-fusion. After that, we provide some insight into using multiple antennas in spectrum sensing. In all the mentioned points, we present some of the work in the literature regarding them. Finally, we speak about the high power consumption problem in high-speed Analog-to-Digital (ADC) devices. These devices are employed in wide-band sensing. We will speak about the 1-bit quantization technique, used as a solution to this problem.

In chapter 3, we present our energy summation cooperative spectrum sensing technique. It is a form of soft data fusion approach in cooperative sensing. We discuss the considered system and signal model and explain the sensing procedure. Next, we present the analysis work for both the non-quantized and 1-bit quantized cases. After that, we present our optimization approach of this system, based on the minimum total error rate. Finally, we provide the simulation results, conclusion, and a summarized discussion of the results.

In chapter 4, we present an extension of the work in chapter 3, where we consider the same system under general received signals' SNR. The objective is to provide some analysis work that better resembles real-life situations. We introduce the system model and provide an analysis of the system. After that, we present the system model and structure of a multi-antenna CR device and discuss its operation in an ideal uncorrelated channels scenario. We present the simulation results, comparing the cooperative sensing and multi-antenna sensing results, followed by the conclusion notes of the chapter.

In the end, we present some final discussion notes and possible future work ideas.

Chapter 2

Background and Literature Review

2.1 Cognitive Radio Networks

The idea of Cognitive Radio Networks came out as an answer to the need of accommodating more and more wireless technologies in a crowded frequency spectrum. The wireless spectrum is quite a valuable resource, meaning it is necessary to find ways to use it more efficiently [4]. The PUs, however, always retain the right to access the spectrum, since it is usually licensed to them. As a result, some concepts like spectrum sharing and opportunistic access came into the picture.

Research efforts and field tests determined that the spectrum assigned to conventional wireless systems is under-utilized [5]. That means there are a lot of spectrum access opportunities to exploit and enable cognitive radios. When we speak about how spectrum sharing goes, there are commonly three distinct schemes: The underlay, overlay and the interweave spectrum sharing schemes [2] [6] [7] [8]. One should keep in mind that there is usually no coordination between primary users PU and cognitive radio CR users (or secondary users SU), to access the spectrum. Therefore, it is necessary that the secondary users only access the spectrum in a way that does not cause harmful interference to primary users.

In underlay spectrum sharing, secondary users are permitted to use parts of the spectrum with minimal power level and spreading techniques, to keep their transmission levels within a specific range, that does not affect primary users or cause harmful interference to them. Fig 2.1 illustrates the idea. From a primary user's perspective, the cognitive radio device transmission would seem like a slight increase in noise level. This kind of spectrum opportunities exists because there is

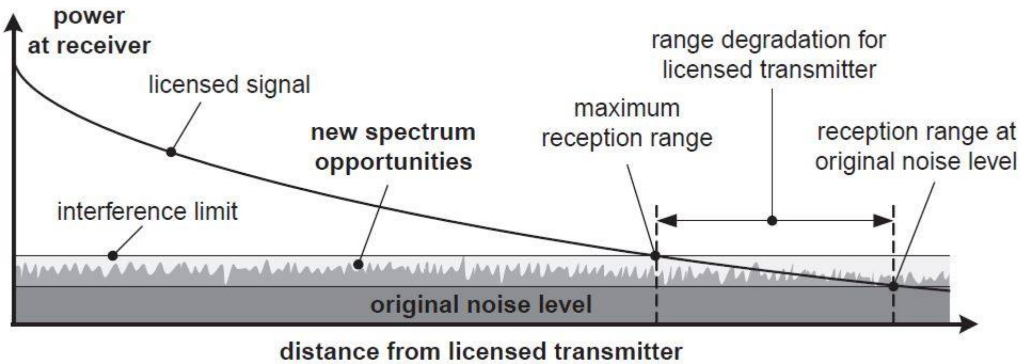

Figure 2.1: Underlay Spectrum Sharing [6]

usually a gap between noise level and primary users' transmission levels, which can be exploited.

In the overlay spectrum sharing scheme [2], the secondary user SU would have some knowledge of the nature of the primary user PU signal, such as the way it is encoded. Knowledge of the primary signal's encoding method can help the secondary user in various ways. For example, the SU can use various encoding techniques on its own signal in a way that minimizes the interference to the PU signal. Other ways to make use of the encoding information also exist, such as assigning part of the SU transmission power to assist the PU in relaying their communications. Overall, it is a useful approach to spectrum sharing but has its own difficulties as well. For instance, there is the need of the SU to listen to the PU transmission, in addition to the encoding and decoding complexity.

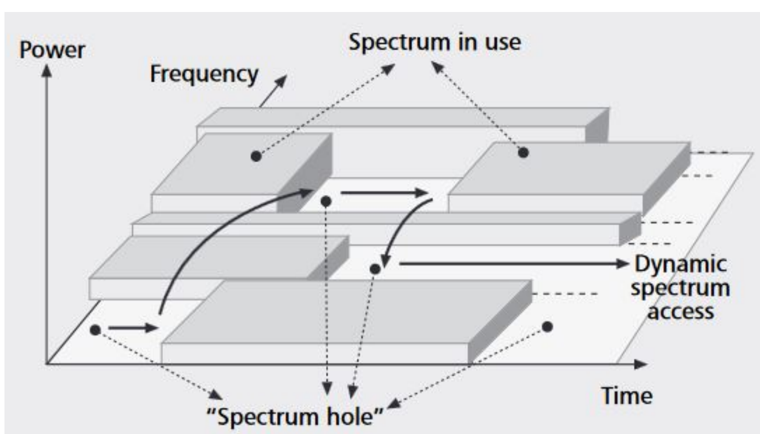

Figure 2.2: Spectrum Holes Concept in Interweave Cognitive Radio Networks [9]

Interweave cognitive radio networks [2] [10] [11] are based on the idea of opportunistic access to the frequency spectrum. This idea came after numerous studies and technical reports [5] [12] determined that large parts of the spectrum at any given moment are under-utilized. This method of spectrum sharing involves analyzing the spectrum by the secondary users to locate the free parts of it, also known as spectrum holes or white spaces (Fig. 2.2). They can use these spectrum holes to communicate their data to other secondary users without interfering with primary users' transmissions.

It should be understood that the wireless spectrum occupancy state is not only in frequency but also in time. That means channels which are occupied at one instant in time could be vacant in another, and vice versa. In other words, the wireless spectrum has a quite dynamic nature and it is always changing. Hence the need for the aforementioned analysis phase of the spectrum before initiating transmission by the SU. This analysis phase is usually referred to as Spectrum Sensing. Moreover, the spectrum occupancy state could also be in the spatial dimension [2], in the case of Multiple Input Multiple Output (MIMO) devices, where certain spectrum holes might exist in a subset of spatial dimensions. As a result, spectrum holes are sometimes referred to as space-time-frequency voids.

Spectrum sensing can involve a single SU or multiple SUs. When multiple users are involved in the sensing operation, special Medium Access Control (MAC) protocols are required, to share the spectrum holes data among them. Some protocols were derived from existing MAC protocols such as ALOHA and CSMA [13], given their similarity with the problem at hand. It is worth mentioning that in practicality, spectrum sensing in interweave networks is usually accompanied by other important concepts, such as spectrum monitoring and spectrum mobility [14]. Spectrum monitoring means that after the SU identifies the free parts in the spectrum and occupies a certain channel to transmit its data, it continues to monitor the channel in case the PU reappears on it. On the other hand, spectrum mobility refers to the SU's ability to quickly clear the channel when the PU appears and resumes its transmission on another vacant channel if needed.

Depending on the size of the frequency band in question, spectrum sensing has two main classifications: narrow-band sensing and wide-band sensing. In brief, narrow-band sensing attempts to determine whether a single wireless channel is free to use or not. On the other hand, wide-band sensing aims to analyze a large slice of the spectrum, comprised of numerous sub-channels, to find the free parts or white holes in it. We will be looking at these two types of sensing in more detail in the following sections.

2.2 Narrow-Band Spectrum Sensing

Narrow-band spectrum sensing deals with attempting to determine whether a specific wireless channel is occupied or not by a PU. This section aims to explain the principles and methods of signal detection and the accompanying issues and difficulties, before moving on later to wide-band sensing. To understand how the detection process goes, let us first look at the signal modeling. Most references state two possibilities about the primary signal presence [2] [7] [14]. When the channel being sensed is vacant, only the noise is received. On the other hand, when it is occupied by a PU signal, a mix of that signal and noise are received. The CR device performs a hypothesis test using some acquired statistic from the received signal, to make a decision. Normally, it will decide on a null hypothesis $\mathcal{H}_0$ which means the channel is vacant, or an alternate hypothesis $\mathcal{H}_1$ which means the channel is occupied. In other words:

$$\begin{aligned}\mathcal{H}_0 &: y(n) = w(n) \\ \mathcal{H}_1 &: y(n) = s(n) + w(n)\end{aligned} \tag{2.1}$$

where n represents time, $y(n)$ is the total received signal by the SU, $s(n)$ is the received PU signal and $w(n)$ is the noise. This noise is commonly considered to be complex symmetric Additive White Gaussian Noise (AWGN) with zero mean and variance σ_w^2 such that $w(n) \sim \mathcal{CN}(0, \sigma_w^2)$. As mentioned before, a CR device acquires a statistic of some kind T, to perform a hypothesis test according to a set threshold value λ. Given the randomness of the observed noise, not to mention the randomness of the received PU signal itself when considering fading channels, it is common to study the performance from a probabilistic point of view.

Two probabilities are usually studied in that regard: the probability of false alarm $P[FA]$ and the probability of detection $P[D]$ [15] [16]. The probability of false alarm $P[FA]$ is the probability of mistakenly deciding that a channel is occupied when it is in fact free. On the other hand, the probability of detection $P[D]$ is the probability of correctly deciding that a channel is occupied when actually it is. Sometimes, an additional probability is considered. The probability of miss-detection $P[MD]$, which refers to mistakenly deciding a channel is free while it is occupied. It is a complement of the probability of detection. In other words:

$$
\begin{aligned}
P(FA) &= P[T > \lambda | \mathcal{H}_0] \\
P(D) &= P[T > \lambda | \mathcal{H}_1] \\
P(MD) &= 1 - P(D) = P[T < \lambda | \mathcal{H}_1].
\end{aligned}
\tag{2.2}
$$

A false alarm case means the SU will miss the chance to communicate its data in that sensing cycle, as the channel is actually free. On the other hand, a miss-detection case means the SU will transmit its data on an occupied channel, causing interference to the PU who has the right to use it. Both are clearly undesirable cases.

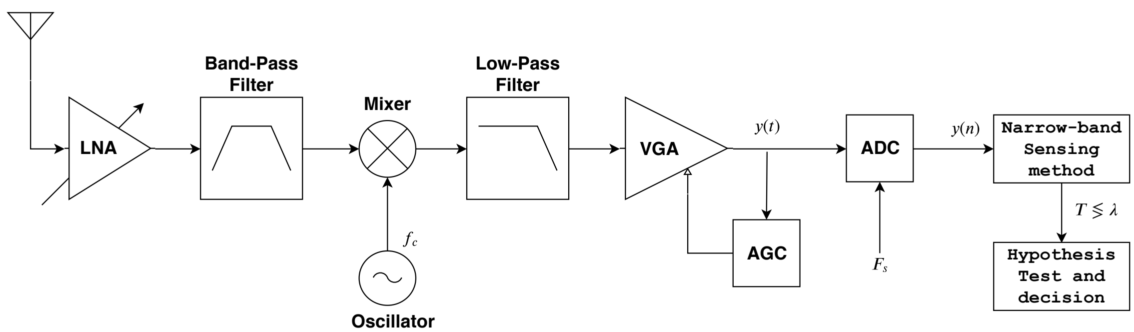

Figure 2.3: General block diagram of a narrow-band spectrum sensing receiver

Fig 2.4 shows a block diagram of a typical narrow-band spectrum sensing device. Adjusting the decision threshold value plays a part in determining the detection accuracy. However, it almost always translates into a trade-off between $P[FA]$ and $P[D]$. Such trade-offs are sometimes considered in cases such as studying the CR network throughput [17]. In most cases, the challenge is to develop reliable sensing techniques that can effectively yield good values of $P[FA]$ and $P[D]$ simultaneously. Fig 2.4 shows some of the narrow-band sensing techniques. They all involve acquiring some sort of a statistic T to compare with a threshold value. N resembles the number of samples used to acquire T, $x[n]$ are the samples, $s[n]$ is the pulse shape (in the Matched Filter (MF) case) and R_{xx} is the autocorrelation function (in the Feature Detection case). Each of these techniques have their advantages and drawbacks as we will see in the following sections.

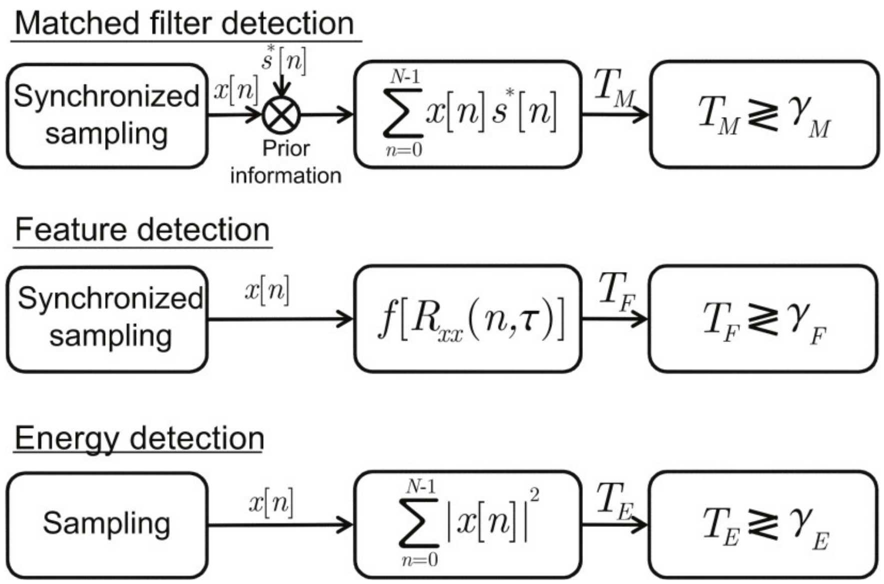

Figure 2.4: Some of the narrow-band sensing techniques [7]

2.2.1 Matched Filter Detection

The concept of matched filter did not emerge with the subject of cognitive radio but rather goes back a long time. It is used in conventional digital receivers because it can provide optimum performance and maximize the received SNR when making decisions on the received symbols [18]. If the physical structure of the PU signal is known, this method can provide very good performance at low SNR. When the cross-correlation with the received signal results in peaks at the output, it infers the presence of a PU. Otherwise, the channel is assumed to be vacant.

Unfortunately, this method has some drawbacks. As a coherent detection method, it requires prior knowledge of the PU signal structure and pulse shape. Additionally, it requires synchronization and sometimes channel estimation. Those matters need knowledge of the preamble and pilot patterns. Aside from that, attempting to apply this method in a wide-band would require the need to know multiple PU information which could be different from one another [7]. Therefore, this method is costly and complicated to implement and has only limited uses.

In [19], the authors investigated the performance of the MF as a spectrum sensing method taking into consideration that the PU could transmit with one of multiple power levels, randomly chosen. Their aim was to attempt matching the practical standards for power adaptation. In addition, they discussed the power mask effect, where a specific power level may be hidden behind.

2.2.2 Feature Detection

Feature detection is another type of coherent detection. Sometimes the PU signal may not be completely known but it is possible to know some of its features, such as the preambles, pilots, hop rate, etc. Some of these statistics can repeat periodically, in which case the signal is called cyclo-stationary [2] [14]. These features are used to form a test statistic, because they can correlate when matched to the known aspects of the signal, unlike noise and interference which do not correlate. Similar to MF detection, feature detection can detect PU signals at low SNR and it is not affected by noise uncertainty. However, it needs some prior knowledge about the signal and the sensing cycle can be relatively lengthy [20], in addition to complexity.

In [21], the authors present a way to detect PU signal by looking for single or multiple cycle frequencies at single or multiple time lags in the cyclic autocorrelation function (CAF) of the noisy PU signal. Their approach is that when no PU signal is present, the resulted measurements would match what is known to originate from colored Gaussian noise with unknown correlation. They present their relatively simple spectrum sensing detector while considering a single antenna and multiple antenna cases, in addition to considering conjugate and non-conjugate CAFs.

In [22], the performance of cyclo-stationary detectors is analyzed under the effects of receiver impairments, mainly cyclic frequency and sampling clock offsets. To counter the effect of this offset, the authors propose a multi-frame test statistic to reduce the resulted degradation in performance. They present a framework to determine the optimum frame length that maximizes the performance of the cyclo-stationary detector given the statistical distribution of the aforementioned receiver impairments. Other efforts with this method aim to reduce complexity, such as [23]. In that paper, the authors present their design of an integrated CMOS based chip CR sensor. The presented design is a quasi-cyclostationary feature detector and combines both feature and energy detection methods. It does not include an ADC converter and works with analog realization, reducing complexity. It works in the VHF/UHF frequency range, with decent performance for low SNR values and a large dynamic range.

2.2.3 Energy Detection

Unlike the matched filter and feature detection, energy detection is a non-coherent method. It does not require any knowledge about the nature or structure of the PU signal, nor does it require synchronization. It merely relies on measuring the PU signal energy within a specific sensing window to form the decision statistic. This statistic is compared to a set decision threshold to decide the PU signal presence or absence.

Since this method does not make any use of the PU signal knowledge, it performs poorly compared to other coherent detection methods. Some of its main limitations are the inability to differentiate between PU signal and noise, and the poor detection performance at low SNR [2] [14] [24]. However, being quite simple to implement and the low complexity of needed computations [25] means it is the most feasible method. Additionally, it is quite suitable to work with multiple channels detection, such as the case of heterogeneous wireless networks [7]. Therefore, most of the research efforts in CR spectrum sensing in interweave networks focus on this method to enhance its performance.

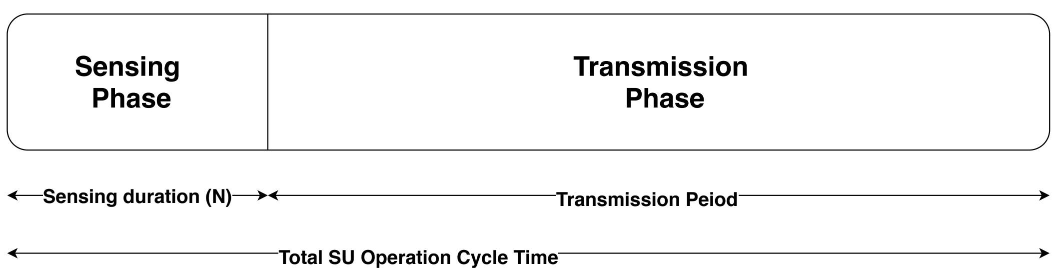

Figure 2.5: Energy detection operation cycle

Fig 2.5 shows an example of an energy detector operation cycle. The sensing phase is when the energy detector performs the sensing operation by acquiring a certain number of samples N. On the other hand, the transmission phase is when the SU communicates its available data. If the CR device detects a PU presence in the sensing phase, it refrains from transmitting in the transmission phase. If it does not detect any PU, it uses the transmission phase to transmit. This cycle has to repeat periodically to account for the possibility of PU reappearance, where the SU has to cease transmission. It is quite clear that there is a trade-off here between performance and throughput. Longer sensing phase would yield better detection performance but less time to transmit data reducing throughput, and vice versa. This trade-off can be used to optimize the sensing duration [26]. The samples acquired in the sensing phase are forwarded into the energy calculation step, such that:

$$T = \frac{1}{N} \sum_{n=0}^{N-1} |y_n|^2 \tag{2.3}$$

where y_n resembles the received samples, N is the number of samples and T is the energy statistic. The statistic T is compared to a suitably chosen threshold λ to decide between $\mathcal{H}_0$ and $\mathcal{H}_1$. Similar to any other detection method, the performance is assessed considering the probabilities of false alarm $P[FA]$ and detection $P[D]$, as in (2.2). Enhancing the performance, i.e. simultaneously attaining high detection probability and low false alarm probability can be done in two ways: enhancing received signal SNR or increasing the degrees-of-freedom of the received signal space [7]. Enhancing the SNR is not always a feasible option, as that would require the PUs to boost their transmission power. On one hand, PU devices are mostly conventional communication devices which have no concern with the CR network operation. On the other hand, they have their own power constraints, not to mention that boosting the SNR may not always provide the desired results as fading and shadowing effects can disrupt the performance. The other option is increasing the degree-of-freedom of the received signal space. Receiving more samples and combining them into an aggregated metric helps in making more accurate decisions as this metric takes more separated and distinct values under the $\mathcal{H}_0$ and $\mathcal{H}_1$ scenarios without boosting the SNR. In (2.3), we say the metric T has N degrees-of-freedom, as N samples were combined in it.

Fig 2.6 shows the Probability Distribution Function (PDF) of the test statistic T with two different values of the degree-of-freedom N. The figure shows the areas that resemble the $P(FA)$ and $P(MD)$ as defined in (2.2), and it can be seen that these areas are smaller with a larger degree-of-freedom in T. Of course, increasing the number of samples means prolonging the sensing period at the cost of the transmission period, resulting in reduced throughput. This is an incentive to look for other ways of improving the degrees-of-freedom, as we will see later.

Analysis of the performance depends on the considered system model. In the simplest form, the channel has no fading or distortion, and it has circularly symmetric Gaussian noise AWGN with

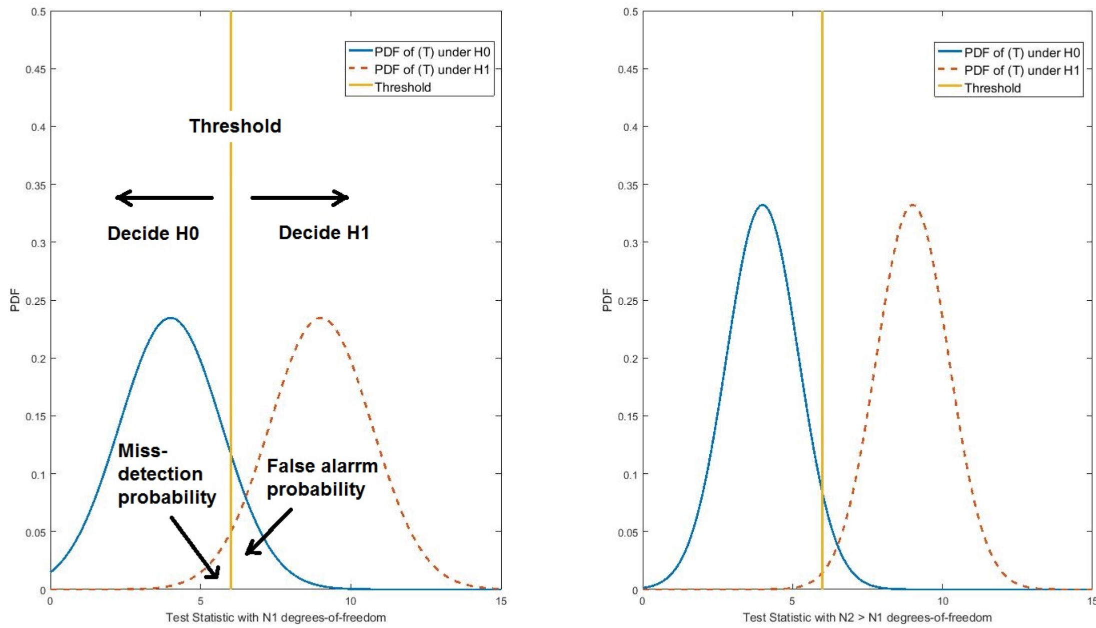

Figure 2.6: An example PDF of the test statistic, with two different degrees-of-freedom

independent samples, zero-mean and variance $E[|\omega_n|^2] = \sigma_\omega^2$, i.e, $\omega_n \sim \mathcal{CN}(0, \sigma_\omega^2)$ [2]. Even with a simple system model such as this, the decision threshold usually depends on the noise variance. Consequently, inaccurate estimation of this variance can affect the performance.

Representation of practical scenarios requires considering a different kind of channels. In [27], the energy detector performance is investigated and closed-form expressions for the $P[FA]$ and $P[D]$ over Nakagami channels. Additionally, the authors came up with an algorithm to calculate the probability of detection for odd numbers of the degree-of-freedom in AWGN channels with low computational complexity. Other more complicated channel conditions were also considered in the literature. In [28], the energy detector was studied considering the cascaded Rayleigh fading channels. The authors derived approximate expressions of the probability of detection $P[D]$ for the no-diversity and the Maximum Ratio Combining (MRC) diversity schemes. Moreover, the performance was investigated when cooperative spectrum sensing is employed. with and without imperfect reporting channels.

In [29], the authors focused on investigating the energy detector performance for the sake of M2M communications in confined spaces. These devices can suffer from some forms of fading worse than Rayleigh fading, known as hyper-Rayleigh fading. These forms of fading were verified to be characterized by the Two-Wave with Diffuse Power (TWDP) model [30]. In addition, the derived expression of $P[D]$ was used to optimize the detection threshold, which was shown to greatly enhance performance. The energy detector performance considering $\kappa - \mu$ and $\kappa - \mu$ extreme fading channels was analyzed in [31]. The authors showed that even small variations in the fading parameters can significantly affect detector performance. In addition, they demonstrated how an increase in the number of SUs involved or diversity branches can greatly enhance performance. Moreover, they showed that the $\kappa - \mu$ extreme fading provides a good characterization of the fading effect at low SNR values.

In addition, some research efforts focus on studying the effect of the receiver device imperfections, such as [32]. In that paper, the authors explain how the inter-modulation products caused by the Low Noise Amplifier (LNA) and mixer non-linearities can degrade the energy detector performance and analyze the effect. After that they propose two Digital Signal Processor (DSP) enhanced architectures to compensate for those effects. One is a post-processing technique, applied to test statistic. The other is a preprocessing technique, applied to the acquired samples before forming the test statistic. Both aim to cancel out the LNA non-linearity effect. Moreover, they proposed an adaptive coefficient weighting method to estimate the inter-modulation distortion and help to implement the preprocessing compensation technique. They finally showed by results that their preprocessing technique is an effective method that enhances the performance without resorting to prolonging the sensing time.

2.3 Wide-Band Spectrum Sensing

Wide-band spectrum sensing comprises the bigger part of the challenge of the interweave cognitive radio networks. Unlike narrow-band spectrum sensing where the goal is to simply determine whether a wireless channel is free or not, wide-band spectrum sensing has to perform the task over a wide frequency range. In this scenario, a CR device has to scan a wide range of wireless channels, to find the empty channels or the frequency voids. These voids are needed to enable CR communications. Performing spectrum sensing over a wide-band requires different methods than narrow-band sensing [14]. A wide-band spectrum sensing technique must be suited to make decisions over multiple slices of the spectrum instead of just one. When the spectrum sensing happens over a wide frequency range, a higher sampling rate is generally needed than the case of narrow-band sensing. In the literature, two main categories of wide-band sensing approaches can be found, depending on the sampling rate. The sub-Nyquist rate, and the Nyquist rate wide-band spectrum sensing.

In sub-Nyquist rate wide-band sensing, the CR device takes samples at a rate lower than the ordinary Nyquist rate, to keep the difficulties and complexities associated with a high sampling rate as limited as possible. The samples are used in different ways to perform sensing, such as attempting to reconstruct the spectrum or perform partial measurements [14]. This category, however, is not the main focus in this thesis and we will concentrate on the Nyquist rate techniques.

In Nyquist rate wide-band sensing, the desired frequency range can be sampled by the ordinary Nyquist rate [24]. This sampling rate is necessary to prevent aliasing in the spectrum of the sampled signal. Different methods are used to segment the frequency range in question into a number of narrow-bands that can be analyzed by narrow-band sensing techniques. Separate decisions are made for each segment or frequency channel. No matter what the used method is, some challenges are always present. These challenges include but not limited to high complexity, ultra-high sampling rate, and long sensing time [14]. Other difficulties arise in practical scenarios. For example, the time delays which result from certain parts of the receiver device such as the Automatic-Gain-Control (AGC) and the Phase-Locked-Loop (PLL), not to mention processing times. In the following sub-sections, we will present some of the main types of Nyquist rate wide-band sensing techniques.

2.3.1 FFT-Based Detection

FFT-based detection is a rather simple technique. The wide-band signal is sampled by a conventional ADC using a high sampling rate and several captures or segments of samples are stored. These segments are then forwarded into a Discrete Fourier Transform (DFT) stage to convert into frequency domain samples. The DFT is implemented using a Fast Fourier Transform (FFT) block. The resulting information from the FFT block is used to obtain an estimate of the energy allocations or the Power Spectral Density (PSD) in various parts of the wide-band. In other words, we

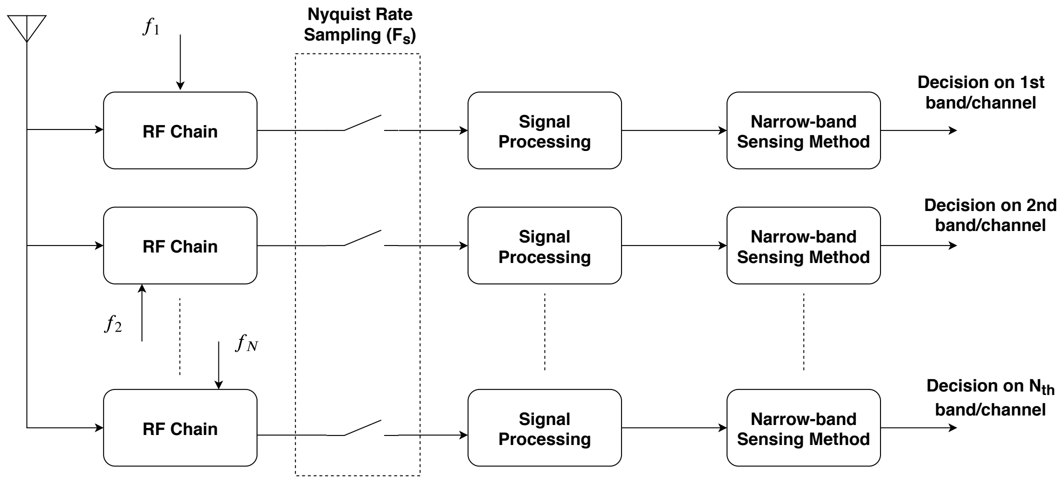

Figure 2.7: General Block Diagram of a Nyquist Rate Wide-Band Spectrum Sensing

end up with narrow-band spectra. Hypothesis tests are conducted on each narrow-band spectrum and decisions are made to find the empty holes in the wide-band spectrum. This technique was first proposed in [33]. One can see the issues in this technique. The high sampling rate needed to capture the wide-band signal can be difficult to implement and the power requirement is high. Moreover, the wider the signal is, the more difficult these issues become. In [3], the FFT-based detection method is combined with a novel technique to solve the power consumption issue. The authors proposed employing a comparator device instead of a high rate sampler and quantify the samples with just one bit. The proposed technique significantly reduces power consumption and complexity. They proceed to prove that the consequent degradation in performance is acceptable.

2.3.2 Wavelet-Based Detection

In this detection method, the PSD of the wide-band signal is modeled as a train of consecutive sub-bands [14]. Discontinuities can be interpreted as transitions between sub-bands and that, in turn, is an edge detection problem. Hence, it is sometimes referred to as an edge detector. The wavelet transform associated with this method can provide information about transition locations and spectral densities. Depending on the PSD information, the sub-bands can be identified as free or occupied. This method was first proposed in [34]. The main limitation of wavelet-based detection is high computational complexity. In [35], the wavelet-based detector was studied and analyzed considering an AWGN channel and a Rayleigh fading channel. In addition, the authors analyzed the PSD sensitivity to the Doppler shift in the wireless channel and quantified it through their simulations.

2.3.3 Filter-Bank Detection

Filter-bank detection is a straightforward wide-band spectrum sensing method where the CR device has a bank of filters, similar in a way to spectrum analyzers. This bank of filters can be modulated to cover the desired range of frequencies. Each filter results in a narrow-band signal that can be down-converted and sensed using a narrow-band sensing algorithm and the sampling rate needed for each band is low. The filter-bank detection method was presented in [36]. The advantage of this wide-band spectrum sensing method is the high performance and reliability of results. However, it is considerably difficult to implement a large number of Radio Frequency (RF) filters in parallel to enable this technique.

Some research efforts were invested in this detection method. In [37], a more efficient technique of filter-bank wide-band sensing was presented. It employs a polyphase DFT filter bank, and the resulting narrow-band spectra are sensed using an energy detector. Furthermore, it was compared with conventional periodogram spectral estimator and time domain sequential sensing, and proven to perform better. The proposed framework aims to reduce the complexity of a regular filter-bank detector. In [38], the authors presented a progressive decimation filter-bank which gives the detector the ability to adjust the detection bandwidth and change the sensing resolution if needed. They showed that the presented design provides performance which is as good as a regular filter-bank detector.

2.4 Cooperative Spectrum Sensing

Cooperative spectrum sensing is a spectrum sensing approach that was proposed and studied in [39]. It involves the collaboration of multiple SUs in the sensing operation. There are various reasons to employ cooperative sensing. A single SU may not be able to achieve the desired performance on its own, especially if energy detection is used and the SNR of PU is too low [40].

In addition, Non-Line-of-Sight (NLOS) conditions, hidden terminal issues [14], and severe fading and shadowing scenarios can compromise a single SU performance. Cooperative sensing exploits the spatial diversity of multiple SUs [7] [41]. A single SU can experience a deep shadowing scenario, and will not be able to make accurate decisions about the PU signal presence. However, when multiple SUs cooperate, the system can still rely on the sensing information from the SUs to make accurate decisions, even if one of them can not effectively sense the spectrum.

2.4.1 Cooperative Spectrum Sensing Models

In cooperative spectrum sensing, there are distributed models [42] and centralized models [43]. In distributed models, the SUs exchange sensing data among each other without a central node to organize their operations [44] [45]. The upside of this model is that every SU can make its own decisions with the help of nearby users and without the need for a central node. However, the downside is that the energy requirements to establish links with all the nearby SUs and process their data can be quite high [41]. On the other hand, in centralized models, the spectrum sensing operation carried out by SUs is organized by a central node, commonly referred to as Fusion Center (FC). The FC performs some tasks to ensure a reliable cooperative sensing operation. It signals to the SUs some instructions such as the frequency range to work with. It receives the sensing results from each SU and processes these results to come up with combined centralized decisions. Afterward, it relays back the sensing decisions to the SUs.

Cooperative spectrum sensing can be employed over narrow-bands or wide-bands. In the case of wide-bands especially, the switching delays and synchronization overheads can be quite significant. One way around that is to have the available SUs simultaneously sense a number of bands rather than one band at a time, and then combine the results at the FC to acquire the sensing results [33]. Other approaches involve having different SUs sense different bands of which their detection probability is maximum with respect to these bands [46]. This is referred to as parallel cooperative sensing.

Fig 2.8 shows a general diagram of centralized cooperative sensing. To enable this approach, a control channel is used by the CR devices to send the local sensing information to the FC, or relay the final decisions back from the FC to the SUs. There are some challenges related to this control

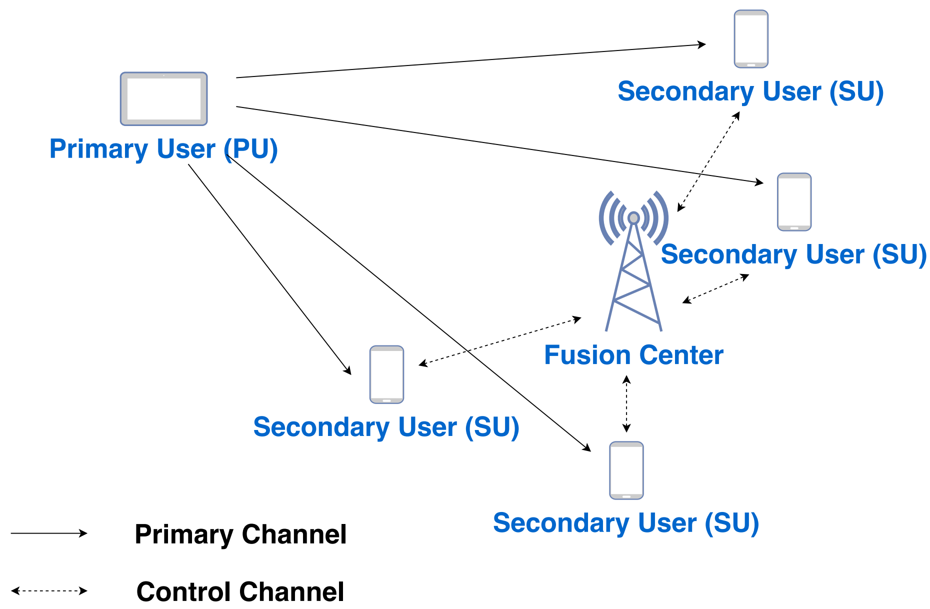

Figure 2.8: Centralized Cooperative Spectrum Sensing

channel. For example, the bandwidth of it can affect the quality of cooperation [47]. In addition, the reliability of the control channel can affect the overall system performance as well.

2.4.2 Sensing Data Fusion

Data fusion refers to the method used by the FC to combine the sensing data of the involved SUs to come up with the global sensing decisions. There are various methods to do so, but they usually fall under two main classifications. Hard-information decision fusion and soft-information decision fusion.

Hard-Information Decision Fusion

In the hard fusion scheme, each SU performs local spectrum sensing operation, acquires the sensing results and forwards them to the FC. The FC combines the results from the SUs according to some rules. One of the popular rules is the majority rule. If the majority of SUs decide the channel (or a certain sub-band in wide-band sensing) is occupied, the FC gives a global decision that it is occupied, and vice versa. Considering that, the total false alarm and detection probabilities are:

$$\begin{aligned} P[FA]_{total} &= \sum_{i=\lceil K/2 \rceil}^{K} \binom{K}{i} P_{FA}^{i} (1 - P_{FA})^{K-i} \\ P[D]_{total} &= \sum_{i=\lceil K/2 \rceil}^{K} \binom{K}{i} P_{D}^{i} (1 - P_{D})^{K-i} \end{aligned} \tag{2.4}$$

where K is the number of involved SUs, P_{FA} and P_D are the average local false alarm and detection probabilities, respectively [41]. A more generalized rule is the Q-out-of-K rule, where a certain global decision is only made when no less than Q secondary users SUs made that decision locally among K users. In other words:

$$\begin{aligned} P[FA]_{total} &= \sum_{i=Q}^{K} \binom{K}{i} P_{FA}^{i} (1 - P_{FA})^{K-i} \\ P[D]_{total} &= \sum_{i=Q}^{K} \binom{K}{i} P_{D}^{i} (1 - P_{D})^{K-i} \end{aligned} \tag{2.5}$$

The parameter Q usually goes into the analysis of these kinds of systems. In [48], the idea of cooperative spectrum sensing with hard-information combining is investigated while employing energy detection. The optimal decision voting rule to minimize the total error rate is found. In addition, the authors proposed a sensing algorithm that satisfies a given error bound with fewer SUs. In [49], the authors propose a cooperative wide-band sensing approach using the Q-out-of-K rule and based on the one-bit quantization. They analyze the performance on the system and the aggregate throughput of the CR network as Q changes. They optimize the throughput and show that their method yields a good performance even when accompanied by the one-bit quantization technique, which aims to reduce power consumption and complexity.

Other hard-information combining rules exist as well, such as the AND rule and the OR rule [14] [41]. Overall, the hard-information fusion offers decent performance, while requiring relatively small overhead, as the SUs send binary information to indicate vacancy/occupancy decisions.

Soft-Information Decision Fusion

In soft-information decision fusion [50], the SUs do not perform local hypothesis testing. The acquired samples or the decision statistics they acquire are reported to the FC over the control channel. The FC combines the sensing information from the SUs using various techniques such as the MRC to come up with a unified global decision. That decision is then relayed back to the SUs. Compared to the hard-fusion scheme, the soft-fusion renders more accurate results, especially when the quantization resolution is high. The sensing data may be accompanied by additional supporting information as well, such as sensing channel quality or sensing decision quality [41]. However, the downside of soft-fusion is the resulting overhead, which can be quite larger than the case of hard-fusion, and the associated time delays.

There are some approaches to reduce the overhead size in soft-fusion schemes. In [50], a softened hard combination method is proposed, where the soft sensing information is quantized using 2 bits. Similarly in [51], the authors discuss a method where the soft sensing information is quantized using a few quantization levels, resulting in a small number of bits. The objective of these softened hard-fusion methods is to have a good trade-off between the minimum overhead size of hard-fusion and the high sensing performance of soft-fusion.

In addition, some other concepts related to data fusion exist in the literature, such as the weighted-fusion. As the SUs can be situated in geographically independent locations, they don't necessarily receive the same average SNR value from the PUs. As a result, the FC assigns different weights to their sensing information before combining, depending on the average SNR values reported by the SUs.

2.5 Spectrum Sensing Using Multiple Antennas

In this section, we will have a look at the idea of using multiple antennas in spectrum sensing, some of the research work in that regard, and a brief comparison with cooperative sensing.

2.5.1 Multiple Antennas in Spectrum Sensing

Using multiple antennas in communications has been a common practice for quite a long time now. MIMO technology offered many improvements in data rates and error rates [52] [53]. Research efforts show that multiple antennas can be used in spectrum sensing as well [54]. A CR device using multi-antenna spectrum sensing has a number of antennas, each one leads to a separate RF chain.

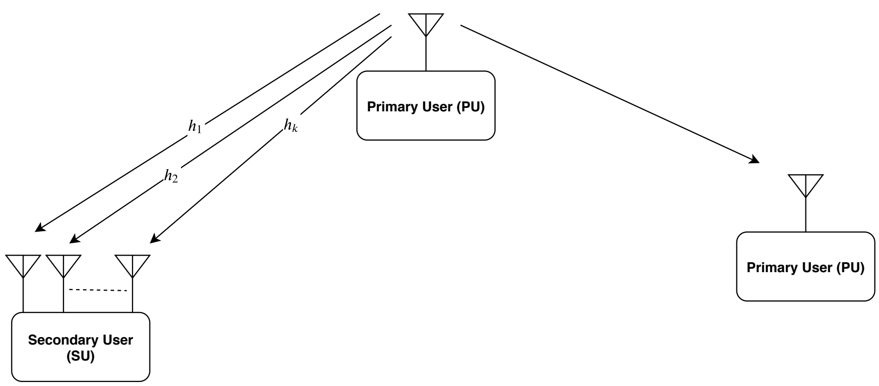

Figure 2.9: Multiple Antenna Spectrum Sensing

In an ideal scenario, the channels h_1, h_2 ... h_k (Fig. 2.9) between the PU and the antennas of the SU fade independently. That means when energy detection is used, the samples received by the different antennas and RF chains are statistically independent. As a result, combining these samples using some techniques such as the MRC will increase the degree-of-freedom of the received signal space, leading to an improved performance without prolonging the sensing time. Generally speaking, the equation (2.3) in case of multiple antennas becomes:

$$T = \sum_{k=0}^{K-1} \sum_{n=0}^{N-1} |y_n|^2 \tag{2.6}$$

where K is the number of antennas, N is the number of samples per antenna and T is the decision statistic. In a practical scenario, however, that is not necessarily the case. The different channels to each antenna may experience a level of correlation between them. The amount of correlation depends on some factors, such as the spacing between antennas, signal frequency, and the distance to the PU which affects the shape of the wavefront, among other factors [55]. The higher the correlation coefficient between antennas, the more degraded the performance of spectrum sensing will be. Analyzing the probability distribution of T in practical scenarios usually involves the eigenvalues of the antennas correlation matrix.

In [54], the authors discuss a multiple antenna system for spectrum sensing. First, they analyze the performance of an optimal detector when some parameters are known, such as the PU signal variance, noise variance and channels gain. After that, they present a Generalized Likelihood Ratio (GLR) detector for the case when some or all of those parameters are unknown and show that the GLR performance is close to the optimal detector.

A multiple antenna spectrum sensing CR is studied in the presence of impulsive noise in [56]. In that work, two multiple antenna based methods are proposed. One is based on the covariation properties of α-stable noise processes and the other tries to filter the corrupted signals before applying a traditional detection method. It was shown that the proposed method performs well in the presence of impulsive noise.

In [57], another multiple antenna system is presented. The authors propose two invariant constant false-alarm rate Eigenvalue-Based (EVB) detectors. They rely on higher-order moments of the sample covariance matrix eigenvalues, and derive false-alarm and detection probabilities expressions. In addition, they compare their detectors with other types of detection algorithms to show their effectiveness.

2.5.2 Multiple Antenna Sensing versus Cooperative Sensing

Using multiple antennas in energy detection spectrum sensing provides better performance than a single antenna, even if there is some correlation between the antennas. Compared to cooperative sensing, a CR device with multiple antennas can provide this improvement on its own without the need for a fusion center FC. However, in the case of deep shadowing, the SNR of the PU at the SU can get very low, compromising the performance of the device. In addition, multiple RF chains draw a lot of power, especially in the case of wide-band spectrum sensing and the needed high-speed ADC operation.

Cooperative sensing, on the other hand, makes use of the spatial diversity of the received signal by the secondary users. When multiple SUs are located in a certain region with enough spacing, the uncorrelated received signals yield decent performance, even if one of them happens to be deeply shadowed. In addition, there is no need for multiple RF chains. However, it still relies on the presence of multiple SUs and an FC to operate, besides the need for the common channel and the possible large frames overhead.

2.6 One-bit Quantization

As we have seen before, wide-band spectrum sensing is necessary for the enabling of interweave spectrum sharing. Scanning a wide range of frequencies is an important task for a CR device to find empty holes in the spectrum and exploit them. Whether it is single-user sensing or cooperative sensing, wide-band spectrum sensing by the Nyquist rate requires the use of ultra-high speed ADC. Optimum performance in the analysis of various CR systems assumes having an infinite resolution of the acquired samples. In reality, the acquired samples are quantized using a certain number of quantization levels.

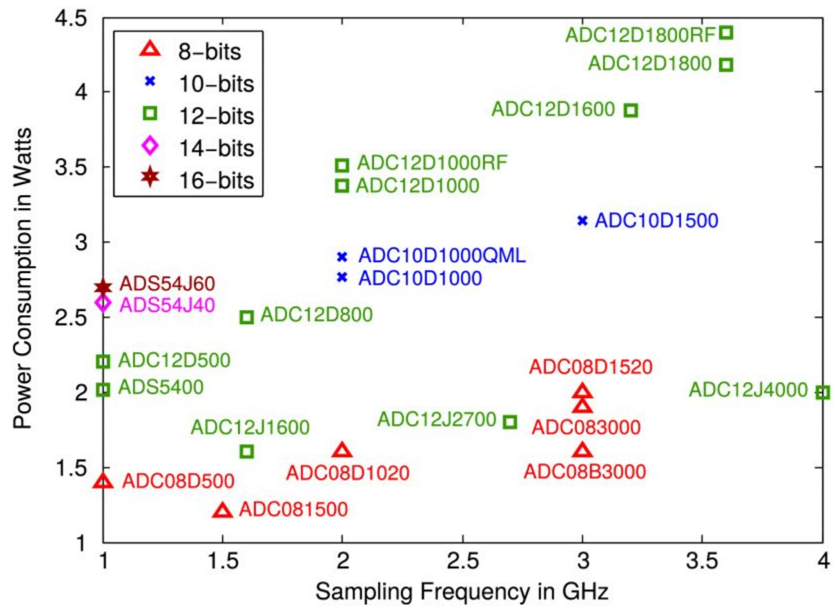

Figure 2.10: Power Consumption of Different High Speed ADC Models [58]

High-speed ADCs consume large amounts of power (Fig 2.10). The exact amount of power consumption depends on the exact sampling rate and quantization resolution, but it is in the order of watts for most ADC devices [58]. CR devices typically rely on battery power, which means that the power consumption of high-speed ADC is a challenging issue [59]. One-bit quantization is a sampling technique that can help with the power consumption issue of the ADC. This technique is used in various research fields, such as neural networks [60] and massive MIMO [61]. The idea is quite simple and straightforward. The received signal is quantized to one of only two quantization levels (usually +1 or -1). That means the resulting quantized signal can be represented with a single bit of data. As a result, power consumption and computational complexity are greatly reduced. Of course, the performance would degrade due to this approach and the associated loss of information. However, research work shows that the trade-off is actually good. The degradation in performance is minor compared to the huge save in power and reduction in complexity.

Using one-bit quantization in wide-band spectrum sensing was proposed in [3]. The impact of the one-bit quantization is quantified and it is shown that the method works well even at low SNR values. In addition, it is shown that the degradation of performance for one-bit quantized systems compared to unquantized systems is only about 2 dB. In [62], the authors presented a spatio-temporal wide-band spectrum sensing technique that employs multiple antennas in addition to using one-bit quantization. The objective is to reduce power consumption and use a reasonable sampling rate. Furthermore, the presented technique estimates the direction of arrival of the PU signal to improve the performance of the system.

2.7 Conclusions

In this chapter, we have taken a summarized look at the main categories and methods of spectrum sensing, employed in cognitive radio (CR) networks. Cognitive radio is a promising technology, found to exploit the under-utilized wireless frequency spectrum, which is a valuable resource. It is needed to accommodate some of the emerging and expanding wireless technologies such as Machine Type Communication (MTC) and the Internet of Things (IoT), etc. The various spectrum sensing methods are mainly employed in interweave spectrum sharing paradigms. They are needed to identify the empty parts of the wireless spectrum (also known as white holes) to exploit them when needed while maintaining the primary users' (PU) right to access the spectrum. In addition, we have looked at the high power consumption issue in wide-band sensing. Wide-band spectrum sensing at the Nyquist rate requires employing a high-speed ADC. One-bit quantization is a possible approach to alleviate this problem, as it greatly reduces power consumption and complexity.

In the following chapter, we will discuss a low power cooperative spectrum sensing approach. This approach can be categorized under soft-information decision fusion. We consider a special case where the SUs receive the PU signal with equal SNR value in order to simplify the analysis. The discussed method involves summing up the energy statistics acquired by SUs at the FC to come up with a unified decision statistic. Moreover, the system employs one-bit quantization to alleviate the power consumption and complexity issues. The simulations and analysis work show the improved performance compared to hard-fusion methods, in addition to the effect of the one-bit quantization.

In chapter 4, we extend the work in chapter 3 to a more general consideration of received SNR values by the SU. The goal is to have the analysis describe more real-life scenarios. We will present the relevant system model, sensing procedure and analysis work. In addition, we will have a look at the technique of using multiple antennas in spectrum sensing and compare it to the cooperative sensing, when the system receives uncorrelated samples by its antennas.

Chapter 3

Cooperative Low-Power Wideband Sensing by Energy Summation Using 1-bit Quantization

3.1 Introduction

In the previous chapter, we have seen the different types of spectrum sharing paradigms. In interweave cognitive radio networks, Secondary Users (SU) seek an opportunistic use to the Primary Users' (PU) frequency band [2]. As an alternative in case the PU appears to occupy the band, the SU should maintain a list of the available spectrum holes [33]. Wide-band sensing is required to observe a wide-band and to identify the occupied portions and those which are free. As discussed before, sampling at the Nyquist rate is one approach to realize wide-band sensing [24]. However, this method suffers from high power consumption, due to the need for a high-speed high precision Analog-to-Digital converter ADC. While maintaining a reasonable performance, one solution is to employ an aggressive 1-bit quantization technique which would consume tens to hundred micro-watts compared to the high precision ADC which typically consumes power in the order of few watts [58].

Single-user wide-band sensing based on energy detection has been analyzed while considering the effect of Signal-to-Noise Ratio (SNR) degradation arising from the aforementioned 1-bit quantization system [3]. To overcome the conventional issues such as the hidden terminal problem and poor channel conditions, cooperative sensing which involves the collaboration of multiple secondary users, has proved to be a promising solution [7]. In [63], a cooperative sensing technique based on two decision thresholds and hard combining was discussed to optimize the performance under noise uncertainty while employing general energy detection. To ultimately reduce the power consumption of the high precision ADC and to improve the sensing performance, a hard-decision cooperative sensing scheme is accompanied by the use of 1-bit quantization under the umbrella of Nyquist-based wide-band sensing [49].

Recently in [64], the authors proposed a Quade hypothesis test in a soft data-fusion based cooperative sensing. Further, they proposed a detector with lower complexity than the Quade test method and a small a overhead, while matching the performance of the Quade test itself. In the same work, it was shown that the proposed method maintains good performance even when multiple SUs simultaneously suffer from the hidden terminal issue. Moreover in [65], the authors considered a linear soft combination method and investigated its performance in different fading environments.

In this chapter, we present a novel low-power wide-band sensing scheme based on soft data-fusion cooperative sensing. Unlike hard-decision combining, SUs fuse the soft estimated energy values from various frequency pins into a centralized Fusion Center (FC) where final decisions are made. In addition to the ultra-low power consumption utilized by employing the 1-bit quantization, detection accuracy is improved without prolonging the sensing period by summing up the energy readings belonging to the same frequency pin from various SUs at the FC. Both simulations and analysis show the effect of the number of secondary users and the effect of the 1-bit quantization on the detection performance. Moreover, we analyze the total error rate as a function of the decision threshold and derive a closed-form expression for the optimum threshold value that minimizes the total error rate.

3.2 System Model

In cooperative wide-band sensing (Fig.2.8), the fusion center (FC) instructs the secondary users to perform wide-band sensing over the required wide-band. Let us consider a wide-band that consists of N sub-bands of equal size B, and this wide-band is sampled by each SU at the Nyquist rate: $F_s = NB$.

To compute an estimate for the Power Spectral Density (PSD) across various sub-bands, each secondary user processes a number of non-overlapped segments of samples. Each segment has exactly N samples. Let R be the $1 \times N$ vector, representing the frequency domain of the received spectrum, which is given by:

$$R = \sum_{m=1}^{M} H_m S_m + W \tag{3.1}$$

where M is the number of active primary users or occupied sub-bands $M < N$, H_m is a diagonal $N \times N$ channel matrix, and S_m is the mth signal spectrum [3]. Considering a Rayleigh fading channel, samples of the received signal will follow a Circularly Symmetric Complex Gaussian (CSCG) distribution. For each occupied sub-band, the primary user signal, if present, is assumed to have a variance of σ_s^2. It should be emphasized that this assumption certainly holds only when primary radios deploy uniform power transmission strategies given no channel knowledge at the transmitter side [33].

The frequency domain noise W is also assumed to be CSCG, and it occupies all the sub-bands. In other words: $E[WW^H] = N\sigma_w^2$. The signals of the primary users and the noise are statistically independent, and $E[RR^H] = M\sigma_s^2 + N\sigma_w^2$. It is also assumed that sub-bands vacancy or occupancy states are fixed during the sensing period, and the channel is static during that period.

3.3 Sensing Procedure And Decision Statistic

In the spectrum sensing mode, a typical cognitive radio device has a receiver RF chain that consists of a low noise amplifier (LNA) and a down-conversion circuit (Fig. 3.1). The in-phase and quadrature components of the base-band signal are each sampled by a 1-bit quantizer (i.e. a comparator) to one of two voltage states $(+1, -1)$. The samples are stored in a buffer. Every capture consists of N samples, to facilitate a Discrete Fourier Transform (DFT). Each SU stores an L number of captures in its buffer, resulting in a window of LN samples. A Received Signal Strength Indicator (RSSI) block provides an estimate of the total power of the received signal using a low sampling rate.

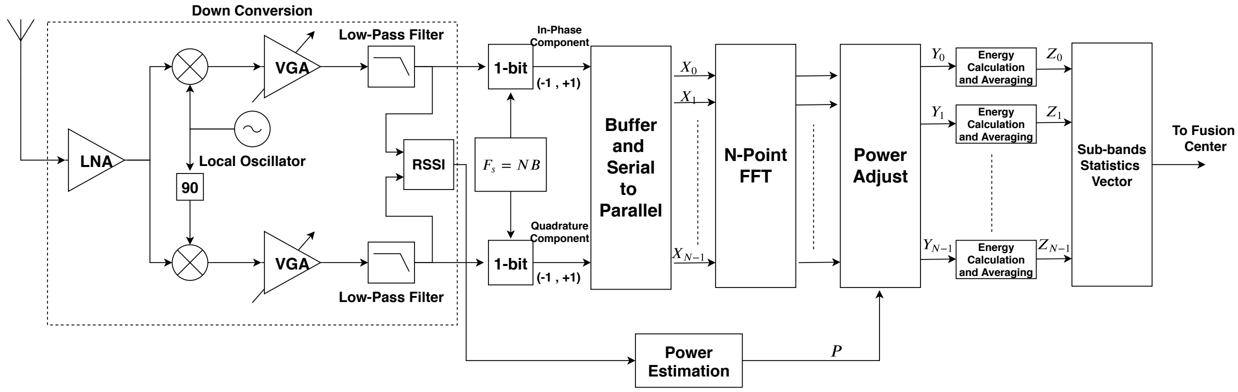

Figure 3.1: Architecture of a wide-band CR receiver in soft-fusion cooperative scheme and including 1-bit quantization

Each capture then proceeds into an N-point Fast Fourier Transform (FFT) block to undergo the aforementioned DFT. Let us define *N* as the number of sub-bands (the number of FFT points), *L* as the number of captures (*L* directly affects the sensing time), *K* as the number of secondary users, *X* as the time domain samples, *Y* as the frequency domain samples at the FFT block output, and *P* as the total signal power for a certain sensing window (Fig. 3.2). We have:

$$Y_{n,l}^{k} = \sqrt{\frac{P}{2N}} \sum_{i=0}^{N-1} X_{i,l}^{k} e^{-j2\pi in/N} \tag{3.2}$$

where $0 < i < N-1$, $0 < n < N-1$, $0 < l < L-1$, $0 < k < K-1$, and $P = E[RR^H]$. Note that the window of samples resulting from the FFT operation has a dimension *N*, that resembles the sub-bands, and the other dimension is *L* that contains frequency domain samples of each sub-band.

An energy statistic *Z* of each sub-band at each SU is calculated using the acquired samples and averaged by L, such that:

$$Z_n^k = \frac{1}{L} \sum_{l=0}^{L-1} |Y_{n,l}^k|^2 \quad . \tag{3.3}$$

This statistic is then forwarded to the FC from each SU and combined over the *K* dimension to obtain the total energy metric *C*, such that :

$$C_n = \sum_{k=0}^{K-1} Z_n^k \tag{3.4}$$

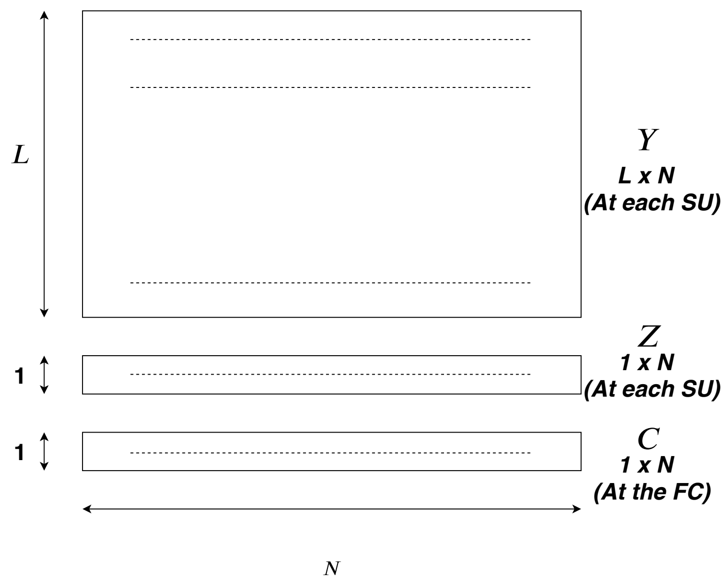

Figure 3.2: Sensing Window at Each Stage of The Cooperative Soft-Fusion Sensing Procedure

where C_n is a vector of *N* elements, located at the FC. The metric C_n is used to make decisions on the vacancy or occupancy of each sub-band.

3.4 Analysis For Non-Quantized Systems

Given the combined statistic C_n, and a defined threshold λ, the FC decides on the vacancy or occupancy of sub-bands, such that:

$$\begin{cases} C_n < \lambda & \longrightarrow \quad \text{Decision : free band} \\ C_n > \lambda & \longrightarrow \quad \text{Decision : occupied band} \end{cases} \tag{3.5}$$

To analyze the performance of the proposed energy summation cooperative sensing, we need to define the probability characteristics of C_n. To do that let us start at the FFT block output $Y_{n,l}^k$. As mentioned earlier, $Y_{n,l}^k$ is assumed to be a random variable with a CSCG distribution, such that:

$$\begin{cases} \mathcal{H}_{0,n} : \sigma_Y^2 = \sigma_w^2 & ;\text{If the band is free} \\ \mathcal{H}_{1,n} : \sigma_Y^2 = \sigma_w^2 + \sigma_s^2 & ;\text{If the band is occupied} \end{cases} \tag{3.6}$$

That is $|Y_{n,l}^k|$ follows a Rayleigh distribution, and $|Y_{n,l}^k|^2$ follows an exponential distribution with a parameter $\frac{1}{\sigma_Y^2}$. From (3.3) and (3.4), we have:

$$C_n = \frac{1}{L}\sum_{k=0}^{K-1}\sum_{l=0}^{L-1}|Y_{n,l}^k|^2 \quad . \tag{3.7}$$

Assuming the SUs are located in some area relatively close to each other and experience almost similar path-loss, we consider the secondary users to receive similar signal-to-noise ratio (SNR) values [63]. Therefore, $Y_{n,l}^k$ is identically distributed for all k. Hence, the random variable C_n follows an Erlang distribution [66], with a shape $\alpha = KL$ and a rate $\beta = (L/\sigma_Y^2)$.
The Cumulative Distribution Function (CDF) of C_n is given by :

$$F_C(c) = 1 - \sum_{i=0}^{KL-1}\frac{(\frac{cL}{\sigma_Y^2})^i}{i!}e^{-\frac{cL}{\sigma_Y^2}} \ , \ c > 0. \tag{3.8}$$

From (3.8), one can assess the performance of the system. In spectrum sensing, the performance is usually evaluated by analyzing the probability of false alarm, and the probability of detection. As explained in the previous chapter, the probability of false alarm is the probability that the system will decide a band is occupied when it is actually free. On the other hand, the probability of detection is the probability that the system will decide a band is occupied while in fact, it is. In other words:

$$\begin{aligned} P(FA) &= P[\text{Decision:Occupied}|\mathcal{H}_0] \\ P(D) &= P[\text{Decision:Occupied}|\mathcal{H}_1] \quad . \end{aligned} \tag{3.9}$$

Hence, we have:

$$\begin{aligned} P(FA) &= P(C_n > \lambda|\sigma_Y^2 = \sigma_w^2) \\ &= 1 - P(C_n < \lambda|\sigma_Y^2 = \sigma_w^2) \\ &= 1 - F_{C_n|\mathcal{H}_{0,n}}(\lambda) \\ &= \sum_{i=0}^{KL-1}\frac{(\frac{\lambda L}{\sigma_w^2})^i}{i!}e^{-\frac{\lambda L}{\sigma_w^2}} \quad . \end{aligned} \tag{3.10}$$

In a similar manner, one can get the probability of detection, which falls under the $H_{1,n}$ hypothesis:

$$P(D) = \sum_{i=0}^{KL-1}\frac{(\frac{\lambda L}{\sigma_w^2+\sigma_s^2})^i}{i!}e^{-\frac{\lambda L}{\sigma_w^2+\sigma_s^2}} \quad . \tag{3.11}$$

By looking at the mean values of Z_n^k and C_n, we can notice the achieved improvement by summing up the energy metrics using cooperative sensing. The metric Z_n^k itself has an Erlang distribution with a shape $\alpha = L$ and a rate $\beta = (L/\sigma_Y^2)$. Hence, the mean value of Z_n^k is:

$$E[Z_n^k] = \frac{\alpha}{\beta} = \sigma_Y^2 = \begin{cases} \sigma_w^2 & ; \quad \mathcal{H}_{0,n} \\ \sigma_w^2 + \sigma_s^2 & ; \quad \mathcal{H}_{1,n} \end{cases} \tag{3.12}$$

while for the combined statistic C_n :

$$E[C_n] = \frac{\alpha}{\beta} = K\sigma_Y^2 = \begin{cases} K\sigma_w^2 & ; \quad \mathcal{H}_{0,n} \\ K(\sigma_w^2 + \sigma_s^2) & ; \quad \mathcal{H}_{1,n} \end{cases} \tag{3.13}$$

The wider gap in the mean value of the statistic between the two cases ($K\sigma_s^2$) helps in making more accurate decisions using proper threshold values.

3.5 Analysis for 1-Bit Quantized Systems

In unquantized systems, the information is usually preserved after the FFT operation. However, it is not the case for 1-bit quantized systems. In the quantized case, the time domain signal gets saturated to one of two values (-1,+1), and the precise power transfer is disrupted.

The quantization effect is modeled as an added noise, where the occupied bands leak power to free bands (and possibly other occupied bands). This power leakage usually affects the neighboring bands more than the bands further away. In [3], an approximation technique is presented, where it is shown that the leakage power can be modeled as Gaussian distributed. Therefore, the FFT output in a 1-bit quantized system has a modified variance under $H_{0,n}$ and $H_{1,n}$ given by:

$$\begin{cases} \sigma_0^2 = \sigma_w^2(1 + \rho\gamma M/N) & ; \quad \mathcal{H}_{0,n} \\ \sigma_1^2 = \sigma_w^2(1 + \gamma - \gamma\rho + \rho\gamma M/N) & ; \quad \mathcal{H}_{1,n} \end{cases} \tag{3.14}$$

where N is the number of sub-bands, M is the number of occupied sub-bands, $\gamma = \sigma_s^2/\sigma_w^2$ is the SNR in one occupied sub-band, and ρ is a constant that basically defines the leakage amount. By repeated simulations, it was found to be $\rho \simeq e^{-1}$. With these adjusted values, the closed-form expressions of $P(FA)$ and $P(D)$ are given by:

$$P(FA)_{1-bit} = \sum_{i=0}^{KL-1} \frac{(\frac{\lambda L}{\sigma_0^2})^i}{i!} e^{-\frac{\lambda L}{\sigma_0^2}} \tag{3.15}$$

$$P(D)_{1-bit} = \sum_{i=0}^{KL-1} \frac{(\frac{\lambda L}{\sigma_1^2})^i}{i!} e^{-\frac{\lambda L}{\sigma_1^2}} \quad . \tag{3.16}$$

3.6 Threshold Optimization Based On Minimum Total Error Rate

It is worth noting that both the probability of false alarm $P[FA]$, and the probability of miss-detection, given as $P[MD] = 1 - P[D]$, change monotonically with the decision threshold. Therefore, it is of interest to find an optimum threshold value based on the total error rate, defined as the sum of $P[FA]$ and $P[MD]$.

To find a closed-form expression for the optimum threshold under that consideration, one needs to approximate the distribution of C_n to a normal distribution. This approximation can be justified using central limit theorem given that the total averaging depth KL is large enough. Accordingly, we have $C_n \sim \mathcal{N}(K\sigma_Y^2, \frac{K}{L}\sigma_Y^4)$, where $\sigma_Y^2 \overset{\mathcal{H}_0}{=} \sigma_0^2$ and $\sigma_Y^2 \overset{\mathcal{H}_1}{=} \sigma_1^2$ from (3.14). Hence:

$$P(FA)_{1-bit} = \frac{1}{\sqrt{2\pi \frac{k}{L}\sigma_0^4}} \int_{\lambda}^{\infty} e^{-\frac{(c-K\sigma_0^2)^2}{2(K/L)\sigma_0^2}} dc \tag{3.17}$$

$$P(MD)_{1-bit} = \frac{1}{\sqrt{2\pi \frac{k}{L}\sigma_1^4}} \int_{-\infty}^{\lambda} e^{-\frac{(c-K\sigma_1^2)^2}{2(K/L)\sigma_1^2}} dc \quad . \tag{3.18}$$

As mentioned earlier, the total error rate (TER) is given by $TER = P(FA) + P(MD)$. To find the optimization point, we differentiate TER with respect to the threshold variable λ and equal the result to zero:

$$\frac{d(TER)}{d\lambda} = \frac{dP(FA)}{d\lambda} + \frac{dP(MD)}{d\lambda} = 0 \quad . \tag{3.19}$$

To find the derivatives of $P(FA)$ and $P(D)$, we make use of the Leibniz rule to differentiate under the integral sign. We get:

$$\frac{dP(FA)}{d\lambda} = -\frac{1}{\sqrt{2\pi(K/L)\sigma_0^4}} \quad e^{-\frac{(\lambda-K\sigma_0^2)^2}{2(K/L)\sigma_0^4}} \tag{3.20}$$

$$\frac{dP(MD)}{d\lambda} = \frac{1}{\sqrt{2\pi(K/L)\sigma_1^4}} \quad e^{-\frac{(\lambda-K\sigma_1^2)^2}{2(K/L)\sigma_1^4}} \quad . \tag{3.21}$$

Substituting (3.20) and (3.21) in (3.19):

$$\begin{aligned}
-\frac{dP(FA)}{d\lambda} &= \frac{dP(MD)}{d\lambda} \\
\frac{1}{\sqrt{2\pi(K/L)\sigma_0^4}} \quad e^{-\frac{(\lambda-K\sigma_0^2)^2}{2(K/L)\sigma_0^4}} &= \frac{1}{\sqrt{2\pi(K/L)\sigma_1^4}} \quad e^{-\frac{(\lambda-K\sigma_1^2)^2}{2(K/L)\sigma_1^4}} \\
e^{-\frac{(\lambda-K\sigma_0^2)^2}{2(K/L)\sigma_0^4}} . e^{\frac{(\lambda-K\sigma_1^2)^2}{2(K/L)\sigma_1^4}} &= \sqrt{\frac{\sigma_0^4}{\sigma_1^4}} \\
\frac{(\lambda-K\sigma_1^2)^2}{2(K/L)\sigma_1^4} - \frac{(\lambda-K\sigma_0^2)^2}{2(K/L)\sigma_0^4} &= ln(\frac{\sigma_0^2}{\sigma_1^2}) \\
\sigma_0^4(\lambda-K\sigma_1^2)^2 - \sigma_1^4(\lambda-K\sigma_0^2)^2 &= 2(K/L)\sigma_0^4\sigma_1^4 ln(\frac{\sigma_0^2}{\sigma_1^2}) \\
\sigma_0^4\lambda^2 - 2K\sigma_1^2\sigma_0^4\lambda - \sigma_1^4\lambda^2 + 2K\sigma_0^2\sigma_1^4\lambda &= 4(K/L)\sigma_0^4\sigma_1^4 ln(\frac{\sigma_0}{\sigma_1})
\end{aligned} \tag{3.22}$$

In the end we have:

$$\lambda_{opt}^2 \; + \; \frac{2K(\sigma_0^2\sigma_1^4 - \sigma_1^2\sigma_0^4)}{\sigma_0^4 - \sigma_1^4} \, \lambda_{opt} \; - \; \frac{4K\sigma_0^4\sigma_1^4 ln(\frac{\sigma_0}{\sigma_1})}{L(\sigma_0^4 - \sigma_1^4)} \; = \; 0 \tag{3.23}$$

Note that (3.23) is a second-degree equation that can be solved to find the optimum threshold λ_{opt} that minimizes the total error rate for a given K, L , σ_0^2 and σ_1^2 .

3.7 Simulation Results

For the simulations, we considered a wide-band composed of $N = 1024$ sub-bands, of which M are occupied. The occupied sub-bands contain signals which are modulated using Quadrature Amplitude Modulation (QAM). A number of 10^4 trials were processed to evaluate the system performance. First, Fig.3.3 shows the Receiver Operating Characteristics (ROC) graph. The results show the possible combinations of $P(FA)$ and $P(D)$ values, depending on the set parameters, and threshold choice. All the simulation results and analysis values were taken by considering a relatively low sub-band SNR value of $\gamma = -6dB$, a typical averaging depth (number of samples of each sub-band) of each secondary user $L = 16$ and a number of occupied bands $M = 100$. It is important to note that the simulation results perfectly match the analysis. It also shows the

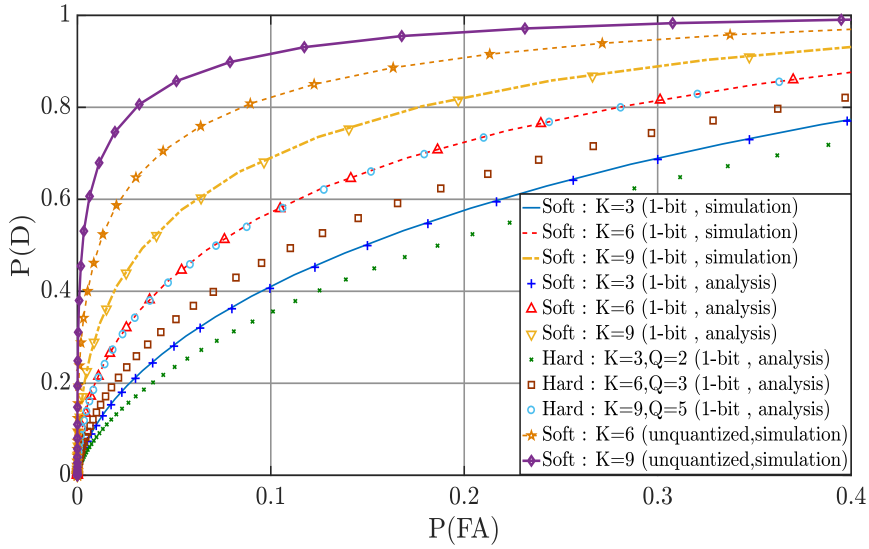

Figure 3.3: ROC comparison between different hard and soft combination methods and number of users, $\gamma = -6dB$, $M = 100$, $N = 1024$, $L = 16$

improvement of the soft combination method using energy summation over the hard combination method.

Fig.3.4 shows the effect of the 1-bit quantization on the performance compared to a non-quantized system. The deterioration of performance is only about 2 dB. The results in Fig. 3.4 considering $M = 100$, $L = 16$ and $P(FA) = 0.1$.

Fig.3.5 shows an example of the total error rate behavior with the change in threshold. Fig.3.6 shows the change in the total error rate at λ_{opt} as the number of cooperating users increases, and for different SNR values. It clearly shows that as the number of cooperating users increases, the probability of accurate decisions increases as well with fewer cases of false alarm or miss-detection.

3.8 Conclusions

A spectrum sensing soft combination approach of secondary users' energy readings. The objective is to enhance the degrees-of-freedom of the received signal space without greatly prolonging the sensing period. The enhanced degree-of-freedom yields more accurate results. It is shown that employing 1-bit quantization helps in greatly reducing power consumption and complexity. In ad-

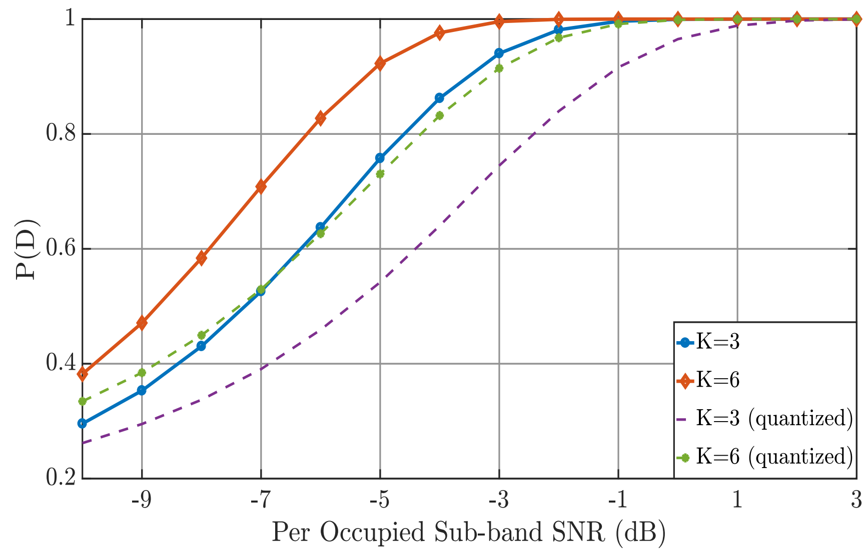

Figure 3.4: Detection performance for different sub-band SNR values, $N = 1024$, $M = 100$, $L = 16$, $P(FA) = 0.1$

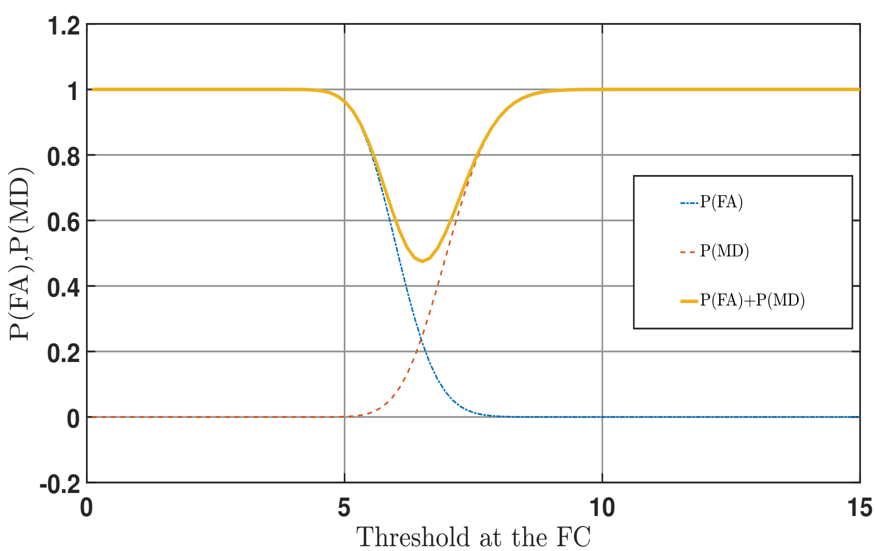

Figure 3.5: Example of Total Error Rate and Optimization point, $N = 1024$, $M = 100$, $K = 6$, $L = 16$, $\gamma = -6dB$

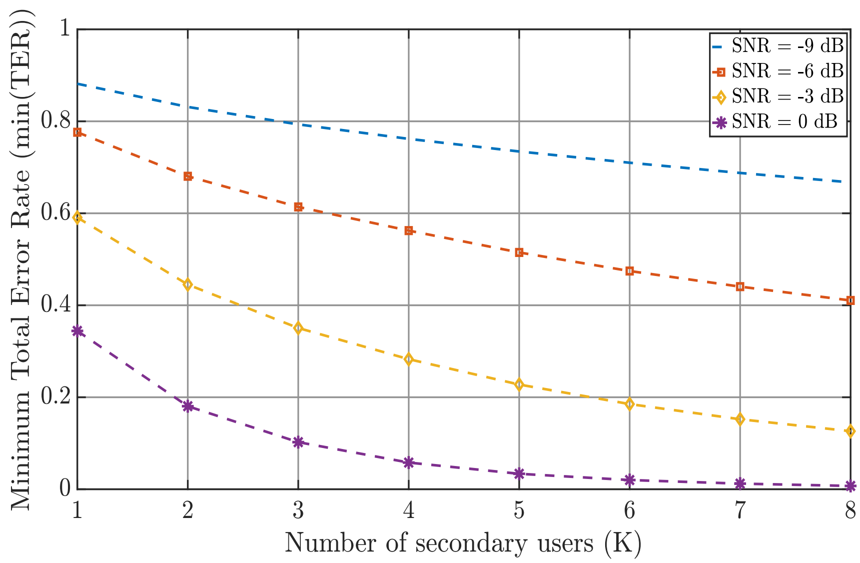

Figure 3.6: The minimum Total Error Rate (at the optimized threshold point) for different number of users and SNR values, $N = 1024$, $M = 100$, $L = 16$

dition, We have shown that the choice of optimum threshold will minimize the undesirable cases of false alarm and miss-detection. We analytically derived a closed-form expression to calculate this optimum threshold for different system parameters, which is shown to improve the performance.

We can summarize some of the most important points we can see as follows:

- Higher received SNR values at the SUs will obviously always improve signal detection performance. However, boosting signal transmission power by the PU is rarely an option. On one hand, boosting the transmission power may not be a useful approach as fading and shadowing effects are always present. On the other hand, PU devices are mostly networks User Equipment (UE), which are battery-powered and have transmission power constraints.

- Storing more captures of samples in the sensing window results in more samples in each sub-band. That will increase the averaging depth (degrees-of-freedom) improving the detection performance without boosting SNR. However, it could have a negative impact on the throughput, as it prolongs the sensing period.

- Having more secondary users cooperating in the spectrum sensing operation will give higher degrees-of-freedom to the unified decision metric C_n, improving performance. Nevertheless, it should be noted that more users mean higher traffic in the protocol that will organize the operation and the common channel that is used to exchange sensing information.

- As discussed before, using 1-bit quantization greatly reduces power consumption. In return, it causes a slight deterioration in detection performance. However, it can be considered a good trade-off when power consumption is a pressing issue.
- It is necessary to have a good received power estimation in order to apply the threshold optimization discussed above. Once done, the optimized threshold can greatly reduce the total error rate. It can also be seen that more SUs means even smaller total error rate at the threshold optimization point.

Chapter 4

Cooperative Sensing Under General SNR Consideration and Multi Antenna Sensing

4.1 Introduction

In chapter 3, we have discussed the performance of a soft-fusion cooperative spectrum sensing. It relies on summing up the energy readings of sub-bands which are acquired by the SUs, in order to have a decision statistic with high degree-of-freedom at the Fusion Center (FC). In addition, we have discussed the effect of the 1-bit quantization approach on the system and shown by simulation results that the performance degradation is small. The small performance degradation and the considerable save in power and complexity are quite a good trade-off [3] [58].

To simplify the analysis of the system and find expressions of the probabilities of false alarm and detection with reasonable complexity, we assumed that the SUs receive equal values of SNR from the PUs. This assumption is not uncommon in the literature of the CR research work [63] [67]. However, it is not an entirely realistic assumption at all times. In a cooperative spectrum sensing scenario, the SUs are likely to be situated in locations where they have different channel gains relative to the PU. Moreover, the SUs may experience different situations resulting in different amounts of fading, deep shadowing or other circumstances. As a result, the SNR values are surely to variate from one SU to another.

In this chapter, we will have a look at the performance of the soft-fusion cooperative spectrum sensing CR system in this more general scenario. We will keep the 1-bit quantization sampling approach as a part of the system. In addition, we will have a look at the performance of the single user multiple antenna sensing, in the special case where samples acquired by the different antennas of the SU device are uncorrelated and compare it to the cooperative sensing scheme.

4.2 System Model

Similar to the system model in chapter 3, we have a number of SUs, cooperating to perform the spectrum sensing operation. Each SU samples the wide-band at the Nyquist rate: $F_s = NB$, where N is the number of the non-overlapping sub-bands, and B is the bandwidth of each sub-band. Each secondary user stores a window of non-overlapping segments of exactly N samples. The frequency domain representation R^k of the received signal by each SU is given as:

$$R^k = \sum_{m=1}^{M} H_m^k S_m + W \tag{4.1}$$

where M is the number of active primary users or occupied sub-bands $M < N$, H_m^k is a diagonal N x N channel matrix relative to each SU, and S_m is the mth signal spectrum. Considering a Rayleigh fading channel again, samples of the received signal by each SU will follow a CSCG distribution. For each SU, the primary signal variance of occupied sub-bands is $\sigma_s^{2^k}$. On the other hand, the frequency domain noise W is assumed to be CSCG as well, and occupied all bands, which means $E[WW^H] = N\sigma_w^2$. The PU signals and the noise are statistically independent, i.e: $E[R^k R^{k^H}] = M\sigma_s^{2^k} + N\sigma_w^2$. It is assumed that the sub-bands vacancy or occupancy states do not change during the sensing period.

4.3 Decision Statistic and System Analysis

The CR receiver architecture is similar to what was described in chapter 3 (Fig 3.1). The segments of time domain 1-bit quantized samples undergo an FFT transformation to acquire a window of frequency domain samples $Y_{n,l}^k$ as in equation (3.2). From there, the energy metric at each SU, Z_n^k is acquired as in equation (3.3). The local vector of energy metrics Z_n^k is forwarded to the FC, and combined from all SUs to acquire the unified statistic vector C_n similar to equation (3.4). The decision about every sub-band is taken by comparing every entry of the vector C_n with a decision threshold λ, such that:

$$C_n \overset{?}{\lessgtr} \lambda \quad \longrightarrow \quad \text{Decision: sub-band } n \text{ is: Free/Occupied} \tag{4.2}$$

To analyze the system performance, let us look at equation (3.6) which describes the variance of the total received signal in a certain sub-band n without quantization. The difference here is that as discussed before, the signal variance σ_s^2 is not the same between SUs and as such, we denote it as σ_s^{2k}. In other words, $Y_{n,l}^k \sim \mathcal{CN}(0, {\sigma_Y^2}^k)$, where:

$$\begin{cases} \mathcal{H}_{0,n} : {\sigma_Y^2}^k = \sigma_w^2 & ; \text{If the band is free} \\ \mathcal{H}_{1,n} : {\sigma_Y^2}^k = \sigma_w^2 + \sigma_s^{2k} & ; \text{If the band is occupied.} \end{cases} \tag{4.3}$$

We have $Z_n^k = (1/L) \sum_{l=0}^{L-1} |Y_{n,l}^k|^2$, which is the vector of energy statistics at each SU. It is an averaged sum of a number of Independent and Identically Distributed (i.i.d) exponential random variables. Therefore, it is a gamma random variable with the shape and scale parameters given as:

$$Z_n^k \sim \Gamma(\alpha = L, \theta = \frac{{\sigma_Y^2}^k}{L}) \, . \tag{4.4}$$

The random variable Z_n^k has identical shape value L between SUs, but the scale value $({\sigma_Y^2}^k/L)$ varies. As a result, when they are combined at the FC to get the vector C_n, we have at our hands a vector of random variables which are the sum of Independent non-Identically Distributed (i.n.i.d) gamma random variables.

The sum of i.n.i.d gamma random variables is a random variable with no defined CDF and a very complicated PDF. In [68], this PDF is given by:

$$f_S(x) \; = \; \frac{Q}{\Gamma(\rho + k)\beta_1^{\rho+k}} \sum_{k=0}^{\infty} \delta_k^{\rho+k-1} exp(-\frac{x}{\beta_1}) \; ; \; x > 0 \tag{4.5}$$

where S is the sum of i.n.i.d gamma random variables, Q and δ_k have their own equations. To deal with this problem, there are some approximation techniques. [69, Lemma 1] states that the sum of i.n.i.d gamma random variables can be approximated as another gamma random variable, with modified shape and scale parameters given by:

$$\begin{aligned} \alpha \; &= \; \frac{(\sum_{k=0}^{K-1} \alpha_k \theta_k)^2}{\sum_{k=0}^{K-1} \alpha_k \theta_k^2} \\ \theta \; &= \; \frac{\sum_{k=0}^{K-1} \alpha_k \theta_k^2}{\sum_{k=0}^{K-1} \alpha_k \theta_k} \end{aligned} \tag{4.6}$$

where K is the number of gamma random variables. In our case, we have $C_n = \sum_{k=0}^{K-1} Z_n^k$, $\alpha_k = L, \theta_k = ({\sigma_Y^2}^k/L)$. Substituting in (4.6), we get the modified shape:

$$\begin{aligned}\alpha_C &= \frac{(\sum_{k=0}^{K-1} L\frac{{\sigma_Y^2}^k}{L})^2}{\sum_{k=0}^{K-1} L(\frac{{\sigma_Y^2}^k}{L})^2} \\ &= \frac{L(\sum_{k=0}^{K-1} {\sigma_Y^2}^k)^2}{\sum_{k=0}^{K-1}({\sigma_Y^2}^k)^2}\end{aligned} \tag{4.7}$$

and the modified scale:

$$\begin{aligned}\theta_C &= \frac{\sum_{k=0}^{K-1} L(\frac{{\sigma_Y^2}^k}{L})^2}{\sum_{k=0}^{K-1} L\frac{{\sigma_Y^2}^k}{L}} \\ &= \frac{\sum_{k=0}^{K-1}({\sigma_Y^2}^k)^2}{L\sum_{k=0}^{K-1} {\sigma_Y^2}^k} .\end{aligned} \tag{4.8}$$

These modified parameters can be applied in the general CDF formula of the gamma distribution to acquire the CDF of the decision statistic C_n:

$$\begin{aligned}F_X(x; \alpha, \theta) &= \frac{\gamma(\alpha, \frac{x}{\theta})}{\Gamma(\alpha)} \\ F_{C_n}(c) &= \frac{\gamma(\alpha_C, \frac{c}{\theta_C})}{\Gamma(\alpha_C)}\end{aligned} \tag{4.9}$$

where the numerator is the lower incomplete gamma function and the denominator is the gamma function. From there, one can use the CDF of C_n to find the $P(FA)$ and $P(D)$ achieved by using a certain decision threshold value λ:

$$\begin{aligned}P(FA) &= P[C_n > \lambda | {\sigma_Y^2}^k = \sigma_w^2] = 1 - F_{C_n|\mathcal{H}_{0,n}}(\lambda) \\ P(D) &= P[C_n > \lambda | {\sigma_Y^2}^k = {\sigma_S^2}^k + \sigma_w^2] = 1 - F_{C_n|\mathcal{H}_{1,n}}(\lambda) .\end{aligned} \tag{4.10}$$

These expressions describe $P(FA)$ and $P(D)$ in the non-quantization case. When the 1-bit quantization method is employed, the term ${\sigma_Y^2}^k$ gets modified under the $\mathcal{H}_{0,n}$ and $\mathcal{H}_{1,n}$ scenarios into σ_0^{2k} and σ_1^{2k} as described before in (3.14).

4.4 Multiple Antenna Sensing with Uncorrelated Channels

We have discussed in chapter 2 the possibility of employing multiple antennas in spectrum sensing. Let us consider a single CR device with a number of receiving antennas A (Fig. 4.1). Each antenna

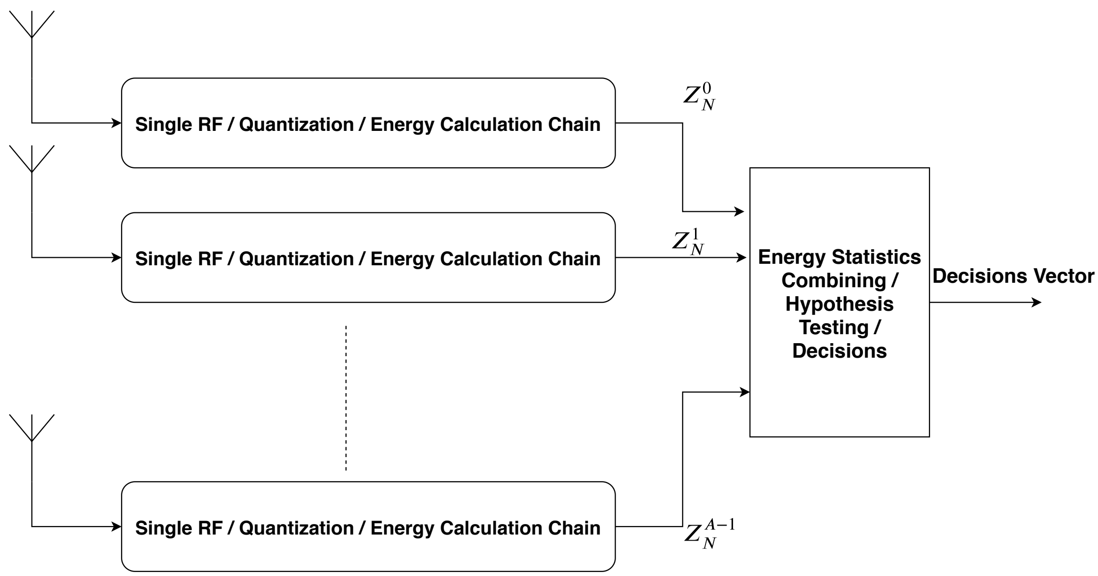

Figure 4.1: A Wide-band Multiple Antenna CR Receiver

is connected to a separate RF and energy calculation chain, similar to the one in Fig 3.1. The only difference is that these chains are located within a single CR device, and the vectors of averaged energy statistics are combined locally without the need for an FC.

Similar to the system model in the previous chapter, we will consider a Rayleigh fading channel. In other words, the received samples of the PU signals at each antenna are CSCG. The noise is considered to be CSCG as well, and it is statistically independent of the PUs signals. For the purpose of this chapter, and as mentioned before, we will consider the channels from the PUs to each antenna to be uncorrelated. This is an ideal case, where the samples acquired by each antenna and RF chain are uncorrelated. Accordingly, we can summarize the analysis of this spectrum sensing system as follows:

$$Z_n^a = (1/L) \sum_{l=0}^{L-1} |Y_{n,l}^a|^2 \tag{4.11}$$

where Z is the vector of energy statistic at the output of each chain, N is the number of sub-bands $(0 < n < N-1)$, L is the number of captures in each sensing window (as in Fig. 3.2)$(0 < l <$

$L-1$), A is the number of antennas ($0 < a < A-1$) and Y is the frequency domain samples.

$$C_n = \sum_{a=0}^{A-1} Z_n^a \tag{4.12}$$

where C_n is the combined decision metrics vector at the final stage of the system. Considering the SNR value to be equal among antennas (as they are located locally), the analysis would follow the same steps taken in the special case cooperative sensing. In other words, taking 1-bit quantization into account, the $P(FA)$ and $P(D)$ will be:

$$P(FA)_{1-bit} = \sum_{i=0}^{AL-1} \frac{(\frac{\lambda L}{\sigma_0^2})^i}{i!} e^{-\frac{\lambda L}{\sigma_0^2}} \tag{4.13}$$

$$P(D)_{1-bit} = \sum_{i=0}^{AL-1} \frac{(\frac{\lambda L}{\sigma_1^2})^i}{i!} e^{-\frac{\lambda L}{\sigma_1^2}} \quad . \tag{4.14}$$

It is logically expected that this kind of system will - in the ideal case of uncorrelated samples - yield similar performance to the cooperative spectrum sensing system. We will confirm that in the simulations results section and give it more discussion later in the chapter.

4.5 Simulation Results

To perform the simulations, we considered a wide-band of N = 1024 sub-bands, of which M are occupied with QAM modulated signals. A number of 10^4 trials were processed to evaluate the system. For the case of cooperative spectrum sensing with variant received SNR values (Fig. 4.2), we considered a scenario where K secondary users are present. They receive the PU signals with a different SNR value each, randomly picked from the [-6,-3] dB range with uniformly distributed probabilities. To further validate the results, we ran the simulation again where all the SU received an equal SNR value of -4.26 dB, which is the mean value of the [-6,-3] dB range. As expected they match each other. Furthermore, it is clear that the analysis matches the simulations as well. To acquire the shape and scale parameters in (4.7) and (4.8) and run the analysis, numerous randomly generated values of the SNR were taken from the [-6,-3] dB range. After that, the shape and scale parameters were calculated accordingly and sample means of them were considered in (4.9) and (4.10). All the curves in Fig 4.2 were plotted considering a number of sub-bands N = 1024,

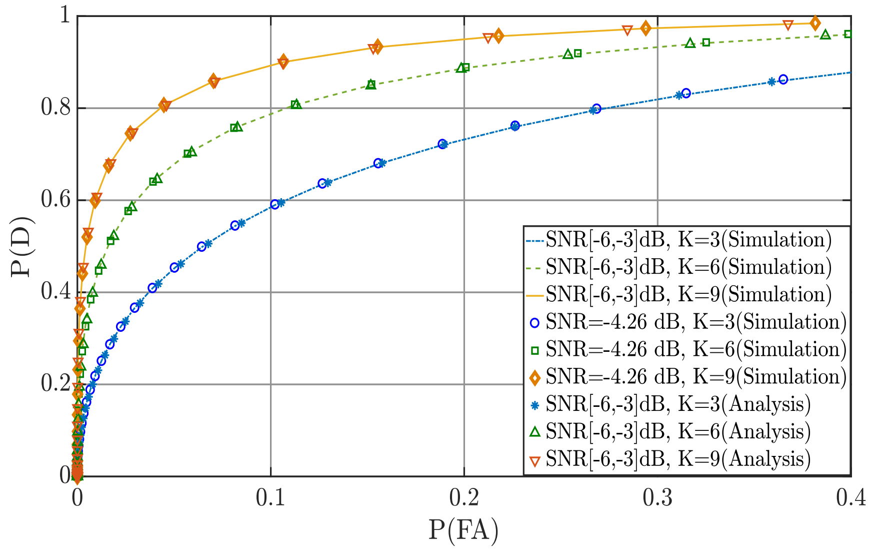

Figure 4.2: ROC curves for the cooperative spectrum sensing under general SNR considerations, $N = 1024$, $M = 100$, $L = 16$, 1-bit quantization

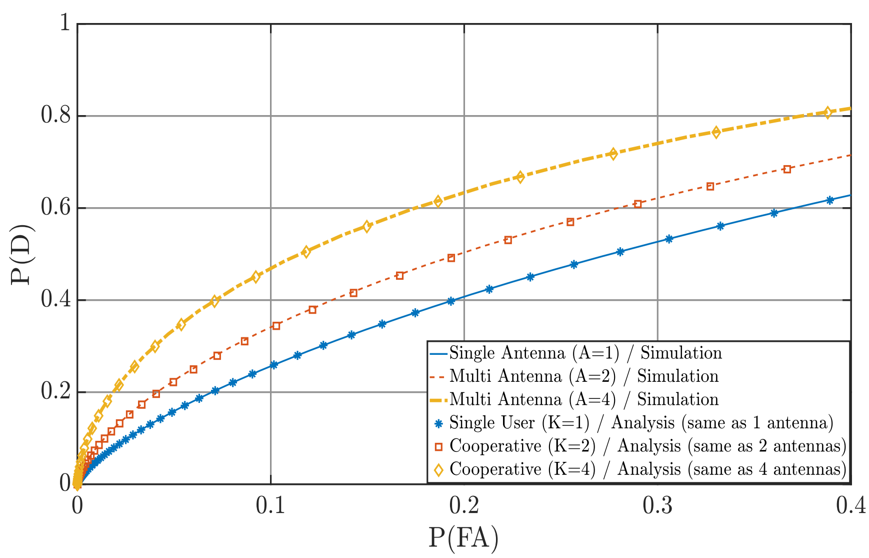

Figure 4.3: ROC curves for the multiple antenna sensing, compared with special case cooperative sensing,$SNR = -6dB$, $N = 1024$, $M = 100$, $L = 16$, 1-bit quantization

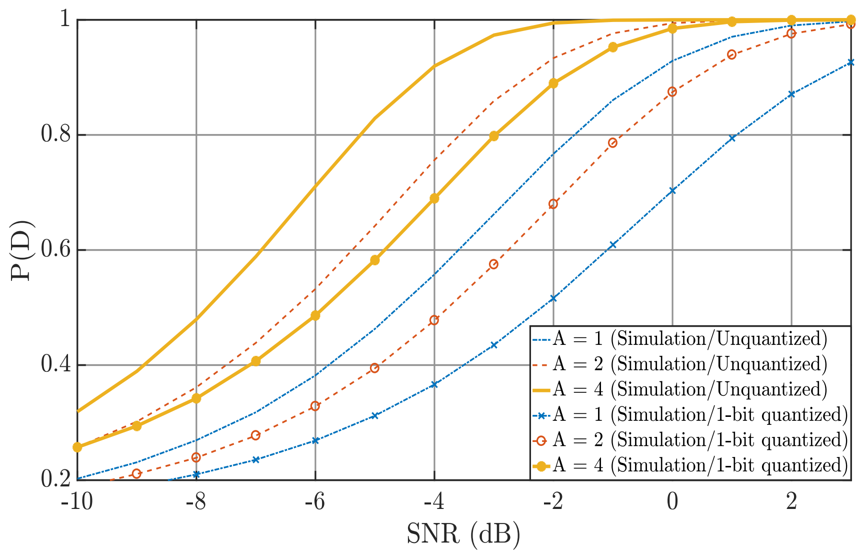

Figure 4.4: Detection performance for the multiple antenna sensing for non-quantization and 1-bit quantization cases, $SNR = -6dB$, $N = 1024$, $M = 100$, $L = 16$, $P(FA) = 0.1$

number of active PUs M = 100, number of captures (averaging depth) $L = 16$, and employing 1-bit quantization technique.

In Fig 4.3, we can see the ROC curves for the multiple antenna spectrum sensing in the scenario we have discussed before, considering typical values for the number of antennas. In addition, the figure shows the performance of the special case of cooperative spectrum sensing (equally received SNR) with similar numbers of cooperating secondary users. As expected they match each other considering uncorrelated samples received by antennas. Finally, in Fig 4.4, we can see the detection performance for the multiple antenna sensing in both cases where 1-bit quantization is used or not. For both figures we have N = 1024, M = 100, L = 16.

4.6 Conclusions and Discussion

In this chapter, we discussed the energy summation soft-fusion approach to cooperative spectrum sensing under general SNR consideration. The objective is to set up the way for further research in this sensing technique, as real-life scenarios most likely dictate that received signals' SNR can easily vary with location. In this chapter, we only considered a case where SNR varies between users while randomly taking values from a uniform distribution. Other types of distribution or approaches of SNR assignments which are closer to real-life can be considered in future research with deeper analysis. Moreover, the figures show that the simulation of this case and its analysis match each other well.

In addition, we took a look at the approach of multiple antenna sensing and considered the case where the channels to each antenna are uncorrelated. In other words, the received signal samples at each antenna are uncorrelated. It can be seen from simulation results and analysis that the performance with this assumption is similar to the cooperative sensing. We considered typical possible numbers of antennas on a single CR device (A=1,2,4). However, a more thorough analysis requires considering the correlation matrix of antennas. That, in turn, requires studying the physical structure of the receiver device including antennas spacing among other factors.

All the summarized points we mentioned in the conclusion of the previous chapter apply here as well. In addition, it is good to remember the comparison we discussed in chapter 2, section 2.5.2, between multiple antenna sensing and cooperative sensing.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

Cognitive radio is a promising technology that offers a viable solution to the scarcity of available wireless bands, exploiting the under-utilization of the spectrum. The interweave spectrum sharing paradigm of cognitive radio networks aims to opportunistically share the licensed spectrum to enable different kinds of wireless communications. To that end, CR devices in interweave networks employ what is known as spectrum sensing. Spectrum sensing is the operation where a CR scans a part of the spectrum to find the empty parts of it. Having a CR capability in a communications device will give it great agility to find open space in the spectrum and use them. Cognitive radio technology will go a long way in assisting the expansion of M2M and IoT communications.

In this thesis, we have focused our attention on cooperative spectrum sensing, after presenting a general review about the main categories and techniques of spectrum sensing in chapter 2. In chapter 3, we investigated the performance of a cooperative sensing technique that depends on combining the energy statistics of sub-bands from multiple SUs. We applied the 1-bit quantization sampling approach to counter the high power consumption issue, a result of employing high speed ADC in wide-band sensing. We presented the analysis work of the system, both for non-quantized and 1-bit quantized cases and shown by results that the performance degradation is small. In addition, we showed that this approach yields better performance than hard-information data fusion approaches. Furthermore, we defined the total error rate as a function of the decision threshold and derived an optimum threshold formula that minimized this rate.

In chapter 4, we extended the work in chapter 3 and discussed the cooperative soft-information data fusion under general SNR consideration and explained the reasons to investigate that case. We presented the analysis for that case and discussed a suitable approximation method that can be a starting point in deeper analysis into that case. We applied the 1-bit quantization technique in this chapter's work as well. In addition, we discussed using multiple antennas in spectrum sensing and compared its performance to cooperative sensing. We showed that the performance matches the cooperative sensing performance in the ideal case and spoke about its advantages and disadvantages.

5.2 Future Work

Here are some of the possible research points related to our work that can be worked upon in the future:

- We only considered Rayleigh fading channels in our work. Other types of channels can be investigated to consider various scenarios.
- We relied on the minimum total error rate to find an expression for the optimum decision threshold. Other aspects can be considered to find this optimum threshold, such as maximizing the cognitive radio network throughput.
- There are other approaches to apply the soft-information decision fusion, such as weighted fusion [7]. At the FC, different weights are given to the data coming from each SU depending on their received SNR, to resemble the trust in their sensing data.
- We only discussed the ideal case in multiple antenna sensing, where the channels to each antenna are uncorrelated. In fact, to resemble a real-life performance, the correlation between antennas must be considered and it is bound to be involved in the analysis of the system.

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