Optimal Cooperative Spectrum Sensing for Cognitive Radio

Oluyomi Simpson

A thesis submitted to the University of Hertfordshire in partial fulfilment of the requirements of the degree of Doctor of Philosophy

The programme of research was carried out in the Science and Technology Research Institute (STRI), University of Hertfordshire,

United Kingdom.

July 2016

Abstract

The rapid increasing interest in wireless communication has led to the continuous development of wireless devices and technologies. The modern convergence and interoperability of wireless technologies has further increased the amount of services that can be provided, leading to the substantial demand for access to the radio frequency spectrum in an efficient manner. Cognitive radio (CR) an innovative concept of reusing licensed spectrum in an opportunistic manner promises to overcome the evident spectrum underutilization caused by the inflexible spectrum allocation. Spectrum sensing in an unswerving and proficient manner is essential to CR. Cooperation amongst spectrum sensing devices are vital when CR systems are experiencing deep shadowing and in a fading environment. In this thesis, cooperative spectrum sensing (CSS) schemes have been designed to optimize detection performance in an efficient and implementable manner taking into consideration: diversity performance, detection accuracy, low complexity, and reporting channel bandwidth reduction. The thesis first investigates state of the art spectrums sensing algorithms in CR. Comparative analysis and simulation results highlights the different pros, cons and performance criteria of a practical CSS scheme leading to the problem formulation of the thesis. Motivated by the problem of diversity performance in a CR network, the thesis then focuses on designing a novel relay based CSS architecture for CR. A major cooperative transmission protocol with low complexity and overhead - Amplify and Forward (AF) cooperative protocol and an improved double energy detection scheme in a single relay and multiple cognitive relay networks are designed. Simulation results demonstrated that the developed algorithm is capable of reducing the error of missed detection and improving detection probability of a primary user (PU).

To improve spectrum sensing reliability while increasing agility, a CSS scheme based on evidence theory is next considered in this thesis. This focuses on a data fusion combination rule. The combination of conflicting evidences from secondary users (SUs) with the classical Dempster Shafter (DS) theory rule may produce counter-intuitive results when combining SUs sensing data leading to poor CSS performance. In order to overcome and minimise the effect of the counter-intuitive results, and to enhance performance of the CSS system, a novel state of the art evidence based decision fusion scheme is developed. The proposed approach is based on the credibility of evidence and a dissociability degree measure of the SUs sensing data evidence. Simulation results illustrate the proposed scheme improves detection performance and reduces error probability when compared to other related evidence based schemes under robust practcial scenarios.

Finally, motivated by the need for a low complexity and minmum bandwidth reporting channels which can be significant in high data rate applications, novel CSS quantization schemes are proposed. Quantization methods are considered for a maximum likelihood estimation (MLE) and an evidence based CSS scheme. For the MLE based CSS, a novel uniform and optimal output entropy quantization scheme is proposed to provide fewer overhead complexities and improved throughput. While for the Evidence based CSS scheme, a scheme that quantizes the basic probability Assignment (BPA) data at each SU before being sent to the FC is designed. The proposed scheme takes into consideration the characteristics of the hypothesis distribution under diverse signal-to-noise ratio (SNR) of the PU signal based on the optimal output entropy. Simulation results demonstrate that the proposed quantization CSS scheme improves sensing performance with minimum number of quantized bits when compared to other related approaches.

Acknowledgments

I give thanks to Almighty God for His steadfast grace, love, guidance, protection, faithfulness and for providing me this opportunity and granting me the capability to proceed successfully.

I would like to express my sincere gratitude to my supervisor, Professor Yichuang Sun for his guidance, support, encouragement in the preparation and development towards my research work and towards the completion of this thesis. His patience, insightful discussion, critical comments, advice both in technical and non-technical matters have been exceedingly valuable and have helped to create a wonderful learning experience. I also want to thank my second supervisor Dr. David Lauder for his excellent advises during the PhD review process.

I cannot express enough gratitude to my family and friends. I warmly thank and appreciate my brother, sister and especially my mother Dr. Theodora Simpson for the love, affection, and spiritual support they have shown me. They have stood by me all the way and have been there for me at all times.

I will also like to thank Dr. Nnamdi Nwanekezie and Yusuf Abdulkadir for their assistance and motivation. I am grateful to my former and current group mates of the Radio and Mobile Communication research group and Optical Network research group, for their friendship, enthusiastic help and cheerfulness.

Table of contents

List of Figures

List of Tables

List of Acronyms

5G	fifth generation
4G	fourth generation
ACF	autocorrelation function
ADC	analogue-digital converter
AF	amplify and forward
AM	ambiguity measure
ASN	average sample number
AWGN	additive white Gaussian noise
BCH	Bose-Chaudhuri-Hocquengham
BER	bit error rate
BP	basis pursuit
BPA	basic probability assignment
BPSK	binary phase shift keying
BS	base station
BW	bandwidth
CD	cyclostationary detector
CDF	cumulative density function

CLT	central limit theorem
CM	correlation matrix
CP	cyclic prefix
CR	cognitive radio
CRAHNs	CR adhoc networks
CSMA	carrier sense multiple accessing
CSS	cooperative spectrum sensing
CU	cognitive user
CV	Chair-Varshney
DF	decode and forward
DSA	dynamic spectrum access
DSP	digital signal processing
DS-THEORY	Dempter-Shafer theory of evidence
DTT	digital terrestrial television
DVB-T	digital video broadcasting - terrestrial
DVB-T2	digital video broadcasting - second generation terrestrial
DySPAN- SC	dynamic spectrum access networks standards committee
ED	energy detector
EGC	equal gain combining
EME	minimum eigenvalue

ETSI	european elecommunications standards institute
FC	fusion centre
FFT	fast fourier transform
FSA	fixed spectrum allocation
FSS	fixed sample size
GLRT	generalized likelihood ratio test
GPS	global positioning system
GSM	global system for mobile communication
HD	hard decision
I.I.D	independent and identically distributed
IFFT	Inverse Fast Fourier Transform
ISI	inter symbol interference
ISM	industrial, scientific and medical band
LDPC	low density parity check
LLR	log-likelihood ratio
LR	likelihood ratio
LRT	log ratio test
LTE	long term evolution
LU	licensed user
MAE	minimum average entropy

MFD	matched filter detector
MIMO	multiple input multiple output
ML	maximum likelihood
MLE	maximum likelihood estimate
MLR	maximum likelihood ratio
MME	max-min eigenvalue
MMSE	minimum mean-squared error
MOE	maximum output entropy
MRC	maximum ratio combining
MV	majority voting
NP	Neyman-Pearson
OFCOM	the office of communications
OFDM	orthogonal frequency division multiplexing
PDF	probability density function
PMF	probability mass function
PSD	power spectral density
PSK	phase shift keying
PU	primary user
QAM	quadrature amplitude keying
QOS	quality of service

RF	radio frequency
ROC	receiver operating characteristics
RSSI	received signal strength indicator
SD	soft decision
SDR	software defined radio
SNR	signal to noise ratio
SPRT	sequential probability ratio test
SS	spectrum sensing
STBC	space time block coding
SU	secondary user
TVWS	tv white spaces
UTQ	uniform threshold quantization
WLAN	wireless local area network
WMAN	wireless metropolitan area networking
WPAN	wireless personal area network
WSS	wideband spectrum sensing

List of Publications

Declaration: The following papers have been published and parts of their material are included in this thesis:

Relevant Journal Publication

1. **Oluyomi Simpson** and Yichuang Sun "*Evidence-based Decision Fusion Scheme for Cooperative Spectrum Sensing in Cognitive Radio Networks*" IEEE Transactions on Wireless Communications. (Under submission)

Relevant Conference Publication

1. **Oluyomi Simpson**, Yusuf Abdulkadir and Yichuang Sun "*Optimal Entropy Quantization for Maximum Likelihood Estimation based Cooperative Spectrum Sensing,*" presented at Wireless Telecommunications Symposium (WTS), London, April 2016.
2. Yusuf Abdulkadir, **Oluyomi Simpson**, Nnamdi Nwanekezie and Yichuang Sun, "Space-*Time Opportunistic Interference Alignment in Cognitive Radio Networks*," presented at IEEE Wireless Communications and Networking Conference (WCNC), Qatar, April 2016.
3. **Oluyomi Simpson**, Yusuf. Abdulkadir and Yichuang Sun, *"Relay-Based Cooperative Spectrum Sensing with Improved Energy Detection in Cognitive Radio,"* presented at Broadband and Wireless Computing, Communication and Applications (BWCCA), Poland, November 2015.
4. Yusuf Abdulkadir, **Oluyomi Simpson**, Nnamdi Nwanekezie and Yichuang Sun, "*A differential space-time coding scheme for cooperative spectrum sensing in cognitive*

radio networks," presented at IEEE Personal, Indoor, and Mobile Radio Communications (PIMRC), Hong Kong, August 2015.

5. **Oluyomi Simpson**, and Yichuang Sun "*Spectrum Sensing of DVB-T2 Signals Against Noise Uncertainty in AWGN and Fading Channels in Cognitive Radio,*" (Under submission).
6. **Oluyomi Simpson** and Yichuang Sun "*Evidence theory based Ambiguity Measure for Cooperative Spectrum Sensing in Cognitive Radio Networks*" (Under submission).

Other Publication

1. Andrew Slaney, Yichuang Sun and **Oluyomi Simpson**, "*A Novel Computationally Efficient Digital Frequency Locking Scheme for Software Defined Radio Modem,*" presented at IEEE International Symposium on Circuits & Systems (ISCAS), Canada, May 2016.
2. Gbenga Owojaiye, Yichuang Sun, Nandini Alinier, Pandelis Kourtessis and **Oluyomi Simpson** "*A Systematic Study of the Behaviour of PMEPR in Relation to OFDM Design Parameters*", presented at 12th Annual Postgraduate Symposium on the Convergence of Telecommunications, Networking and Broadcasting, Liverpool, June 2011.

1 Introduction

This chapter provides a brief introduction of the thesis. This includes the motivation of the research, the research scope and objectives, the original contributions and the thesis structure.

1.1 Motivation

Wireless communication and the utilization of the radio frequency spectrum have experienced a remarkable rise in the past few decades. The vast number of wireless devices (e.g., smart phones, laptops, tablet, remote controlling devices) and technologies (e.g., mobile telephony and wireless internets) available, the unprecedented increase in the number of mobile-cellular subscribers is growing exponentially from less than a hundred million subscribers in 1996 to nearly 7 billion in Aprils 2015 [1] as shown in Figure 1.1. The introduction of new applications such as wireless sensor networks, smart home systems, telemedicine, automated vehicles, various emerging applications from research ideas to concrete systems and the continuous need for high quality data rates are reasons for the radio frequency spectrum becoming more saturated [2]. With this growth the accessibility of high quality wireless frequency spectrum has become severely limited which is evident from the spectrum frequency allocation for the United Kingdom [3]. This has led to a widespread belief that the spectrum frequency is a scarce resource and it is difficult to locate spectrum frequency from a new application. However, real-time spectrum measurements carried out in various regions around the globe have shown that the frequency spectrum is inefficiently utilised with spectrum utilization ranging between five and fifty percent [4-6]. Consequently, the real challenge is not the frequency spectrum scarcity but the incompetent spectrum utilization.

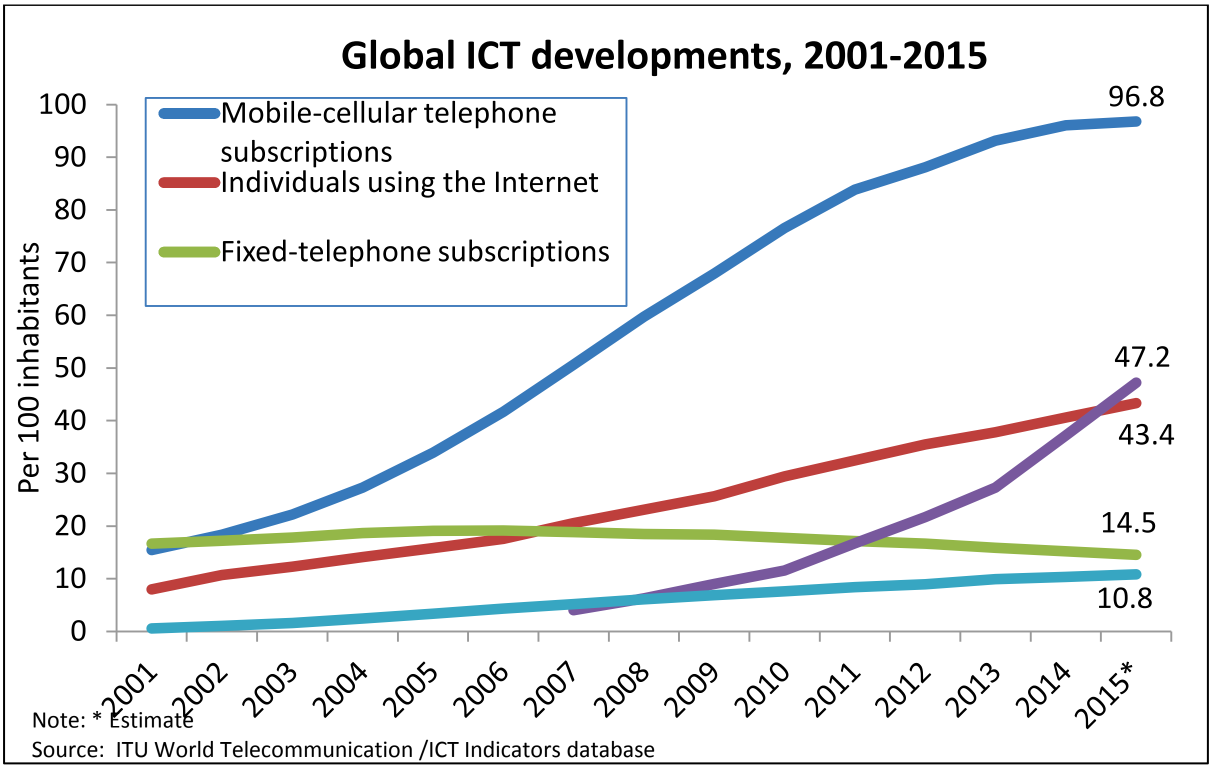

Figure 1.1 Global ICT developments, 2001-2015 [1].

Furthermore, this advance brings about the need for systems, devices, and technologies that are aware of their neighbouring radio frequency environment, consequently facilitating non-complex, efficient, consistent operations and utilization of the available spectral resources. Wireless communication systems ought to gather information about the radio frequency spectrum in order to adjust their operations and behaviour to provide an improved match to the prevailing conditions. Consequently, cognitive radio (CR) has become vital to recent and future wireless communication systems for identifying underutilized frequency spectrums, characterizing interference and consequently achieving reliable and competent operations.

In [7, 8] the term CR was referred to as an intelligent radio that is aware of its surrounding environment. In addition, a CR is capable of learning, adapting its behaviour and operation to provide an improved match to its surrounding environment as well as to the user's requirements. Learning is based on the feedback received from the environment. The feedback is realised as the outcome of the CR decisions and actions [7, 8].

The present spectrum regulation is based on a fixed frequency allocation policy. According to these polices, licenses are granted the rights for exclusive use. Examples of licensed technologies are 4G long term evolution (LTE) advanced [9] and global system for mobile communication (GSM) [10]. The frequency spectrum is split into frequency bands with each frequency band given to a certain wireless system which results in an irregular spectrum utilization that varies deeply based on frequency, time and spatial location in a rigid manner. For example, the frequency band 890-960 MHz is assigned to the GSM cellular system [10]. This means that only the GSM system can access this spectrum band at any time. This static allocation of the available spectrum resources, leads to several portions of the licensed bands being unused or underused at many times and/or locations. These unused channels are called spectrum holes or white spaces [11] as shown in Figure 1.2.

In CR terminology, a PU is defined as licensed user who has higher rights on particular part of spectrum whilst unlicensed cognitive users with lower priority are defined as SU. A SU can access the spectral resources of a PU when the PU is utilizing them. However, the SU has to vacate the frequency band or may stay in the same band but alters its power level and modulation method for avoiding interference to the existing licensed users in that band immediately the PU becomes active. Opportunistic access of the PU resources by the SU has been described as dynamic spectrum access (DSA) [12]. Presently, the major application area of CR's is DSA. To access the spectrum in a dynamic manner the CR's are required to sense the spectrum to make out spectrum opportunities and to prevent interfering with the licensed users.

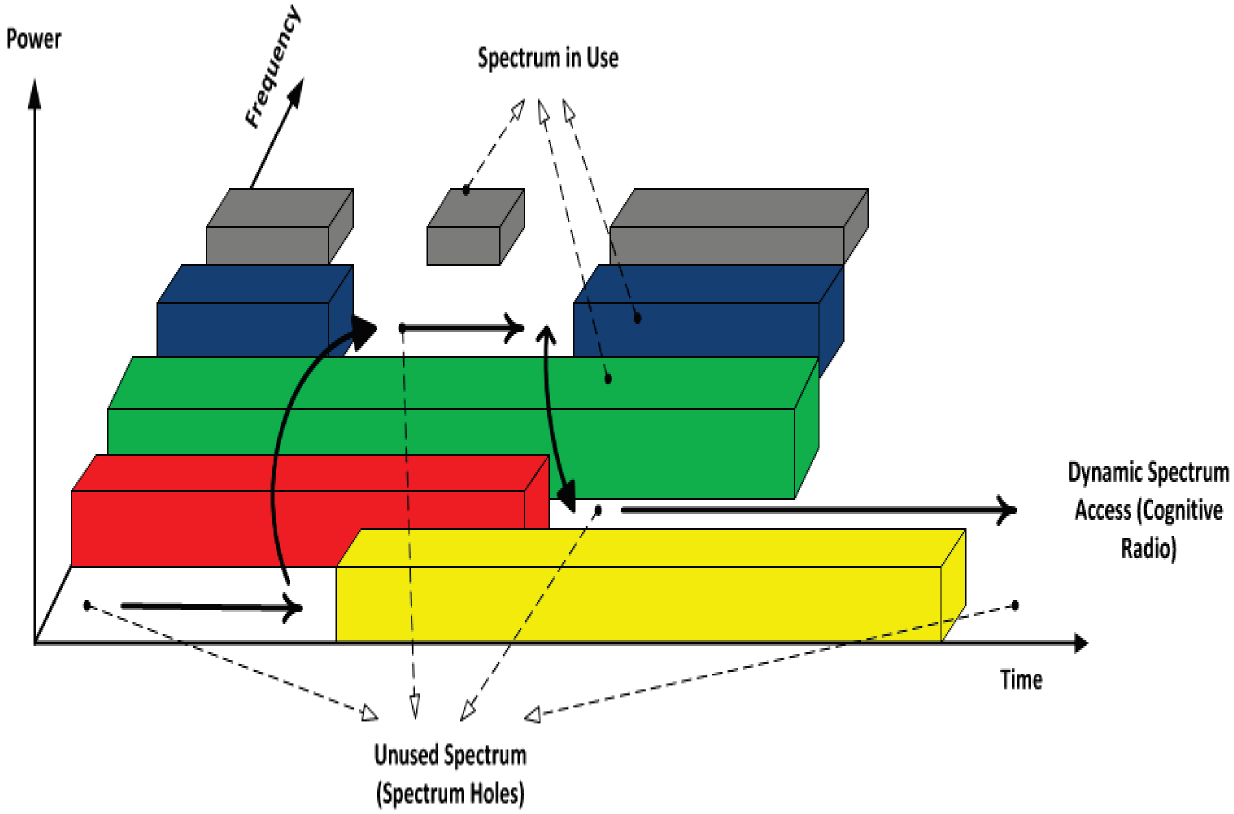

Figure 1.2 Spectrum Holes (White Space)

Spectrum sensing is an essential part in CR as it involves the monitoring of the available radio spectrum, gathering information and detection of the spectrum holes. It lets the SU discover and take advantage of the vacant PU frequency spectrum efficiently. In addition, it is essential for managing the interference caused to the PU's of the spectrum. Spectrum sensing fundamentally can be conducted at each individual cognitive user based on the detection of signals transmitted from the primary transmitter. This is called a single sensing node, local sensing or local detection. However, a single sensing node in facing propagation environments like multi-path fading, Doppler spread, and shadowing may lead to the hidden terminal problems. When such a situation occurs a SU has to differentiate between a spectrum hole, where there is no primary signal, and a deep fade, where it is difficult to detect the PU signal. In order to minimise the hidden terminal problem, cooperative spectrum sensing (CSS) where different SU work in partnership to detect the presence of a PU and provides diversity gains to tackle the fading and shadowing effects that have been considered in several works [13, 14]. CSS also helps to increase the signal to noise ratio (SNR) gain and CR network coverage, decrease the detection time, and simplify the design of the sensing detector. Nevertheless, for an optimal implementation of a CSS scheme in a practical CR network, it is still a challenge and requires more research to improve the reliability and efficiency. Motivated by the aforementioned, this research primarily concentrates on the design and development methods for an optimal performance of a CSS scheme.

1.2 Scope and Objectives of the Thesis

Spectrum sensing is a fundamental function for a CR network to protect transmission of primary system as mentioned above in section 1.1. CSS, which can assist in increasing sensing performance, is regarded as one of the most promising methods in realizing a reliable CR network. Therefore, the main aim of the research is to design and development of optimal CSS schemes for CR network which maximize the probability of detecting unused frequency spectrum while meeting a required reliability of detecting PU activity where there is minimal knowledge about the primary signal at the same time still possessing the means to differentiate among different signals as well as being robust to noise uncertainties. There are four major objectives considered in this research of CSS for CR:

- diversity performance ,
- detection accuracy performance,
- low computational complexity and

- cooperative reporting channel bandwidth reduction.

Firstly, an amplify-and-forward relay-based CSS using an improved double threshold energy detector is proposed to overcome the imperfection in the reporting channels, in order that a SU experiencing a weak sensing channel and a strong reporting channel and a SU experiencing a strong sensing channel and a weak reporting channel, can complement and cooperate with each other to overcome the effects of fading and improve the overall performance of the CSS.

To overcome the hidden terminal problem and increase the spectrum sensing reliability while increasing SU agility an evidence based CSS scheme will be considered. This will focus on the fusion combination rule in a centralized CSS where the basic probability assignment (BPA) of the sensing data is received from each involved SU. A novel evidence-based decision fusion CSS that uses both the credibility and dissociability degree measure of SUs sensing data evidence is proposed.

Finally, the most important incentive for the use of CR is spectrum efficiency whereby it is not practical to use a wideband for collecting the raw sensing data. Therefore, quantized soft combining schemes where each SU quantize their local sensing data and forwards the quantized data for fusion at the FC to lessen the control channel communication overhead is proposed to reduce cooperative reporting channel bandwidth and sensing time. The quantization methods are proposed including evidence based CSS quantization scheme and a maximum likelihood estimate (MLE) entropy quantizer based CSS scheme.

1.3 Thesis Contribution

The major contributions of this thesis are summarized as follows:

Chapter 3

The design of a novel relay-based AF CSS architecture for CR networks using an improved cooperative ED to achieve high sensing efficiency and sensing accuracy of PUs.

- Combining the PU and relay (SUs) transmissions to achieve diversity against fading using AF cooperation which has the potential of reduced complexity and cost.
- Analytically deriving expressions for a "soft 1-bit" double threshold combination scheme to reduce the communication overhead, improve the local probability of detection and hence the global probability of detection taking into account all sensing performance to exploit all the observed information from local SUs.

Chapter 4

The design of a novel evidence-based decision fusion scheme CSS for CR networks that uses both the credibility of SUs sensing data evidence and dissociability degree measure of SUs sensing data evidence, in the form of a weighted averaging factor. To increase sensing reliability and SU agility

- Analytically deriving expressions for the credibility of evidence from the SUs sensing data which represents the similarity or the relation among different SUs sensing data evidence. In addition, deriving the correlation coefficients between the local decisions using a distance of evidence rule and a correlation matrix (CM).

- Evaluating and deriving expressions for a dissociability degree measure of evidence from the SUs sensing data which indicates the quality or clarity of the SUs sensing data evidence.
- Developing an algorithm for a weighted averaging factor and final fusion determined by the credibility value and dissociability degree measure of the SU sensing data evidence.

Chapter 5

The design of a novel optimal entropy quantization for (MLE) for CSS for CR networks using a uniform threshold quantizer (UTQ) and an output entropy quantization scheme to reduce reporting channel over head and increase throughput.

- Deriving a maximum likelihood estimator (MLE) for a CSS scheme and optimize it by adjusting the parameter associate with the threshold distribution.
- Deriving Maximum Likelihood estimator for a CSS scheme and optimize it by adjusting the parameter associate with the threshold distribution.
- Evaluate and deriving expressions for a proposed (UTQ) and an output entropy quantizer and evaluating their performance for a low SNR range.

Designing a novel evidence-based decision fusion CSS quantization scheme for CR network.

- Evaluating and deriving expressions for a proposed (UTQ) and an output entropy quantizer using a log likelihood ratio of the sensing data.

- Developing an algorithm for the quantization of the credibility value and dissociability degree measure of the SU sensing data evidence.

1.4 Structure of Thesis

The remainder of this thesis is structured as follows:

In chapter 2, an overview on spectrum sensing for CR and problem formulation was presented. The rest of chapter 2 is organized as follows: Firstly in section 2.2, a general description of CR for dynamic spectrum access was described. Brief overviews are presented on different problems related to the dynamic spectrum access and standardization efforts are presented in section 2.3 and section 2.4, respectively. A review of the fundamentals of spectrum sensing and state of the art spectrum sensing techniques such as matched filtered, energy detection and feature detection and their performance criteria are presented in section 2.5 and section 2.6, respectively. In section 2.7 and section 2.8, spectrum sensing test statistics and detection criteria are presented, respectively. Various spectrum sensing techniques are present in section 2.9 and section 2.10. A comparative analysis of spectrum sensing is presented in section 2.11. CSS that is collaboration between multiple SUs are considered and different data fusion algorithms presented in section 2.12 and section 2.13, respectively. CSS techniques are presented in section 2.14. A literature review and problem formulation of CSS is presented in section 2.15 and section 2.16, respectively. Finally conclusions are drawn in section 2.18.

In chapter 3, an amplify-and-forward relay-based CSS using an improved double threshold energy detector was presented. The rest of chapter 3 is organized as follows: A non-cooperative and a CSS with an improved ED are presented in section 3.2 and 3.3, respectively. In section 3.4 the proposed relay-based AF CSS system model are presented and analysed in detail. In section 3.5 and section 3.6 an AF CSS with a single relay and multiples are presented, respectively. In section 3.7 a direct in was presented. Performance analysis and simulation results are presented in section 3.5 and 3.9, respectively. Finally, conclusions are drawn in section 3.10.

In chapter 4 evidence based decision fusion scheme for CSS is designed. The rest of chapter 4 is organized as follows. The rest of this chapter is organised as follows: A CSS system model and the detection problems for local sensing at SUs are presented in section 4.2. A review of DS theory of evidence has been presented in section 4.3. In section 4.4, the proposed evidence based CSS scheme and the local SUs energy detection algorithm are introduced. In section 4.5, the BPA estimation of the SUs sensing data is presented. The evaluation of the credibility and dissociability degrees are presented in section 4.6 and 4.7, respectively. The analysis of the modified combination rule and the analysis of the final decision are detailed in section 4.8 and 4.9, respectively. In section 4.10, a summary of the proposed algorithm is outlined. Simulation results and analysis are presented through receiver operating characteristics (ROC) curves, and other performance related curves in section 4.11. Finally, conclusions are drawn in section 4.12.

In chapter 5, quantization schemes for CSS are presented. In section 5.2 a Lloyd-Max quantization algorithm, which nearly all quantization methods are primarily based on is discussed. In section 5.3, MLE optimal entropy quantization CSS schemes are presented which include a proposed uniform threshold and output entropy scheme, simulation results are also presented. In section 5.4, an evidence based CSS quantization scheme is covered followed, simulation results are presented. Finally, conclusions are drawn in section 5.5

Finally, chapter 6 summarizes the thesis and states possible future research.

2 Spectrum Sensing for Cognitive Radio: An Overview and Problem Formulation

---

The availability of the radio frequency spectrum has in recent times been hampered by the growth of radio access technologies. This is due to the fact that the higher rate requirements of these new technologies are more bandwidth demanding, thus utilizing more spectrum resources. Cognitive radio (with emphasis on spectrum sensing) has emerged as a viable solution that will optimize radio spectrum utilization and allow these new technologies to be deployed. In this chapter, a general description of cognitive radio for dynamic spectrum access (DSA) is presented. Brief overviews are presented on different problems related to the DSA and standardization efforts. An overview of spectrum sensing, which is one of the fundamental prerequisites for the successful deployment of cognitive radio networks is presented. The most common spectrum sensing techniques, with which the cognitive radio users are able to monitor the activities of the primary user, are outlined. A review and comparative analysis of the fundamentals of spectrum sensing algorithms such as matched filter, energy detection, feature detection, and other sensing techniques and their performance criteria are presented. To address the limitations of the spectrum sensing techniques by a single secondary user, cooperative spectrum sensing and its main elements are discussed. Several fusion rules such as the maximum ratio combining (MRC), equal gain combining (EGC), K-out-of-N and Chair-Varshney rule are discussed. A general system model for the problem formulation is presented. Finally conclusions are drawn on issues surrounding spectrum sensing as well as their possible solutions.

2.1 Introduction

The increased demand for higher data rates in wireless communications, even in the face of limited spectral resources has motivated the introduction of CR [15, 16]. The present spectrum regulation is modelled on a fixed spectrum allocation (FSA) policy and according to these policies, licensees are granted the rights for exclusive use on a long term basis over fixed geographical areas. These policies are normally decided by the regulatory bodies in each country such as The Office of Communications (Ofcom) in the United Kingdom. Though the present frequency allocation scheme assures low interference, due to each system operating in a different spectrum band, it is also very strict and rigid. Furthermore, this static allocation of the available spectrum resources leads to several portions of the licensed bands being unused or underutilized at many times and/or locations [4, 17], especially when the licensed users are idle. However, despite these unused portions of the spectrum, the FSA policy forbids its exploitation [8]. Research conducted by Ofcom on the radio frequency spectrum suggests that there is justified demand for more efficient utilization of the radio spectrum through an alternative policy termed dynamic spectrum allocation (DSA) policy. With DSA, the spectrum is still allocated to the licensed users, but its usage is not exclusively granted. Unlicensed users, referred to as secondary users (SU) are also able to access the radio spectrum when the licensed (primary) users are idle [8, 18]. To support DSA, SUs are required to sense the radio frequency spectrum environment, and an SU with such a cognition capability is also called a *cognitive radio* (CR) [8]. Cognitive Radio (CR) is a new concept that utilizes the licensed spectrum in an unlicensed manner [11, 19]. A CR network typically consists of the primary users (PU) and SUs, and its operation typically revolves around the main functionalities of spectrum sensing, spectrum sharing and cognitive processing of which, spectrum sensing is the most essential function of CR [8]. The process of spectrum sensing, where SUs are constantly seeking for opportunities to make use of the frequency spectrum when the PUs are inactive [11, 19] tends to be a source of increased interference to the PU system [7]. As such, its impact on the PU system ought to be kept at levels below certain thresholds. There are other methods of avoiding excessive interference to the PU system such as overlay and underlay systems, making use of algorithms such as dirty paper coding that have been researched in literature [20, 21], but they are outside the scope of this thesis.

In spectrum sensing, CR users search for the vacant resources commonly referred to as spectrum holes or white spaces in the frequency bands, and if found transmits on that particular frequency [16]. In some rare cases, frequency bands are allocated to a PU system, even though they are unused [7]. Such spectrum holes could also be employed by SUs. There are various techniques used for the spectrum sensing, each one has its own limitations. Generally, three different techniques are used for spectrum sensing, including transmitter detection, cooperative detection, and interference based detection [22, 23]

In this chapter, some areas in spectrum sensing for CR, which have been of enormous interest in recent research activities, are discussed. Some formulation problems and current techniques for signal detection in spectrum sensing are highlighted. A model for signal detection is presented along with state of the art detectors such as energy detector. Some essential limits for spectrum detection are also discussed. In addition, feature detectors which exploit knowledge about the signal to be detected are presented and the concepts of CSS detection are outlined. Several fusion rules are described such as log ratio test (LRT), maximum ratio combing (MRC), equal gain combing (EGC), Chair-Varshney (CV), and *K-out-of-N*. The focus of this work in this chapter is on transmission detection techniques. Particular attention is paid to techniques with practical purposes in this thesis.

2.2 Cognitive Radio

2.2.1 Definitions

In general CR is a broad theory and has diverse interpretation in several literatures [4, 7, 11]. The term CR was coined by Mitola as “an intelligent radio which is aware of its surrounding environment and capable of changing its behaviour to optimise the user experience” [7, 11]. A more applicable definition of a CR is given by Haykin [11]:

> *“Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:*
>
> - *Highly reliable communications whenever and wherever needed.*
> - *Efficient utilisation of the radio spectrum.”*

2.2.2 Applications and Technologies

CR has numerous innovative applications apart from DSA. For example, CR can be applied to simplify location services, uninterrupted mobility, optimal performance and existence of heterogeneous wireless communication systems [24]. CR can offer location services by enabling the user to find services like fuel station, shopping centres, bus stations, schools, etc. CR can also assist uninterrupted mobility through interoperability with diverse systems such as, WMAN, Bluetooth, WIFI, WLAN etc. CR can be constructive in obtaining optimal performance of spectrum utilisation, data rates, economics, energy reduction and energy efficiency. Coexistence of heterogeneous technologies in the same spectrum bands e.g., IEEE 802.15.4 Zigbee [25] and IEEE 802.11 [26]. WLAN can lead to harsh interference [27] degrading the system performance. CR can provide answers relating to interference among the coexisting heterogeneous wireless systems and improves their performance [28]. One thing that all these applications have in common is that they all require various other technologies to merge in order to affect the outcome of the cognitive abilities [29]. Such technologies include software technologies, software defined radio (SDR) and sensors [28] [7, 29].

Software technologies, which are enabling CR, include policy engine, machine learning, advanced signal processing, and networking protocols [28].

SDR is a radio communication system where components implemented in hardware are implemented in software by means of digital signal processing (DSP). Hence, replacing software programs can totally change the function of the radio [7, 29].

Sensors are needed to generate awareness about the spectrum surroundings [29]. Some examples of sensors are RF receiver, microphone, camera, biometric scanners (fingerprint, iris, retina), global positioning system (GPS). Sensors such as microphone, camera, and biometric scanners can be used for user awareness, which is helpful in avoiding unauthorised access and providing user centric experience in a multiuser scenario. GPS enables several useful applications for a CR by providing the location awareness [29].

2.3 Dynamic Spectrum Access

DSA continues to generate interest among policy makers, regulators, network operators, and researchers [4, 16, 30]. The main functions of DSA include [15]:

- Spectrum awareness,
- Spectrum sharing, and
- Cognitive processing.

Spectrum awareness generates awareness about the frequency spectrum [19]. Spectrum awareness can be obtained in two ways by using either active or/and passive methods. In the active method or spectrum sensing, the radios become spectrum aware by detecting and estimating the spectrum. Active methods have broader application areas and lower infrastructure requirement. In passive methods, the information regarding the unoccupied spectrum is provided to the SU [19].

Spectrum sharing offers techniques to take advantage of the existing spectrum opportunities for efficient reuse [15]. Spectrum sharing process consists of five major steps namely: spectrum sensing, spectrum allocation, spectrum access, transmitter-receiver handshake and spectrum mobility [15].

Cognitive processing is the intelligence and decision making function which includes quite a few subtasks such as learning about the radio environment, designing efficient sensing, and access policies alongside managing interference for coexistence of the SU and PU systems [7, 15].

2.4 Standardization

In the midst of the increasing interest in CR, wireless standards being developed in recent times have started incorporating cognitive characteristics. IEEE 802.22 [31] is the first worldwide attempt to define a wireless standard based on CR techniques for the opportunistic use of TV white spaces (TVWS) [32]. The main application of this standard is fixed broadband access especially for difficult to access, small population areas such as rural regions [29]. Other standardization initiatives related to CRs include IEEE 802.11af [32], dynamic spectrum access networks standards committee (DySPAN- SC) [33], IEEE 802.16 [34] and IEEE 802.19 [35].

IEEE 802.11af standard, defines modifications to IEEE 802.11 PHY/MAC for TVWS operation [32]. IEEE 802.16h [34] defines modifications to IEEE 802.16 PHY/MAC for coordinated and uncoordinated coexistence among homogeneous or heterogeneous users in an unlicensed band. The DySPAN-SC develops standards for radio and spectrum management [33]. IEEE 802.19 [35] focuses on coexistence between different unlicensed wireless networks in 802.11 group of standards like IEEE 802.11 (WLAN), IEEE 802.15 (WPAN), 802.16 (WMAN), and 802.22.

2.5 State of the Art Spectrum Sensing Techniques

One of the most prominent features of CR networks will be the ability to switch between radio access technologies, transmitting in different portions of the radio spectrum as unused frequency band slots become available [8, 11, 15]. This spectrum sensing feature is off course one of the fundamental requirements for transmitters to adapt to varying channel quality, network congestion, interference and service requirements [8, 11, 15]. Sensing techniques are further broken down into four broad categories. The first two broad categories are coherent and non-coherent [15]. In coherent detection, a priori knowledge of the PU signals is needed. In non-coherent detection, a priori knowledge of PU signals is not required [15]. The other categories, based on the bandwidth requirements for sensing, are the narrowband and wideband detection techniques. The classifications of sensing algorithms are shown in Figure 2.1 [36]. Spectrum sensing proposed in literature [11, 15, 28, 29, 36-39] can be divided into three classes based on the PU information: energy based detector, feature detector, and matched filter detector. A description of the workings and implementation of the three primary detection techniques are analysed under the non-cooperative spectrum sensing techniques in section 2.9.

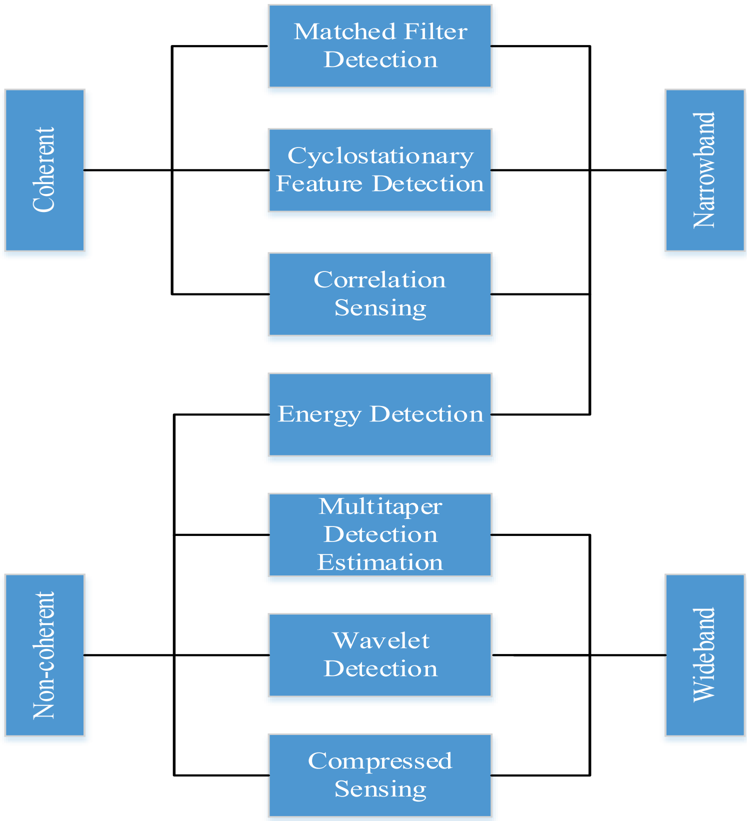

Figure 2.1 Classification of spectrum sensing techniques.

2.5.1 Interference Management and Spectrum Sensing

In order to share the spectrum with PU networks, CR networks will have to operate according to a set of policies, as defined by regulatory agencies [4, 11, 15, 18]. These policies are based on the idea where secondary systems which are allowed to use the licensed spectrum as long as they do not disturb the communications of the primary systems. In summary, these policies deal with controlling the amount of interference that the SUs can incur to PUs. Thus, the problem is one of interference management [11, 15], which can be addressed from two different points of view: receiver centric or transmitter centric.

2.5.2 Receiver Centric Interference Management

In the receiver centric approach [11, 15], an interference limit at the receiver is calculated and used to determine the restriction on the power of the transmitters around it. This interference limit, called the interference temperature, is chosen to be the worst interference level that can be accepted without disturbing the receivers operation beyond its operating point. Although very interesting, this approach requires knowledge of the interference limits of all receivers in a PU system. Such knowledge depends on many variables, including individual locations, fading situations, modulations, coding schemes and services [11, 15].

2.5.3 Transmitter Centric Interference Management

In the transmitter centric approach, the focus is shifted to the source of interference [11, 15]. The transmitter does not know the interference temperature, but by means of sensing, it tries to detect spectrum holes. The sensing procedure allows the transmitter to classify the channel status to decide whether it can transmit and with how much power. In actual systems, however, since the transmitter does not know the location of the receivers or their channel conditions, it is not able to infer how much interference these receivers can tolerate. Thus, spectrum sensing solves the problem for worst case scenario, assuming strong interference channels, so the secondary system transmits only when it senses a vacant channel [11, 15].

2.6 The General Spectrum Sensing Problem

There are several algorithms available for spectrum sensing, each with its own set of advantages and disadvantages that depends on the specific scenario. Ultimately, a spectrum sensing device must be able to give a general picture of the medium over the entire radio spectrum. This allows the CR network to analyze all degrees of freedom (time, frequency and space) in order to predict the spectrum usage.

2.6.1 Fundamentals of Spectrum Sensing Techniques

Spectrum sensing is based on a well-known technique called signal detection [40]. In a nutshell, signal detection can be described as a method for identifying the presence of a signal in a noisy environment. Analytically, signal detection can be reduced to a simple identification problem, formalised as a hypothesis test [41]:

$$\begin{cases} H_0 : y(t) = n(t) \\ H_1 : y(t) = h(t)s(t) + n(t) \end{cases} \tag{2.1}$$

for $t = 1,...,M$. Here t represents the discrete time index and M denotes the number of observation, H_0 and H_1 are the hypotheses of indicating a vacant channel and occupied channel of the PU's signal, respectively, $y(t)$ denotes the received signal at the SU, $h(t)$ represents the channel gain between PU and SU, $s(t)$ is the signal transmitted from the PU and $n(t)$ is noise of variance σ^2.

2.6.2 Performance Criteria

The performance of spectrum sensing techniques can differ in different scenarios. Hence, it is imperative to evaluate and chose the most adequate scheme for a given scenario. Different characteristics that can be used to evaluate the sensing algorithms are discussed in this section.

- **Probability of false alarm:** It is the probability that the detector declares the presence of the PU, when the PU is actually absent. Considering a binary hypothesis test there are two types of errors that can be made, type I and type II errors, respectively [28]. A type I error is made if H_1 is accepted when Ho is true. The probability of making a type I error is often called the probability of false alarm, which is a significant design parameter since false alarms leads to missing spectral opportunities [28]. Therefore, controlling the probability false alarm is crucial for efficient spectrum usage [28].

- **Probability of missed detection:** It is the probability that the detector declares the absence of PU, when the PU is actually present. A type II error is made if H_0 is accepted when H_1 is true. Missed detection probability also called type II error, comes about as a result of probability of missed detection and can lead to collisions with the PU transmission and hence, reduced rate for both the PU and SU, respectively [28]. Establishing distributions of decision statistics helps in controlling the probabilities of missed detection and false alarm [28].

On the whole a CR system ought to satisfy constraints on both the false alarm and missed detection probability respectively [42]. Designing a detection rule brings about a trade-off between both probabilities. Nevertheless, if the detectors behaves reasonably, as the number of samples increases, both constraints may be satisfied by selecting the number of samples to be big enough [39]. For implementation it is advantageous to have the schemes whose threshold and performance may be set analytically. In a practical scenario the probability of detection and the samples required to achieve a given detection probability will have to be determined experimentally because of variables, such as the fading channel, channel errors, and noise power uncertainty affecting their observations [39].

- **Signal-to-noise-ratio (SNR)**: Type I and type II errors are linked to each other through sensing time, SNR, and detection threshold. The SNR at the SUs depends on the PU transmitted power and the spectrum environment. The detection performance improves with an increase in the SNR.

- **Sensing time:** If the receiver is time-duplexed for both receiving and sensing, it is advantageous to have shorter sensing and longer data times [29]. If the sensing time is too long, the data transmission duration reduces thereby reducing the throughput of the SUs [29].
- **Detection range:** It is an important performance criterion as it is the limit on the distance between the SU and the PU for a detector to sense the PU accurately [7]. It depends on the detection performance of the SU, sensing time, SNR at the receiver and spectrum environment.
- **Complexity**: It is advantageous to have straightforward sensing techniques that are energy efficient. The hardware economics and energy efficiency through computational complexity of the technique is a vital criterion [29].

2.7 Test Statistics

Generally, in practical scenarios, a scalar test statistic is calculated from the observation vector **x** and a threshold η splits the observation into two regions [39]. Detection is based on comparing the test statistic T to the threshold η in such a scenario. If the test is greater than the threshold, then H_1 is affirmed true if not H_0 is affirmed true. The chosen threshold value depends on the decision making scheme and the test statistics distributions under different hypotheses. The choice of the test statistic and decision scheme also depends on the desired performance parameters [39]. The received observations are assumed to be independent from each SU, the optimal test statistic for a simple hypothesis test under quite a few detection criteria is the likelihood ratio test (LRT) [43]. The LRT statistic T_{lrt} is given by [43]:

$$T_{lrt} = \frac{\prod_{t=1}^{M} p(y(t) \mid H_1)}{\prod_{t=1}^{M} p(y(t) \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_{lrt}. \tag{2.2}$$

In the event that the received PU signal depends on unknown characteristics, the test develops into a composite hypothesis T_c [43]:

$$T_c = \frac{\prod_{t=1}^{M} \int p(y(t) \mid \theta_1; H_1) p(\theta_1) d\theta_1}{\prod_{t=1}^{M} \int p(y(t) \mid \theta_0; H_0) p(\theta_0) d\theta_0} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_c \tag{2.3}$$

where θ_i for $i = 0,1$, are the unknown random characteristics.

An alternative is to estimate the unknown characteristics using the maximum likelihood (ML) estimator and substitute the obtained parameters into the LRT. The resulting test is called the generalised likelihood ratio test (GLRT) [39]. The GLRT is given by [39]:

$$T_{glrt} = \frac{\prod_{t=1}^{M} \max_{\theta_1} p(y(t) \mid \theta_1; H_1)}{\prod_{t=1}^{M} \max_{\theta_0} p(y(t) \mid \theta_0; H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_{glrt}. \tag{2.4}$$

2.8 Detection Criteria

The choice of a detection criterion is based on the optimization of the desired objective function involving different performance parameters discussed in section 2.6.2. There are several detection criteria [39]:

- Neyman-Pearson,
- Bayesian,
- locally optimum,
- sequential detection, etc

Neyman-Pearson (NP) increases the probability of detection for a given constraint on the false alarm probability [39]. Noise statistics are necessary for implementation and may be estimated. Bayesian formulations are used to reduce the Bayes' risk, which depends on the prior probabilities of two hypotheses, cost assignments, and conditional densities of the observations under the two hypotheses [39]. Locally optimum detection is the optimal detection scheme for weak signal detection as it increases the slope of the probability of detection at a point where the signal strength tends to be minimal [39]. Sequential detection reduces the detection time for fixed false alarm and missed detection probabilities, respectively [39].

2.8.1 Optimality Criteria: Bayesian versus Non-Bayesian

Given two decision rules (detectors) δ_1 and δ_2, one detector may be better than another detector in one aspect but not in another aspect. For example, detector δ_1 might be computationally more efficient, in that it gives the output faster compared to δ_2, whereas decisions of the detector δ_2 might appear to be accurate more often than those of δ_1 [44].

2.8.2 The Bayesian approach

In general, there is no best trade-off. It depends on what is considered as the suitable trade-off. The Bayesian approach is to treat the two hypotheses H_0 and H_1 as being random themselves. That is, with the relative frequency interpretation of the probabilities, sometimes, the underlying hypothesis may be H_0, and other times, the underlying hypothesis may be H_1 [44]. The Bayesian approach assumes that there are a priori probabilities, p_0 and p_1, associated with each of the hypotheses H_0 and H_1 being true, respectively. If an ensemble of observations is considered, some of them will correspond to an underlying hypothesis H_0, while the others will correspond to an underlying hypothesis H_1 [44]. A given detector will have a P_M miss probability on those observations corresponding to an underlying true hypothesis H_1, while it will have a P_F false alarm probability on those observations corresponding to an underlying true hypothesis H_0 [44]. It is known that no detector can minimise both these probabilities simultaneously. However, now to find a detector that minimises the average (overall) error probability denoted as P_E, over the whole ensemble of H_0 and H_1 hypotheses [44]:

$$\begin{aligned} P_E &= \mathrm{P}(H_1 \mid H_0)\mathrm{P}(H_0) + \mathrm{P}(H_0 \mid H_1)\mathrm{P}(H_1) \\ &= \mathrm{p}_0 P_F + p_1 P_M \end{aligned} \tag{2.5}$$

A decision rule that minimises this average error probability P_e is called a Bayesian optimal decision rule or more precisely, a Bayesian minimum probability of error decision rule. In general, any detector that minimises a cost function averaged over a priori probabilities is called an optimal detector [45]. Hence, minimum average error probability detection is just one special case of the Bayesian optimal detection. The distinguishing feature of the Bayesian approach is the averaging of an assumed cost function with respect to the priori probabilities. Hence, the Bayesian approach presumes that [44, 45]:

i. Hypotheses can be modelled as endowed with a certain prior distribution.

ii. This prior distribution is known.

2.8.3 A Non-Bayesian Approach: Neyman–Pearson Optimality Criterion

There are situations in which either or both the two key assumptions of the Bayesian approach may not be valid. There are situations in which either the Bayesian assumption may not be justified or that the prior distribution of the hypotheses may not be known. Then, there is a situation in which Bayesian averaging cannot be justified or cannot be evaluated [45]. There are many natural problems in which this is the case, including the CR spectrum sensing problem. When the Bayesian approach is not applicable or possible, a suitable alternative optimality criteria for binary hypothesis testing is needed [45, 46].

The two types of errors in a binary hypothesis testing problem are the missed and false alarms. Simultaneous minimisation of both these errors is the natural optimality criterion [44]. The need for alternatives arises because it is not possible to simultaneously minimise these two types of errors. Reducing one type of errors increases the errors of the other type, hence the need for a trade-off. The Bayesian minimum error probability approach was to minimise the weighted sum of these two types of errors, in which weights were chosen to be equal to the priori probabilities of the two hypotheses. Essentially, it gives the two types of errors an importance that is proportional to the relative frequencies of the two hypotheses [34, 44].

Every time the detector falsely declares the presence of a PU, network resources are still spent. So, there is a price, or a cost, to pay for each false alarm. If there was no cost attached to these false alarms, then a detector that always declared hypothesis H_1 might be reasonable [45]. But all practical situations of interest involve some cost attached to false alarms. In such scenarios, there is a maximum limit on how much false alarms can be tolerated on average. This then gives a natural alternative optimality criterion that does not require Bayesian prior probabilities [45]. A constrained optimisation problem can be posed to find the detector that maximises the detection probability subject to a given maximum level of false alarms [47]. This is called the Neyman–Pearson optimality criterion [48]. It is a non-Bayesian approach since it does not assume nor does not need a prior distribution. A detector that maximises the detection probability subject to a maximum false alarm probability constraint is thus called a Neyman–Pearson optimal [44, 47]. The Neyman–Pearson formulation also arises naturally in the context of dynamic spectrum sharing CR systems [48].

2.8.4 Bayesian Optimal Detection

Assuming a FC combines data from M local SUs, which is denoted by $\mathbf{y}^{\mathbf{T}} = \{y_1, y_{2,\dots,} y_M\}$, The Bayesian' criterion is to determine the decision rule so that the average cost $E[C]$, also known as risk $\Re$, is minimised. The average cost is calculated by [45]:

$$\Re = E[C] = [C_{00}(1 - P_F) + C_{10}P_F]p_0 + [C_{01}(1 - P_D) + C_{11}P_D]p_1 \tag{2.6}$$

where the cost $C = \{C_{ij}\}, (i = 0,1; j = 0,1),$ is the cost incurred by choosing hypothesis H_i when hypothesis H_j is true, p_0 and p_1 are the priori probabilities of hypothesis H_0 and H_1, respectively. P_F and P_D is corresponding to the false alarm and miss detection probability and are defined by [45]:

$$P_F = \mathrm{P}[H_1 \mid H_0] = \int_{Z_1} f_{\mathbf{y}|H_0}(\mathbf{y} \mid H_0) d\mathbf{y} \tag{2.7}$$

and

$$P_D = \mathrm{P}[H_1 \mid H_1] = \int_{Z_1} f_{\mathbf{y}|H_1}(\mathbf{y} \mid H_1) d\mathbf{y} \tag{2.8}$$

where $Z_j, (j = 0,1),$ is the region of deciding H_j hypothesis and $f_{\mathbf{y}|H_1}(\mathbf{y} \mid H_j)$, $(j = 0,1)$, is the PDF of $\mathbf{y}$ when hypothesis H_j is true. Substituting equation (2.8) and equation (2.7) into equation (2.6), the risk function is determined by [45]:

$$\begin{aligned} \Re = {} & p_0 C_{00} + p_1 C_{11} + \\ & \int_{Z_0} \{[p_1(C_{01} - C_{11}) f_{\mathbf{y}|H_1}(\mathbf{y} \mid H_1)] - [p_0(C_{10} - C_{00}) f_{\mathbf{y}|H_0}(\mathbf{y} \mid H_0)]\} d\mathbf{y} \end{aligned} \tag{2.9}$$

Considering the terms inside the brackets of the integrand, the risk is minimised by selecting the decision region Z_0 to include only those points of $(\mathbf{y})$ for which the second term is larger, and hence the integrand is negative. Specifically, the region Z_0 are assigned to those points for which [45]:

$$p_1(C_{01} - C_{11}) f_{\mathbf{y}|H_1}(\mathbf{y} \mid H_1) < P_0(C_{10} - C_{00}) f_{\mathbf{y}|H_0}(x \mid H_0) \tag{2.10}$$

All values for which the second term is greater will be excluded from Z_0 and assigned to Z_1. The values for which the two terms are equal do not affect the risk, and can be assigned to either Z_0 or Z_1 [45]. Consequently, if

$$p_1(C_{01} - C_{11}) f_{\mathbf{y}|H_1}(\mathbf{y} \mid H_1) > P_0(C_{10} - C_{00}) f_{\mathbf{y}|H_0}(x \mid H_0) \tag{2.11}$$

then H_1 is decided, otherwise H_0 is decided. Hence, the decision rule resulting from the Bayesian' criterion is the likelihood ratio test as follows [45, 47]:

$$\frac{f_{\mathbf{y}|H_1}(\mathbf{y} \mid H_1)}{f_{\mathbf{y}|H_0}(\mathbf{y} \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{p_0(C_{10} - C_{00})}{p_1(C_{01} - C_{11})} \tag{2.12}$$

The likelihood ratio (LR) $L(\mathbf{y})$ is defined by [45, 47]:

$$L(\mathbf{y}) = \frac{f_{\mathbf{y}|H_1}(\mathbf{y} \mid H_1)}{f_{\mathbf{y}|H_0}(\mathbf{y} \mid H_0)} = \frac{f_{\mathbf{y}|H_1}(y_1, y_2, \ldots, y_M \mid H_1)}{f_{\mathbf{y}|H_0}(y_1, y_2, \ldots, y_M \mid H_0)} \tag{2.13}$$

It is assumed the collected local data from different detectors are independent, the LR can be re-written as [45, 47]:

$$\begin{aligned} L(\mathbf{y}) &= \frac{f_{\mathbf{y}|H_1}(y_1, y_2, \ldots, y_M \mid H_1)}{f_{\mathbf{y}|H_0}(y_1, y_2, \ldots, y_M \mid H_0)} \\ &= \frac{f_{\mathbf{y}|H_1}(y_1 \mid H_1) f_{\mathbf{y}|H_1}(y_2 \mid H_1) \ldots f_{\mathbf{y}|H_1}(y_M \mid H_1)}{f_{\mathbf{y}|H_0}(y_1 \mid H_0) f_{\mathbf{y}|H_1}(y_2 \mid H_0) \ldots f_{\mathbf{y}|H_0}(y_M \mid H_0)} \\ &= \prod_{t=1}^{M} \frac{f_{y|H_1}(y_t \mid H_1)}{f_{y|H_0}(y_t \mid H_0)} = \prod_{t=1}^{M} L(y_t) \end{aligned} \tag{2.14}$$

Substituting (2.14) into (2.12) and taking the logarithms of both sides, the log likelihood ratio (LLR) test statistic is obtained as follows:

$$T_{llr} = \sum_{t=1}^{M} \Lambda_t \underset{H_0}{\overset{H_1}{\gtrless}} \eta_{llr} \tag{2.15}$$

where Λ_t denotes the LLR value of the t-th local detector and η_{llr} is the Bayesian optimum threshold for making final decision. The LLR of t-th detector is determined by [12]:

$$\begin{aligned}\Lambda_t &= \log L(y_t) \\ &= \log\left(\frac{f_{y|H_1}(y_t \mid H_1)}{f_{y|H_0}(y_t \mid H_0)}\right)\end{aligned} \tag{2.16}$$

The threshold η_{llr}, which minimises the average cost or risk function, is calculated by [12]:

$$\eta_{llr} = \log \frac{p_0(C_{10} - C_{00})}{p_1(C_{01} - C_{11})} \tag{2.17}$$

If the cost of an error and the cost of a correct decision are selected to be one and zero, respectively; that is, $C_{01} = C_{10} = 1,$ and $C_{11} = C_{00} = 0,$ then the risk function reduces to

$$\Re = (1 - P_D)p_1 + P_F p_0 = P_E \tag{2.18}$$

Thus, in this case, minimising the average cost $\Re$ is equivalent to minimising the probability of error P_E. The Bayesian' criterion is now the minimum probability of error criterion. The threshold reduces to [12]:

$$\eta_{llr} = \log \frac{p_0}{p_1} \tag{2.19}$$

2.9 Non-Cooperative Sensing Techniques

In a realistic spectrum sensing scenario, there are situations in which only one sensing terminal is available, or in which no cooperation is allowed due to the lack of communication between sensing terminals. Single user sensing schemes are presented in this section, some of which will serve as basis for the development of the cooperative ones, investigated in section 2.14. Considerable study has been done on single user spectrum sensing approaches because of its relationship to signal detection [11, 15, 28, 29, 36-39]. Some of these approaches include the energy detector [41, 49], the matched filter [21, 50] and the cyclostationary feature detection [5, 51].

2.9.1 Energy Detector

The most well-known spectrum sensing technique is the energy detector [49]. It is based on the principle that the energy of the signal to be detected is always higher than the energy of the noise [49]. The energy detector is said to be a blind signal detector because it ignores the structure of the signal. It estimates the presence of a signal by comparing the energy received with a known threshold η [41, 49, 52], derived from the statistic of the noise σ^2. In practice, instead of using the actual received energy power *E,* the energy detector uses the approximation $\hat{E}$ for E [49], where

$$\hat{E} \triangleq \frac{1}{M}\sum_{t=1}^{M}\left|y(t)\right|^2. \tag{2.20}$$

As the number of samples *M* becomes large, then by the law of the large numbers and the Central Limit Theorem (CLT) $\hat{E}$ converges to E [53]. The energy detector is one of the simplest signal detectors. Its operation is very straight forward and it is easy to implement, since it depends only on readily available information [41].

In spite of its simplicity, the energy detector is far from a perfect solution. One of its weak aspects is based on the approximation of signal energy E gets better as M increases. Thus, the performance of the energy detector is directly linked to the number of sample. A larger number of samples may lead to a longer sensing time. Furthermore, the energy detector relies completely on the variance of the noise σ^2 which is taken as a fixed value [41]. This is generally not true in practice, where the noise floor varies. Essentially this means that the energy detector will generate errors during those variations, especially when the average SNR is very low, when there is an area of uncertainty surrounding the threshold in contrast with when perfect noise knowledge is considered [41, 49].

2.9.2 Characterisation of Energy Detector in AWGN Channels

The energy detection is the optimal signal detector in AWGN considering no prior information on the signal structure [21]. In order to understand the inner workings of the energy detector in this scenario, an understanding of how the probability of detection $P_D = \mathrm{P}\{\hat{E} > \eta \mid H_1\}$ and probability false alarm $P_F = \mathrm{P}\{\hat{E} > \eta \mid H_0\}$ behaves with the measured received signal energy is required.

Let's take $n(t) \sim \mathcal{NC}(0,\sigma^2)$ be the AWGN noise sample. It is known that for the noise only case, the distribution of the energy of n can be approximated by a zero mean chi-square distribution χ^2_{2u} [41], where u is the time bandwidth product. Similarly, the energy of a signal plus noise, can be represented by a non-central chi-square distribution $\chi^2_{2u}(2\gamma)$, where γ is the non-centrality parameter [41]. Briefly:

$$\hat{E} \sim \begin{cases} \chi^2_{2u} & , H_0 \\ \chi^2_{2u}(2\gamma) & , H_1 \end{cases}. \tag{2.21}$$

With these considerations, P_D and P_F can be restated as:

$$P_D = Q_u(\sqrt{2\gamma}, \sqrt{\eta}) \tag{2.22}$$

$$P_F = \frac{\Gamma(u, \eta / 2)}{\Gamma(u)} \tag{2.23}$$

where $Q_u(.,.)$ is the generalised Marcum Q-function, $\Gamma(.)$ is the gamma function and $\Gamma(.,.)$ is the incomplete gamma function.

2.9.3 Characterization of Energy Detector in Fading Channels

The performance of the energy detector in fading channels was studied in [52]. Analytical expressions for the energy detector over the Rayleigh fading channel case also analysed the Rician and Nakagami cases numerically in [52]. The problem was revisited in [49], who provided an alternative analytical development for these three kinds of fading channels. In this section, however, we will restrict the analysis to the more commonly adopted Rayleigh fading. Taking equation (2.21) into consideration, let the statistics of the energy of the signal for both the H_0 and H_1 cases, be under the assumption that $h(t)$ is Rayleigh distributed [49]:

$$\hat{E} \sim \begin{cases} \chi^2_{2u+1} & , H_0 \\ e_{2(\xi^2+1)} + \chi^2_{2u}(2\gamma) & , H_1 \end{cases}. \tag{2.24}$$

where $e_{2(\xi^2+1)}$ is the exponential distribution with parameter $\alpha = 2(\xi^2+1)$ with PDF function $f(y,\alpha) = \alpha e^{-\alpha y}$ and ξ is the SNR.

$$P_F = \frac{\Gamma(u,\eta/2)}{\Gamma(u)}. \tag{2.25}$$

Notice that in this case the probability of false alarm P_F remains the same as in the AWGN case, since it is independent of the SNR [49]. However, the H_1 case behaves differently and by using equation (2.22) the probability of detection P_D is given by [49]:

$$P_D = e^{-\hat{E}/2}\sum_{n=0}^{u-2}\frac{1}{n!}\left(\frac{\hat{E}}{2}\right)^n + \left(\frac{1+\bar{\xi}}{\bar{\xi}}\right)^{u-1}\left[e^{-\frac{\hat{E}}{2(1+\bar{\xi})}} - e^{\frac{-\hat{E}}{2}}\sum_{n=0}^{u-2}\frac{1}{n!}\left(\frac{\hat{E}\bar{\xi}}{2(1+\bar{\xi})}\right)\right]. \tag{2.26}$$

Although an energy detection technique can be used in an environment that has no prior information about the PU signal characteristics [41], it still has some boundaries:

(i) reduced performance under low SNR situation due to not precisely establishing the noise variance at low SNR [54].

(ii) its failure to differentiate between interference from other SUs sharing the PU channel [54].

(iii) long sensing time to accomplish a given probability of detection [54].

In this thesis, we focus on energy detection due to its advantages as well as its practical uses.

2.9.4 Matched Filter Detector

As described in the section 2.9.1, the best sensing technique in an AWGN environment without any knowledge of the signal structure is the energy detector. If some knowledge of the signal structure is assumed, then an improved performance can be achieved [36]. Majority of the wireless technologies in operation include the transmission of some sort of pilot sequence, to allow channel estimation, to beacon its presence to other terminals and to give a synchronisation reference for subsequent messages. SU systems can exploit pilot signals in order to detect the presence of transmissions of primary systems in their vicinity.

If a pilot signal is known, then the matched filter signal detector achieves the optimal detection performance in AWGN channel [5], as it maximises the SNR. The following assumptions can be made [36, 55]:

1. The signal detector knows the pilot sequence $x(t)$, the bandwidth and the centre frequency in which the signal will be transmitted.
2. The pilot sequence is always appended to each primary system's transmission.
3. The signal detector can always receive coherently.

If $y(t)$ is a sequence of received samples at the SU, for $t = 1,..., M$. The decision rule can be stated as [50]:

$$\text{decide for} \begin{cases} H_0 \ , & \text{if } \hat{\mathcal{S}} < \eta \\ H_1 \ , & \text{if } \hat{\mathcal{S}} \geq \eta \end{cases} , \tag{2.27}$$

where

$$\hat{\mathcal{S}} = \sum_{t=1}^{M} y(t)x(t)^* \ . \tag{2.28}$$

$\hat{\mathcal{S}}$ is the decision criterion, η is the threshold to be compared and $x(t)^*$ is the transpose conjugate of the pilot sequence. The threshold η is not the noise variance as it was for the energy detector. The hypothesis decision is simplified as the matched filter maximises the power of $\hat{\mathcal{S}}$ as seen in equation (2.28). This means it performs well even in a low SNR regime. Matched filter pilot detection for CRs has been proposed in [50, 56], for digital video broadcasting - terrestrial (DVB-T) standard in order to take advantage of the well-defined pilot structure in the DVB-T signal.

The matched filter has some drawbacks. A SU spectrum sensor might not know which networks are in operation in the environment at a given moment. Therefore it may not know which sets of pilots to look for. If it tries to match an incorrect pilot, it will sense an absence of the PU signal and incorrectly conclude that the medium is free. The matched filter requires that every medium access be "signed" by a pilot transmission, but this is not the case in general. Furthermore, pilot sequences are only transmitted in the downlink direction. This leaves the uplink transmissions uncovered. Finally, the matched filter requires coherent reception, which is generally hard to achieve in practice [36].

2.9.5 Characterisation of the Matched Filter

Signal detection using the matched filter was studied in [50], and shown that $\hat{\mathcal{S}}$ is Gaussian [50]:

$$\hat{\mathcal{S}} \sim \begin{cases} \mathcal{N}(0,\sigma_n^2\varepsilon) \ , & H_0 \\ \mathcal{N},(\varepsilon,\sigma_n^2\varepsilon) \ , & H_1 \end{cases}, \tag{2.29}$$

where σ_n^2 is the variance of the noise and

$$\varepsilon = \sum_{t=1}^{M} x(t)^2. \tag{2.30}$$

Based on this information, the probabilities of false alarm P_D and detection P_F are:

$$P_F = Q\left(\frac{\hat{S}}{\sqrt{\varepsilon\sigma_n^2}}\right), \tag{2.31}$$

and

$$P_d = Q\left(\frac{\hat{S}-\varepsilon}{\sqrt{\varepsilon\sigma_n^2}}\right). \tag{2.32}$$

2.9.6 Cyclostationary Feature Detection

Radio frequency signals are generally non-stationary with statistical properties that exhibit periodicity. Since the periodicity varies periodically with time, radio signals and other associated signals that exhibit periodicity, are referred to as cyclostationary signals [57]. In wireless communication, periodicity may be caused by sampling, multiplexing, modulation, and coding operations [57] or can also be intentionally produced to aid channel estimation and synchronisation. As described in section 2.9.4, although it performs well, even in the low SNR regime, the matched filter requires a good knowledge of the signal structure, which SUs may not have. The next consideration is to find out whether spectrum sensing can be performed with a limited knowledge of the signal structure, perhaps based on a characteristic that is common to most known transmitted signals [36].

The cyclostationary feature detector relies on the fact that most signals exhibit periodic features present in pilots, cyclic prefixes, modulations, carriers and other repetitive characteristics [5, 51, 58, 59]. Since the noise is not periodic, the signal can be successfully detected. In [58] the cyclostationary feature detector is based on the magnitude-squared of the spectral coherence, which for any random process X is given by [58];

$$\left|p_X^{\alpha}(f)\right| = \frac{\left|S_X^{\alpha}(f)\right|^2}{\left[<S_X>\left(f+\frac{\alpha}{2}\right)<S_X>\left(f+\frac{\alpha}{2}\right)\right]^{\frac{1}{2}}}, \tag{2.33}$$

where S_X is the spectral correlation density function, α is the cyclic frequency and f is the spectral frequency. In the specific case of the cyclostationary feature detector, substituting $p_X^{\alpha}(f)$ by $\hat{p}_X^{\alpha}(f)$ and S_X by $\hat{S}_X$, which are the estimated versions of the same quantities, the decision metric is given by [58]:

$$\hat{\mathcal{M}} = \left|p_X^{\alpha}(f)\right| = \frac{\left|S_X^{\alpha}(f)\right|^2}{\left[<\hat{S}_X>\left(f+\frac{\alpha}{2}\right)<\hat{S}_X>\left(f+\frac{\alpha}{2}\right)\right]^{\frac{1}{2}}}, \tag{2.34}$$

which goes into the decision statistic, given by [50]:

$$\text{decide for } \begin{cases} H_0\ , & \text{if } \hat{\mathcal{M}} < \eta \\ H_1\ , & \text{if } \hat{\mathcal{M}} \geq \eta \end{cases}, \tag{2.35}$$

It is thought that the cyclostationary feature detector is the most promising signal detection technique, as it combines good performance with low requirements on the knowledge of the signal structure [60]. It is an optimised technique that can easily isolate the noise from the

PU's signal. This is because noise is a stationary signal with no correlation, while modulated signals are cyclostationary signals with spectral correlation due to the embedded redundancy of signal periodicity [15]. This makes cyclostationary feature detection outperform energy detection when discriminating against noise due to its robustness to the uncertainty in noise power [15]. However, the drawbacks of cyclostationary feature detection, when compared with energy detection, are the need for a priori knowledge of the PU's signal such as the modulation scheme and its implementation complexity. Another disadvantage of the cyclostationary detection method is its poor performance when an SU experiences shadowing or fading effects. This is because the method cannot distinguish between an unused band and a deep fade in such cases [61].

2.10 Other Spectrum Sensing Techniques

2.10.1 Autocorrelation Detection

In many cases, the autocorrelation function (ACF) of the signal is not only non-stationary, but is also periodic [48]. Most man-made signals show periodic patterns related to symbol rate, chip rate, channel code or cyclic prefix [48]. Such second order periodic signals can be appropriately modelled as second-order cyclostationary random processes [48]. It is highly probable that most of the PUs will be OFDM based systems. Hence, detecting an OFDM based system in a CR scenario is crucial.

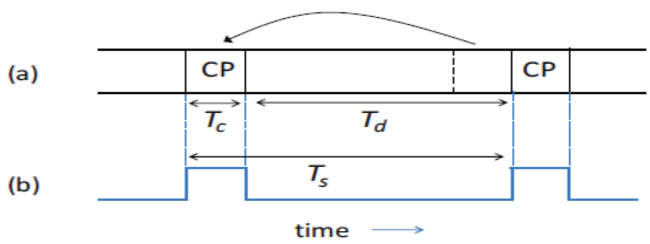

Figure 2.2 (a) CP based OFDM symbol (b) Corresponding autocorrelation function [36].

Figure 2.2 [36] shows a CP based OFDM symbol. Let T_d, T_c and T_s be the number of data samples, CP and total number of samples, respectively, in an OFDM symbol,

$$T_s = T_c + T_d \tag{2.36}$$

The last T_c samples of the data information block are copied to the front of the data block. This results in the autocorrelation function $r(t,\tau) = E[y(t)y^*(t+\tau)]$ at lags $\tau = \pm T_d$ to be periodic as shown in Figure 2.2. Where $y(t)$ is the signal received by SUs for $t = 1,...,M$. Here t represents the discrete time index and M denotes the number of observation. The periodic autocorrelation can be expressed using the Fourier series [62] as:

$$r(t,\tau) = R^0(\tau) + \sum_{k=-T_s/2, k\neq 0}^{k=T_s/2-1} R^k(\tau) e^{j2\pi kt/T_s} \tag{2.37}$$

where $R^k(\tau)$ is the cyclic autocorrelation function at the cycle frequency k/T_s and given by [62]:

$$R^k(\tau) = \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} y^*(t) y(t+\tau) e^{-j2\pi kt/T_s} \tag{2.38}$$

If the received observations are denoted by $[y(0),...,y(M+\tau-1)]$, then the ML estimate autocorrelation at the lag τ is given by [63]:

$$\hat{R}(\tau) = \frac{1}{M} \sum_{t=0}^{M-1} y(t) y^*(t+\tau) \tag{2.39}$$

Quite a few detectors based on the correlation characteristics have been proposed to detect the OFDM signal in [63].

2.10.2 Wavelet Detection

The wavelet detection method uses the principle of wavelet transformation where multi-resolution analysis mechanisms decompose the input signal into different frequency components [64]. Each component is then studied with resolutions matched to its scales. Wavelet transform uses irregularly-shaped wavelets as basic functions and offers better tools to represent sharp changes [65]. To identify the locations of idle frequency bands, the entire wideband is modelled as a train of consecutive frequency sub-bands where the power spectral properties are smooth within each sub-band, but changes suddenly on the border of two neighbouring sub-bands [66]. By analysing the irregularities in the PSD properties with wavelet transformation, the spectrum hole can be located. Its advantage is that it can perform optimally without a priori knowledge information of the PU's signal [66].

2.10.3 Compressed Sensing

Energy or cyclostationary detection is based on a set of observations sampled by an analogue-digital converter (ADC) at Nyquist rate in the band of interest [45]. In either, the spectrum sensing scheme senses one band at a time because of their hardware limitations on the sampling speed. In order to sense multiple frequency bands using either technique, the CR or the SU needs to use multiple radio frequency front-ends for sensing multiple bands. Hence, using these techniques for wideband sensing will either cause a long sensing delay or incur higher computational complexity and hardware cost. Recent advances in compressed sensing enables the sampling of the wideband signals at sub-Nyquist rate to relax the ADC requirements [67, 68]. Based on the assumption that the spectrum is underutilised compressed sensing can be utilised to approximate and recover the sensed spectrum, which facilitates the detection of sparse primary signals in wideband spectrum. The techniques of compressed sensing provide promising solutions to promptly recover wideband signals and facilitate wide-bands sensing at a reasonable computational complexity [67, 68].

In a conventional compressed sensing scheme [69], the first step is to generate measurements $\mathbf{y}_t$ of size $K \times 1$ by sub-Nyquist-rate random sampling. If $\mathbf{r}_t$ of size $M \times 1$ is the discrete-time vector of the received wideband signal $r(t)$, the compressed sensing process be represented by $\mathbf{y}_t = \mathbf{S}^T \mathbf{r}_t$, where $\mathbf{S}^T$ is the $M \times K$ projection matrix, $K < M$. The second step is to reconstruct wideband spectrum $\mathbf{r}_f = \mathbf{F}_M \mathbf{r}_t$ from $\mathbf{y}_t$, where $\mathbf{F}_M$ is M - point discrete Fourier transform. To achieve this, efficient reconstruction methods such as basis pursuit (BP) [25, 69], can be used to solve the following convex optimisation problem with the sparseness constraint in $\mathbf{r}_f$ [25]:

$$\hat{\mathbf{r}} = \arg\min_{\mathbf{r}_f} \left\| \mathbf{r}_f \right\|_1, \quad \text{s.t.} \mathbf{y}_t = (\mathbf{S}^T \mathbf{F}_M^{-1}) \mathbf{r}_f. \tag{2.40}$$

2.10.4 Sequential Detection

Sequential hypothesis testing has been of great interest in statistics and also in signal detection for many years [70]. In centralised schemes for signal detection, sequential testing offers the possibility of making final decisions within a given reliability requirement as soon as enough data has been collected to stop further data acquisition and declare a result [70]. Sequential procedures are useful when data acquisition is costly and when both reliability and decision delay are important considerations [70]. Sequential detection needs a smaller amount of samples to achieve a similar performance levels as the fixed sample size (FSS) test [46]. The sequential detection test statistics after receiving *i* data samples is given by [46]:

$$\begin{cases} T_i \leq \eta_{a\,,} & \text{Decide } H_0 \\ T_i \geq \eta_{\mathrm{b}\,,} & \text{Decide } H_1 \\ \mathit{Otherwise}, & \text{Take Next Data Sample} \end{cases} \tag{2.41}$$

where T_i is the test statistic after *i* data samples while η_a and η_b are the upper and lower thresholds. $\eta_a < 0$ and $\eta_b > 0$ are predetermined constants according to the sensing object. Detailed literature on sequential detection can be found in [39, 46, 71]. Most of the proposed sequential detectors are based on the sequential probability ratio test (SPRT) proposed by [34]. In terms of the LLRs, the SPRT [70] after receiving *k* data samples is

$$\begin{aligned} &\sum_{m=1}^{k} L_m \leq \log B, && \text{Decide } H_0 \\ &\sum_{m=1}^{k} L_m \geq \log A, && \text{Decide } H_1 \\ &\mathit{Otherwise}, && \text{Take next data samples.} \end{aligned} \tag{2.42}$$

where L_m is the LLR corresponding to the *m*-th observation, $A = \dfrac{1-B_s}{\alpha_s}$ and $B = \dfrac{B_s}{1-\alpha_s}$. Here α_s and B_s are the constraints on the probabilities of false alarm and missed detection, respectively. The performance of sequential detectors is generally expressed in terms of the average sample number (ASN) for given α_s and B_s. Among all the tests with equal and or smaller error probabilities, the SPRT is optimal for testing simple hypotheses test as it minimises the ASN under H_0 and H_1 [72].

2.10.5 MIMO Detector

Multiple input multiple output (MIMO) technology uses multiple antennas at the transmitter and receiver to improve communication performance. MIMO systems provide direction of arrival information of the signal. Due to these advantages, MIMO has attracted a lot of attention in the field of wireless communication. MIMO is an important part of wireless communication standards e.g. WLAN IEEE 802.11, (3GPP) LTE-Adavnced, WiMAX. These multiple antennas in MIMO can also be used for the spectrum sensing tasks. MIMO can be a trade-off between beamforming gain, parallel sensing gain and diversity gain for detecting the PU. Beamforming helps improve the received average SNR while parallel sensing reduces the sensing time and diversity gain helps overcome the effects of the hidden terminal multipath fading channel which is the main focus of this thesis. Numerous MIMO sensing algorithms have been proposed in literature [73, 74].

Other methods of spectrum sensing techniques found in literature include waveform based, multi-taper spectral estimation, and radio identification etc. It is common to find a combination of sensing techniques to improve time response or save computation. Some solutions are more specific regarding their application and exploit some prior degree of knowledge about the sensing environment, either as part of the sensing strategy, or by definition of the approach [38].

2.11 Comparative Analysis of State of the Art Spectrum Sensing Techniques

Various state-of-the-art sensing techniques have been presented in this chapter. In this section, comparisons performance simulation on some of the described spectrum sensing techniques described for particular scenarios are considered. Table 2.1 shows performance comparison of representative spectrum sensing schemes belonging to different categories.

Table 2.1 Comparison of spectrum sensing techniques

Spectrum sensing technique	Advantages	Disadvantages
Energy detection	• Low complexity • No primary knowledge required	• Poor performance for low SNR • Cannot differentiate primary user's signals • Long sensing time
Matched filter detection	• Optimal performance • Low computational cost	• Requires prior knowledge of the primary user's signal
Cyclostationary detection	• Robust in low SNR region • Robust against interference	• Requires partial prior information • High computational cost
Wavelet Detection	• Efficient for wideband signal detection	• Requires high sampling rate analog-to-digital converter • High computational cost
Compressed sensing	• Low sampling rate • Low signal acquisition cost • Efficient for wideband signal detection	• Sensitive to design imperfections
Multitaper spectral estimation	• Near optimal performance for wideband signals • No primary knowledge required	• High implementation complexity

It is obvious from the performance comparison Table 2.1 and discussion on advantages and disadvantages of the detectors, that not one single detector has the best performance for all scenarios.

2.11.1 Primary Signal - DVB-T2 Signal

The PU network signal used is assumed to be a Digital Video Broadcasting - Second Generation Terrestrial (DVB-T2) signal [75], hence a brief description of a DVB-T2 signal is given in this section.

In CR systems, DVB-T signals are one of the most important types used by PUs in TV bands [75]. DVB-T2 is the world's most advanced digital terrestrial television (DTT) system, offering more robustness, flexibility and 50% more efficiency than any other DTT system. It supports SD, HD, UHD, mobile TV, radio, or any combination thereof [75]. DVB-T2 signals are more resilient against certain types of interference than DVB-T. Since its publication in 1997, over 70 countries have deployed DVB-T services and 69 countries have now adopted or deployed DVB-T2 [75]. This well-established standard benefits from massive economies of scale and very low receiver prices. Due to the European analogue switch-off and increasing scarcity of spectrum, DVB drew up commercial requirements for a more spectrum-efficient and updated standard [75]. DVB-T2 easily fulfils these requirements, including increased capacity, robustness and the ability to reuse existing reception antennas [75].

From a spectrum sensing point of view, important DVB-T2 parameters (see also Table 2.2) are represented by: channel bandwidth (that ranges from 1.7 to 10 MHz), the OFDM Cyclic Prefix (CP) length (that ranges from 1/128 to 1/4 of the OFDM symbol length), and the presence of OFDM pilots (continual and scattered) [84]. DVB-T2 uses the same error correction coding as used in DVB-S2 and DVB-C2: LDPC (Low Density Parity Check) coding combined with BCH (Bose-Chaudhuri-Hocquengham) coding, offering a very robust signal. The number of carriers, guard interval sizes and pilot signals can be adjusted, so that the overheads can be optimised for any target transmission channel [75]. The presence of pre-determined patterns in the transmitted DVB-T2 signal determines the cyclostationary property shown by OFDM signals. DVB-T2 uses OFDM modulation with a large number of sub-carriers delivering a robust signal, and offers a range of different modes, making it a very flexible standard [75].

Table 2.2 Main parameter of DVB-T2

	DVB-T2
FEC	LDPC + BCH 1/2 , 3/5, 2/3, 3/4, 4/5, 5/6
Modes	QPSK, 16QAM, 64QAM, 256QAM
Guard interval	1/4, 19/256, 1/8, 19/128, 1/16, 1/32, 1/128
FFT size	1K, 2K, 4K, 8K, 16K, 32K
Scattered Pilots	1%, 2%, 4%,8% of total
Continual Pilots	0.4%-2.4%(0.4%-0.8% in 8K-32K)
Bandwidth	1.7, 5, 6, 7, 8, 10 MHz
Typical data rate (UK)	40 Mbit/s
Max. data rate (@20 dB C/N)	45.5 Mbit/s (using 8M Hz/)
Required C/N ratio (@24 Mbit/s	10.8 dB

As a common assumption in the literature on spectrum sensing, the primary signal is modelled as a Gaussian process. In [75], it is shown that in the case of DVB-T2 signals, this assumption is well motivated. In this thesis, in most chapters a DVB-T2 signal is assumed to be the PU signal.

2.11.2 Simulation Results

In order to evaluate the performance of some of the main techniques for spectrum sensing, simulation are carried out using theoretical test statistics, which can be found in Table 2.3. The energy detector requires the noise power σ_n^2 to be known. The Autocorrelation detector does not require any knowledge about the noise power σ_n^2, but the number of data samples T_d is known. For the pilot detector the noise power σ_n^2, the number of data samples T_d and T_c the number of samples in the CP are known.

Table 2.3 Summary of Detectors

Detector	**Reference**	**Test Statistic**	**Prior Knowledge**
Pilot	[76]	$\max_{\theta \in \{0,1,\ldots,4(T_d+T_c)-1\}} \left\| \sum_{k=0}^{M-\theta-1} s_p[k] y^*[k+\theta] \right\|$	σ_n^2, T_d, T_c
Energy	[77]	$\Lambda \triangleq \sum_{k=0}^{M} y[k] y^*[k]$	σ_n^2
Autocorrelation	[48]	$\dfrac{\frac{1}{M-T_d}\sum_{k=0}^{M-T_d-1}\mathrm{Re}(r[k])}{\frac{1}{M}\sum_{k=0}^{M-1}\left\|y[k]\right\|^2}$	T_d
		where T_d : number of data samples, T_c : number of samples in the CP M : total number of samples s_p : deterministic signal $y[k]$: time discrete received sequence $r[k]$: sample value product	

The PU network is assumed to be a DVB-T2 signal as in [78], the bandwidth of the PU signal is 8 MHz, and modulation type QPSK. The average occupancy rate for the PU is set to 50%, i.e. the probability of presence and absence of the PU signal is fixed to an equal probability (0.5), respectively. AWGN, Rayleigh and Rician channels are considered.

The simulation was based on the Monte Carlo method in MATLAB with 100,000 iterations. The three main sensing schemes are considered i.e. energy detector, matched filter and autocorrelation detector. A summary of the simulation parameters which is common for all scenarios for analysing the detectors algorithm's performance evaluation is shown in Table 2.4.

Table 2.4 Simulation parameters for the detector's algorithm

Parameter	**Value**
PU bandwidth	8 MHz
Local sensing	50 μs
Frame length	60
FEC blocks per frame	50
Channel condition	AWGN, Rayleigh
SNR range	-40dB to 0 dB
Iterations	100,000
DVB-T2 signal mode	2K
False alarm probability	0.05
SU	1
Sensing time	10ms, 50ms

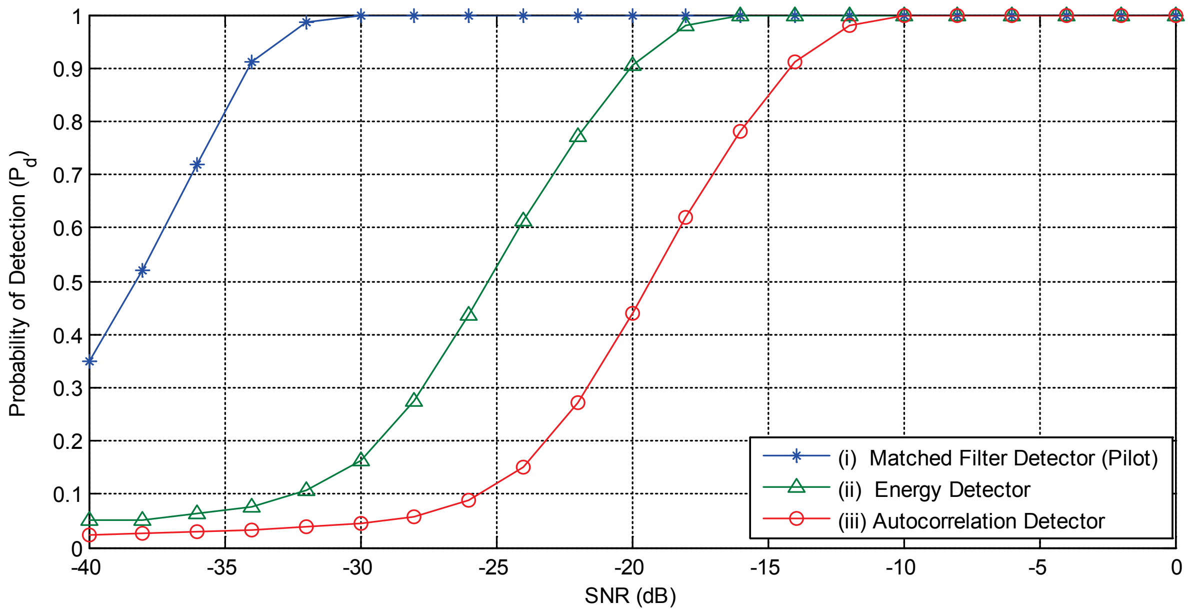

Figure 2.3 Probability of detection comparison between "Energy detector", "Matched filter" and "Autocorrelation detector" under conditions with SNR = -40 dB to 0 dB for an AWGN channel. Sensing time = 10 ms.

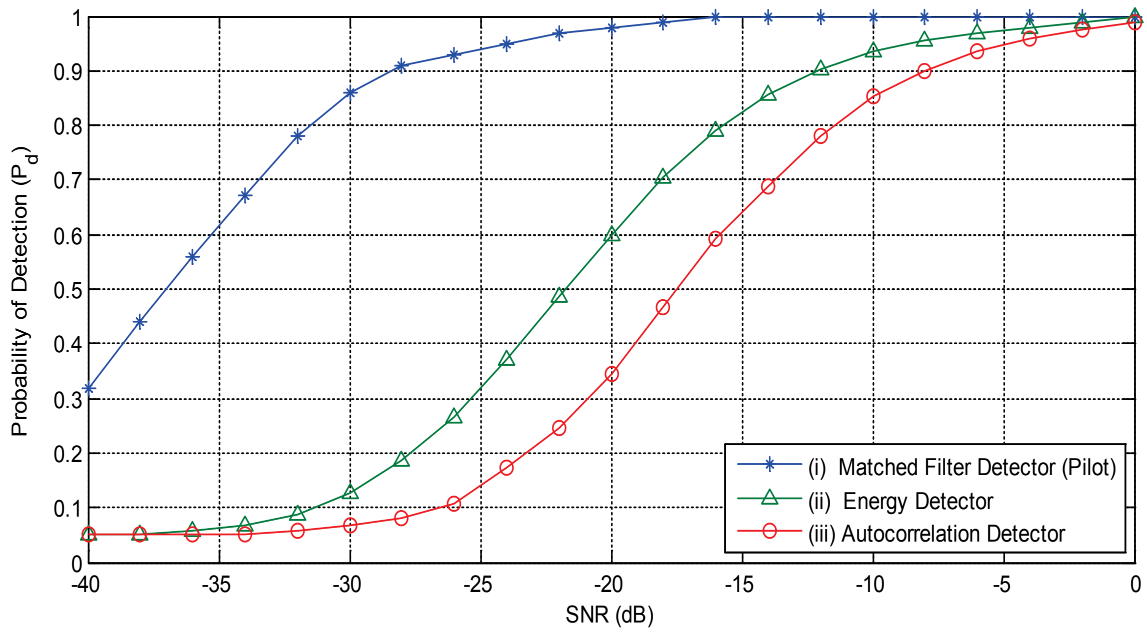

Figure 2.4 Probability of detection comparison between "Energy detector", "Matched filter" and "Autocorrelation detector" under conditions with SNR = -40 dB to 0 dB for Rayleigh fading. Sensing time = 10 ms.

In Figure 2.3 and Figure 2.4 a probability of detection as a function of SNR for a pilot, energy and autocorrelation detector are illustrated, with SNR ranging from -40dB to 0dB and probability of false alarm $P_F = 0.05$. An AGWN channel and Rayleigh channel with 10 ms sensing time was considered in Figure 2.3 and Figure 2.4, respectively. It has been observed that the pilot based detector outperforms both the energy detector and the autocorrelation-based detector. For example, at -25dB under Rayleigh conditions, the pilot detector had an improvement in detection of approximately 66% and 80% over the energy detector, and autocorrelation-based detector, respectively. Apart from the pilot based detector the other presented algorithms do not rely on the information about the structure of the PU signal. The only assumption is that the length of the cyclic prefixes and total duration of the symbol are known for the autocorrelation detector.

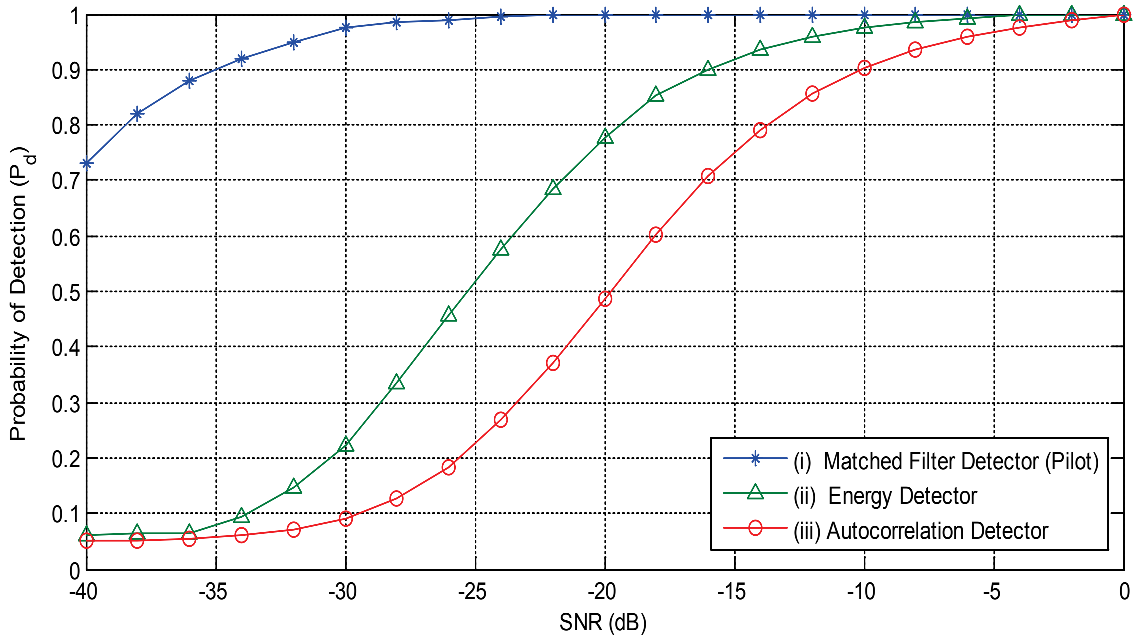

Figure 2.5 Probability of detection comparison between “Energy detector”, “Matched filter” and “Autocorrelation detector” under conditions with SNR = -40dB to 0dB for Rayleigh fading. Sensing time = 50 ms.

In Figure 2.5, a probability of detection as a function of SNR for a pilot, energy and autocorrelation detector are illustrated, with SNR ranging from -40dB to 0dB and probability of false alarm $P_F = 0.05$. A Rayleigh channel with 50 ms sensing time was considered. That is, the sensing time was increased in Figure 2.5 compared to that of Figure 2.4 while keeping all other parameters the same. It was observed that as the sensing time increased from 10 ms to 50 ms the detection probability increased for all the detectors. For example in the pilot detector at SNR = -30dB there was a detection increase rate of approximately 12%. While for energy detector and autocorrelation detector, there was an increase of approximately 10 % and 5 % respectively. It was observed that the pilot detection has the highest detection gain at a low SNR (-40dB). However, it requires perfect synchronisation making it highly vulnerable to frequency offsets.

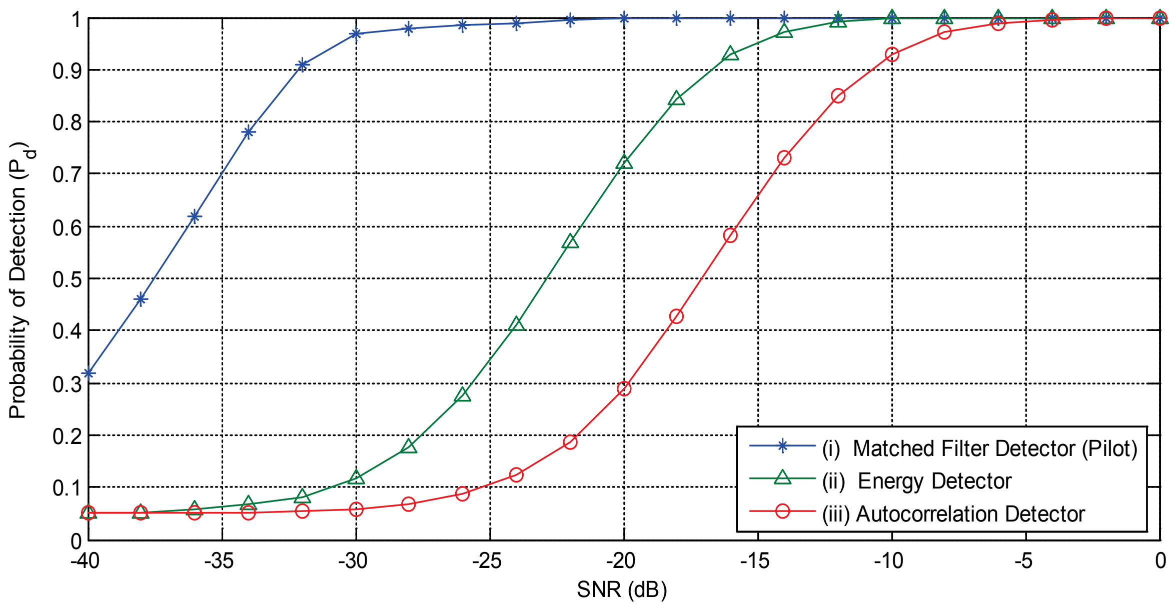

Figure 2.6 Probability of detection comparison between "Energy detector", "Matched filter" and "Autocorrelation detector" under conditions with SNR = -40dB to 0dB for Rician fading. Sensing time = 10 ms.

In Figure 2.6, a probability of detection as a function of SNR for a pilot, energy and autocorrelation detector are illustrated, with SNR ranging from -40dB to 0dB and probability of false alarm $P_F = 0.05$. A Rician fading (K=5) channel with 10 ms sensing time was considered. It has been observed that the pilot based detector outperforms both the energy detector, and autocorrelation-based detector just as in the AWGN and Rayleigh case. A general observation when comparing all the scenarios is that the channel type does not influence the performance of the presented algorithms by a great deal, with the exception of the pilot based detector. Thus, even when the channel is frequency selective, the PU signal can be exploited for detection. In spite of which spectrum sensing scheme is employed, each algorithm provides a trade-off between the probability of false alarm and the probability of detection.

2.12 Cooperative Spectrum Sensing

In CSS, information from multiple SUs are incorporated for the detection of the primary signal. In the literature, cooperation is discussed as a solution to problems that arise in spectrum sensing due to the hidden terminal problem [5, 79].

The hidden terminal

The hidden terminal problem in CSS is similar to the hidden node problem in Carrier Sense Multiple Accessing (CSMA) [36]. This problem can be caused by many factors including severe multipath fading or shadowing that SUs observe while scanning PUs transmissions [36]. Figure 2.7 shows an illustration of the hidden terminal problem, where the building causes unwanted interference to the primary transmitter signal leading to multipath fading and shadowing on the signal received by an SU [61].

Spectrum sensing using a single CR has a number of limitations. Firstly, the sensitivity of one sensing device might be limited due to energy constraints. Furthermore, in wireless channels, the hidden terminal problem will lead to a very low SNR [61]. Although the CR might be out of sight from the PU's transmitter, this does not mean it is also blocked from the PU's receiver. As a result, the PU is not detected but the secondary transmission could still significantly interfere at the PU's receiver. In this thesis, CSS is considered to optimise, improve the sensitivity of CR spectrum sensing and to make it more robust against the hidden terminal problem.

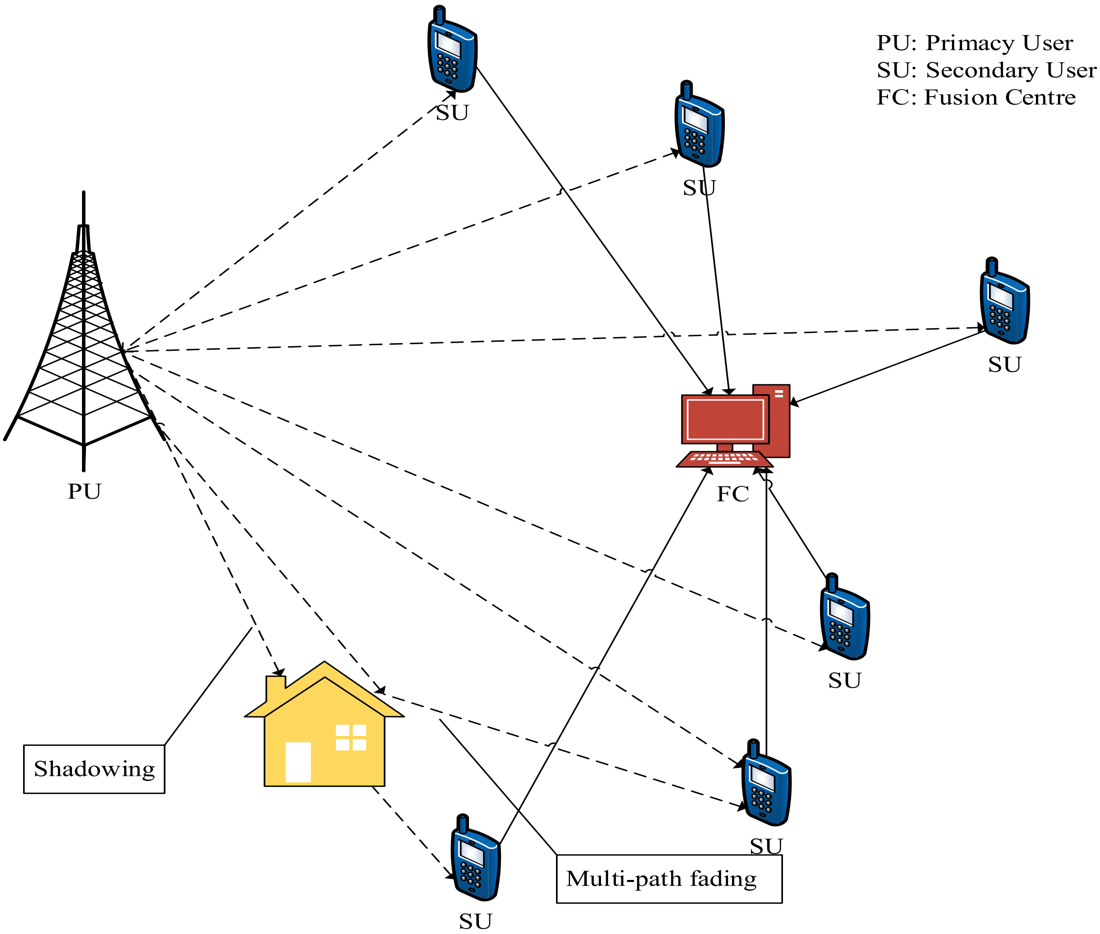

Figure 2.7 Illustration of the hidden terminal problem in cognitive radio systems.

The main idea of CSS is to use multiple CR users and combine or fuse their measurements into one global decision. There are typically two components in a CSS scheme; namely the local sensor and the fusion centre (FC). The local sensor can be any of the detectors which were presented in section 2.9, in this thesis the local sensor is assumed to be embedded to the SU. Consequently, each local SU will collect the information of the primary signal, such as energy, basic probability estimate (BPA), maximum likelihood estimate (MLE) and log-likelihood ratio (LLR). Give that not all spatially distributed SUs in a CR environment will simultaneously experience similar shadowing or fading i.e. the hidden terminal problem. Hence, when the SUs cooperate with each other and share the spectrum sensing results among each other, the combined cooperative decision derived from the spatially collected observations can overcome the deficiency of individual observation of each SU.

2.12.1 Advantages of Cooperative Spectrum Sensing

The performance of spectrum sensing depends on the local channel conditions of the CR, i.e. it depends on the multipath, shadowing and local interference. These conditions can result in regimes where the SNR is below the detection threshold of the local CR, resulting in missed detections and in false alarms creating the impact mapping illustrated in Figure 2.8. To overcome this limitation the use of cooperation has been proposed in several works [42, 45, 64, 80-82]. Advantages of CSS over non-CSS include:

i) **Diversity gain**: Since the signal strength varies with the CRs location, the worst fading conditions can be avoided, if multiple CRs in different spatial locations share their local sensing measurement, i.e. take advantage of the spatial diversity. Taking advantage of spatial diversity leads to a higher accuracy of detection of the primary due to a higher accuracy in signal detection multipath, shadowing and local interference [36].

ii) **Sensing time**: The longer the sensing time of a CR the higher the probability of detecting the PU signal but the less the throughput. Using multiple CRs the sensing time can be reduced. CSS reduces the sensing time, and thus it increases transmission throughput [61] .

iii) **Robustness**: Robustness to changing networks and fast convergence is yet another advantage of CSS [61]. Other advantage of CSS includes increased coverage and simpler detector design.

Some draw backs of CSS include [36]:

- Higher complexity to the CR system collaboration, higher power demands, and increased overhead traffic.
- The information forwarded to FC implies requires a dedicated control channel and a consequent coarse synchronisation to avoid a modification of the electromagnetic environment during the spectrum sensing phase.
- The increase of the number of SUs leads to a consequent increment in costs.

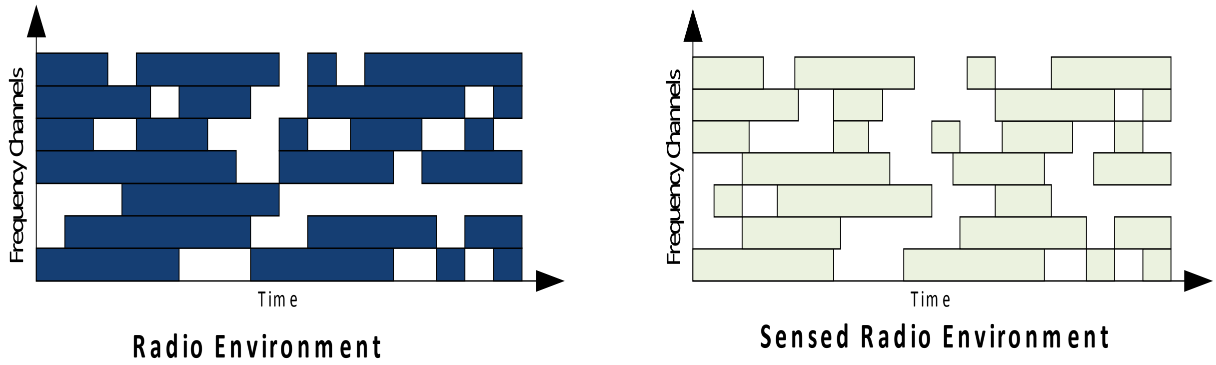

Figure 2.8 Impact mapping of the radio environment and sensed radio environment [36].

CSS are categorised into three classes based on how cooperating CR users share the sensing measurement within the network namely centralised, distributed and relay-assisted, and they are illustrated in Figure 2.9, Figure 2.10 and Figure 2.11, respectively.

2.12.2 Centralised Cooperative Spectrum Sensing

In a centralised CSS, a central node called the master node or FC controls the three step process of CSS. Firstly, the FC selects a channel or a frequency band of interest for sensing and instructs all cooperating SUs to individually perform local sensing. Secondly, all cooperating CR users report their sensing results via the control channel. Then the FC combines the received local sensing information, determines the presence of PUs, and diffuses the decision back to cooperating SUs. As shown in Figure 2.9, the FC is the master node and SU_1-SU_5 are the cooperative SUs performing local sensing and reporting the sensing data back to the FC. The FC collects sensing information from SU_1-SU_5, identifies the vacant spectrum and broadcasts the information to SU_1-SU_5 [36]. The centralised CSS can occur in either a centralised or distributed CR networks. In centralised CR networks, a CR base station (BS) is naturally the FC. Alternatively, in CR adhoc networks (CRAHNs) where a CR BS is not present, any SU can act as a FC to coordinate CSS and combine the sensing information from the cooperating neighbours [83].

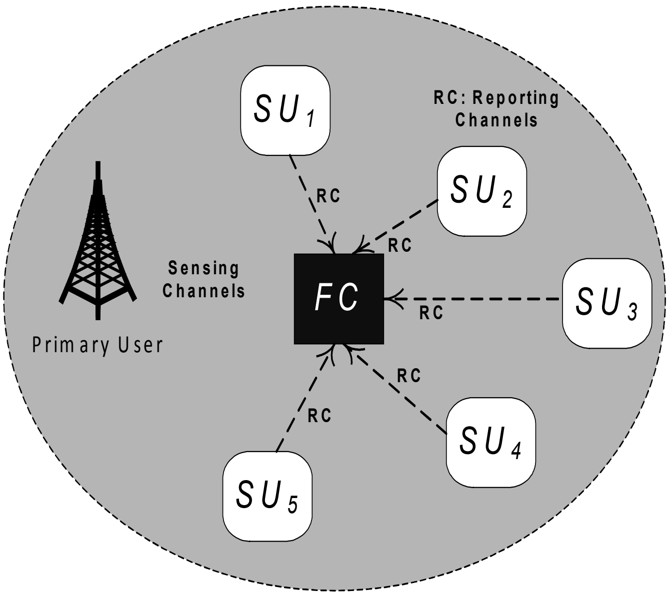

Figure 2.9 Centralised Cooperative Spectrum Sensing [36].

2.12.3 Distributed Cooperative Spectrum Sensing

Distributed CSS, as shown in Figure 2.10 does not rely on the FC for making the final global decision. In this case, SUs communicate among themselves and converge to a unified decision on the presence or absence of PUs by iterations. As shown in Figure 2.10, after local sensing, SU_1-SU_5 share their local sensing results amongst each other and make their own decisions as to which part of the spectrum they can utilise. If there are no evident decisions after this initial process, SUs pass their combined results to other users and repeat the sensing process until the scheme is converged and a decision is reached [16]. The disadvantage of distributed CSS is a decision delay possibility because several iterations may be required to reach a unanimous cooperative decision hence increasing the chance of the PU interference. To overcome this limitation, different decision strategies may be used, which result in different delay [36].

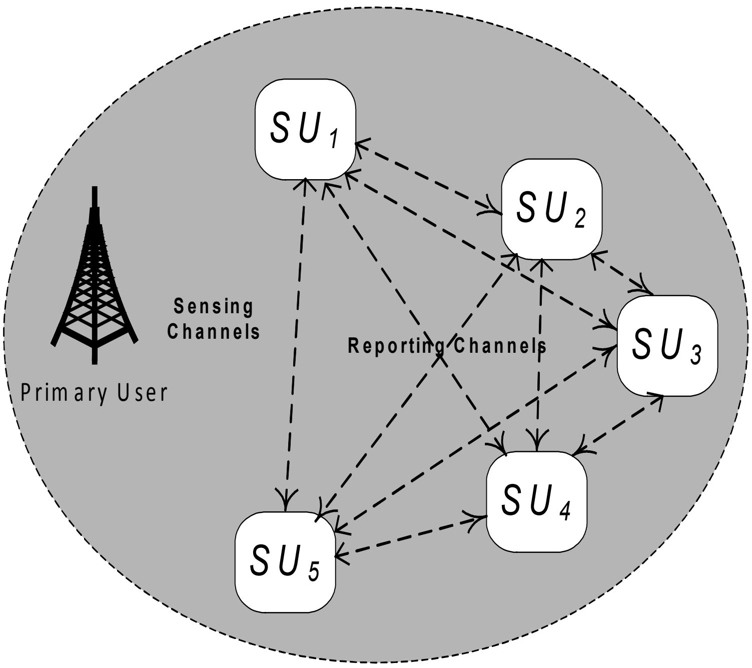

Figure 2.10 Distributed Cooperative Spectrum Sensing [36].

2.12.4 Relay-assisted Cooperative Spectrum Sensing

A relay-assisted CSS can be used to overcome the imperfection in both sensing and reporting channels. Meaning, a SU experiencing a weak sensing channel and a strong reporting channel, and a SU experiencing a strong sensing channel and a weak reporting channel can complement and collaborate with each other to improve the overall performance of the CSS [66]. In Figure 2.11, SU_1, SU_4, and SU_5, who observe strong PU signals, may suffer from a weak reporting channel. SU_2 and SU_3 who have strong reporting channels serve as relays to assist in forwarding sensing results from SU_1, SU_4, and SU_5 to the FC. The reporting channels from SU_2 and SU_3 are known as relay channels [36]. Although Figure 2.11 shows a centralised structure, the relay-assisted CSS can exist in a distributed scheme. In fact, when the sensing results need to be forwarded by multiple hops to reach the intended receive node, all the intermediate hops are relays. Thus, if both centralised and distributed structures are one-hop CSS, the relay-assisted structure can be considered as multi-hop CSS.

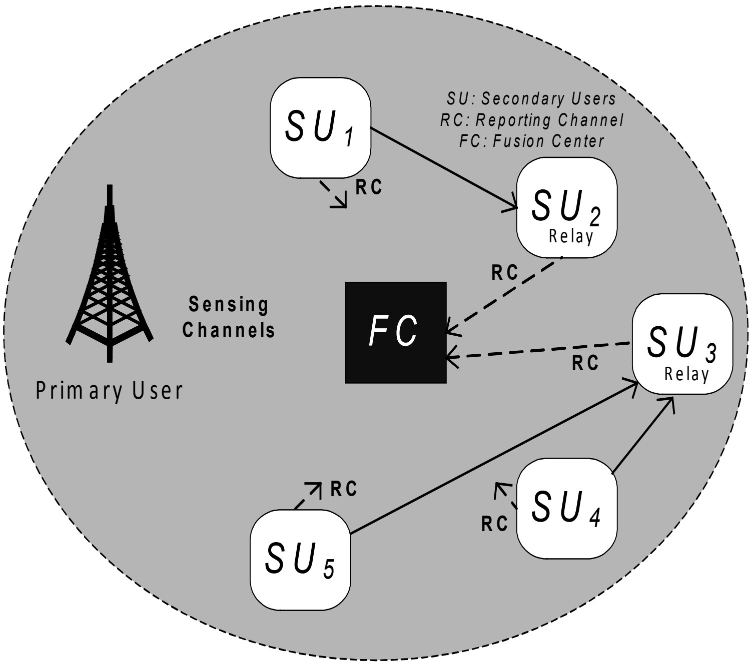

Figure 2.11 Relay-assisted Cooperative Spectrum Sensing [36].

2.13 Data fusion Schemes

In CSS, data fusion is an element of CSS for combining local sensing data for hypothesis testing. Reported sensing results maybe of different forms, types, and sizes depending on the control channel bandwidth requirement. In common, the sensing data sent to the FC or shared with neighbouring users can be combined in three different ways [84]:

- **Hard Combining**: CR users make a local decision and transmit the one-bit decision for hard combining at the FC.
- **Soft Combining**: CR users can transmit the entire local sensing samples or the complete local test statistics for soft decision.
- **Quantised Soft Combining**: CR users can quantise the local sensing results and send only the quantised data to the FC for soft combining in order to alleviate the control channel communication overhead.

Soft combining at the FC can achieve the best detection performance among all the three but at the cost of control channel overhead, while the quantised soft combining and hard combining require much less control channel bandwidth with possibly degraded performance, due to the loss of information from quantisation. The fusion rules for the CSS schemes can be classified as lossless fusion and lossy fusion [36].

2.13.1 Lossless fusion

Each SU can send an adequate statistic, such as, a maximum likelihood ratio (MLR) or LLR of its observations to the FC, where it is possible to fuse the decision statistics such that there are no performance losses in such a CSS scheme. Each of the N cooperating SUs evaluates a LLR L_n and sends it to the FC. The LLR L_n at the n-th SU is given by [85]:

$$L_n = \log \frac{\prod_{t=1}^{M} p(y_n(t)|H_1)}{\prod_{t=1}^{M} p(y_n(t)|H_0)} \tag{2.43}$$

where $y_n(t)$ are the observations at the n-th SU. For t = 1,2,..., M, here t represents the discrete time index and M denotes the number of observations. Assuming the independence of the observations at the SUs are conditioned on either hypothesis, the optimal statistics formed at the FC is given by [85]:

$$T_{llr} = \sum_{n=1}^{N} L_n. \tag{2.44}$$

While the equivalent LLRT is given by [85]:

$$T_{llr} = \underset{H_0}{\overset{H_1}{\gtrless}} \eta_{llr} \tag{2.45}$$

where η_{llr} is the threshold at the FC.

2.13.2 Lossy fusion

Soft Fusion

It may become impractical to implement a lossless fusion rule at the FC at certain times due to the difficulty in evaluating the sufficient statistic or the threshold [36]. An alternative is to use the maximum ratio combining (MRC) or equal gain combining (EGC) for N cooperating SUs by using a linear fusion rule given by [86]:

$$T_{lin} = \sum_{n=1}^{N} w_n E_n \tag{2.46}$$

where $E_n = \frac{1}{M}\sum_{t=1}^{M}|y(t)|^2$ and w_n is the weighting coefficient such that $0 \le w_n \le 1$ and $\sum_{n=1}^{N} w_n = 1$ [39]. $y(t)$ is the observations at the n-th SU. For $t = 1, \ldots, M$, here t represents the discrete time index and M denotes the number of observations. The optimal combining coefficients can be found for the MRC if the source signal power received by each user is known [39]. For the low SNR scenario, the optimal weights [14] are given by $w_n = \sigma_{s,n}^2 / \sum_{i=1}^{N} \sigma_{s,n}^2$, where $\sigma_{s,n}^2$ is the received signal power at the n-th SU. If there is no information on the source signal power received by each user, EGC can be used where the weighting coefficients are given by $w_n = 1/N, \forall_n$ [36].

Hard Fusion

In hard decision (HD) combining, each of the SUs sends a one-bit HD to the FC which fuses these decisions to arrive at the global decision. Examples of one-bit HD combining are Boolean fusion rules such as OR, AND, and majority which are special cases of the general *K*-out-of-*N* rule. Those decision fusion rules can be summarised as below [87]:

- ***K*-out-of-*N* rule**: In this fusion rule, the FC decides on the presence of the PUs transmission if, and only if, *K* or more than *K* SUs out of the total *N* cooperating SUs report the detection of the PU signal, where $K \in [1, N]$. Therefore, in the *K*-out-of-*N* rule, if *K* users or more decide in favour of H_1, then the cooperative decision declares that H_1 is true. If the decisions from all the SUs are independent, the network probabilities of detection and false alarm are, respectively, given by [14]:

$$P_D = \sum_{n=0}^{N-K} \binom{N}{K+n} (1 - P_{d,n})^{N-K-n} (P_{d,n})^{K+n}, \tag{2.47}$$

and

$$P_F = \sum_{n=0}^{N-K} \binom{N}{K+n} (1 - P_{f,n})^{N-K-n} (P_{f,n})^{K+n}, \tag{2.48}$$

where $P_{d,n}$ and $P_{f,n}$ are the probabilities of detection and false alarm of the *n*-th SU and $\binom{N}{K+n} = \dfrac{N!}{(K+n)!(N-K-n)}$.

- **Majority voting (MV) rule**: In the MV fusion rule, also known as half voting rule, if half, or more than half, the local SUs decide that there is a PUs transmission, then the final decision at the FC declares that there is a PUs transmission [87]. Therefore, for the MV rule, the cooperative decision declares H_1 only if half or more than half of the SUs decide on H_1, i.e., $K = \left\lceil \frac{N}{2} \right\rceil$ in equation (2.47) and equation (2.48), where $\left\lceil \frac{N}{2} \right\rceil$ denotes the smallest integer not less than $\frac{N}{2}$. If the decisions from all the SUs are independent, the network probabilities of detection and false alarm are given by [14]:

$$P_D = \sum_{n=0}^{N-\left\lceil \frac{N}{2} \right\rceil} \binom{N}{\left\lceil \frac{N}{2} \right\rceil + n} (1 - P_{d,n})^{N-\left\lceil \frac{N}{2} \right\rceil - n} (P_{d,n})^{\left\lceil \frac{N}{2} \right\rceil + n}, \tag{2.49}$$

and

$$P_F = \sum_{n=0}^{N-\left\lceil \frac{N}{2} \right\rceil} \binom{N}{\left\lceil \frac{N}{2} \right\rceil + n} (1-P_{f,n})^{N-\left\lceil \frac{N}{2} \right\rceil - n} (P_{f,n})^{\left\lceil \frac{N}{2} \right\rceil + n}. \tag{2.50}$$

- **Logical OR rule**: In this fusion rule, the fusion decides on the presence of PUs transmission if any of the SUs reports the detection of the PUs transmission. Therefore, for the OR rule, the cooperative decision declares H_1 if any of the SUs decide on H_1, i.e., setting $K=1$ in equation (2.47) and equation (2.48). Since a SU occupying a licensed frequency band may cause interference to the PUs, the risk of SUs causing interference to the PUs is minimised using the logical OR rule. If the decisions from all the SUs are independent, the network probabilities of detection and false alarm are, respectively, given by [14]:

$$P_D = 1 - \prod_{n=1}^{N} (1-P_{d,n}), \tag{2.51}$$

and

$$P_F = 1 - \prod_{n=1}^{N} (1-P_{f,n}). \tag{2.52}$$

- **Logical AND rule**: In the AND fusion rule, if all local detectors decide that there is a PUs transmission, then the final decision at the FC declares that there is a PUs transmission [87]. Therefore, for the AND rule, the cooperative decision declares H_1 only if all of the SUs decide on H_1, i.e., setting $K = N$ in (2.47) and equation (2.48).

Using this fusion rule, the probability of false alarm is minimised, but the risk of causing interference to PUs will increase. If the decisions from all the SUs are independent, the network probabilities of detection and false alarm are, respectively, given by [14]:

$$P_D = \prod_{n=1}^{N} P_{d,n} \ , \tag{2.53}$$

and

$$P_F = \prod_{n=1}^{N} P_{f,n} \tag{2.54}$$

Advantages of HD combining include being easy to implement and reducing the bandwidth requirement on the reporting channel between the SUs and the FC. These advantages come at the cost of performance loss resulting from the quantisation. HD combining has been studied in the detection literature [39, 88]. If x_n is the decision sent by the n-th SU, then the optimal fusion rule for both the Bayesian formulation and NP formulation is a likelihood ratio [39].

$$T_{cv} = \sum_{n=1}^{N} \left[x_n \left(\log \frac{1-P_{m,i}}{P_{f,i}} \right) + (1-x_n)\log\left(\frac{P_{m,i}}{1-P_{f,i}} \right) \right] \tag{2.55}$$

This fusion rule is also known as the Chair-Varshney fusion rule and is a weighted sum of incoming local decisions, where the weights are dependent on the local probabilities of false alarm $P_{f,i}$ and missed detection $P_{m,i}$.

In general, it can be concluded that there is more performance gain with soft combining than in the case of hard combining. However, the performance difference between soft and hard combining can be relatively small [89].

2.14 Cooperative Spectrum sensing techniques

In this section, some of the state-of-the-art CSS techniques will be discussed.

2.14.1 Voting Based Sensing

It is expected that among several SUs, even though some will suffer from fading or imprecision due to the choice of the threshold, some will be able to correctly sense the PU. This is the main idea behind the collaborative spectrum sensing based on voting, researched in a number of works [50, 79, 90]. In a voting spectrum sensing scheme each secondary receiver RX_i uses spectrum sensing to form its own decision. Consider the vector of all responses $\mathbf{r}$ such that:

$$\mathbf{r} = [r_1 \ r_2 \ r_3 ... r_M], \tag{2.56}$$

where $r_i \in \{1, 0\}$ is the binary response for each sensor *I, M* denotes the number of observations. After all measurements are gathered the voting procedure takes place [50, 79, 90]:

$$\text{decide for} \begin{cases} H_0, & \text{if } \eta = 0 \\ H_1, & if\ \eta \geq 0 \end{cases}, \tag{2.57}$$

where

$$\eta = \sum_{t=1}^{M} r_t \, . \tag{2.58}$$

The voting schemes selects H_1 if at least one of the SUs decides for H_1, which is known as the OR rule. Although this may seem too pessimistic, as it will favour false alarms, according to [50, 79, 90], this already gives improvements over the simple energy detection case even for two users. The probabilities of detection and false alarm for the cooperative approach are [23]:

$$Q_F = 1 - (1 - P_F)^M \tag{2.59}$$

and

$$Q_D = 1 - (1 - P_D)^M \, , \tag{2.60}$$

respectively.

2.14.2 Eigenvalue Based Sensing

Eigenvalue based sensing is a CSS technique, based on evaluating the eigenvalues of a matrix formed by the samples collected by multiple sensors in relation to the Marchenko-Pastur law [91]. In order to better understand how this spectrum sensing procedure works, the following assumptions are made: The K base stations in the secondary system share information between them. This can be performed by transmission over a wired high speed backbone, where the base stations are analysing the same portion of the spectrum. Considering the following $M \times N$ matrix consisting of the samples received by all the M SUs RX_i [91]:

$$\mathbf{Y} = \begin{bmatrix} y_1(1) & y_1(2) & \cdots & y_1(N) \\ y_2(1) & y_2(2) & \cdots & y_2(N) \\ y_3(1) & y_3(2) & \cdots & y_3(N) \\ \vdots & \vdots & \cdots & \vdots \\ y_M(1) & y_M(2) & \cdots & y_M(N) \end{bmatrix}. \tag{2.61}$$

Then, the objective of the eigenvalue based approach is to perform a test of independence of the signals received at RX_i. In the H_1 case, all the received samples are expected to be correlated, whereas when in the H_0 case, the samples are decorrelated [92]. The eigenvalues of the covariance matrix are computed, and in turn, are used to compute the test statistic as given in [92]. Two test statistics are proposed by [92] based on the maximum $(\varepsilon_{\max})$ and the minimum $(\varepsilon_{\min})$ eigenvalues. The test statistic is given by [73]:

$$T_{ev} = \frac{\varepsilon_{\max}}{\varepsilon_{\min}} \gtrless \eta_1 \tag{2.62}$$

known as the max-min eigenvalue (MME) technique with threshold η_1, and

$$T_{ev} = \frac{\xi}{\varepsilon_{\min}} \tag{2.63}$$

known as the energy with minimum eigenvalue (EME) technique with threshold η_2, where ξ is the energy of the sensed signal. The detection methods based on the test statistics above do not require the knowledge of the noise power but are based purely on the sensed signal itself, thus considered to be fully blind sensing techniques [92].

2.15 Performance Criteria for CSS

Cooperation among SUs leads to gain and overhead as compared to a single local sensing case. Cooperation gain can be any improvement in one or more of the performance parameters while cooperation overhead can be any degradation in one or more of the sensing performance parameters. Generally, most of the performance parameters for a CSS algorithm are the same as for the local sensing algorithms explained in section 2.6.2. A few parameters which are specific to CSS are:

Delay: It is the time taken to report the decision statistics from the SUs to the FC and processing the statistics at the FC. Cooperation delay adds to the local sensing time hence increasing the overall sensing time band. Therefore this constraint should be as small as possible.

Reporting overhead: A reporting channel is needed for sharing sensing information with the FC or other SUs. The reporting channel can be a dedicated channel in licensed or unlicensed bands. Reporting overhead is the amount of bandwidth and energy required for reporting the sensing information through the reporting channels hence determines the size of cooperation between SUs.

Number of SU: Performance gain in CSS depends on the number of SUs. It is a good idea to have as few SUs as possible since the reporting overhead increases with an increase in the number of SUs. For AWGN channels, the gain is predominantly SNR gain that increases with the number of cooperating SUs. On the other hand, the diversity gain for multipath channels is obtained with diminishing returns as the number of SUs increases.

Security: Sensing a frequency band requires energy and time. Therefore, SUs have a motivation to sense for a shorter duration. The resource allocation of the vacant frequency bands is based on the quality of decisions the SUs send. Therefore, there is an incentive for malicious users to fake the detection results. The presence of un-trusted SUs has been shown to degrade CSS performance [37, 93, 94].

Imperfect reporting channels: Erroneous reporting channels corrupt the decision statistics sent by the SUs to the FC. This may increase the probabilities of error at the FC [95] and thus affect the CSS performance.

2.16 Literature Reviews and Problem Formation

There are many research problems that need to be investigated in CSS in CR network systems. Firstly many researchers have concentrated on improving the accuracy of the detection. In [90, 96] a double threshold energy detector is used. A censoring method using double thresholds in energy detection was proposed to reduce the communication traffic [97]. Deriving from this idea and in contrast to [97], in chapter 3 a relay based Amplify and Forward (AF) CSS using, an improved cooperative ED to improve the local probability of detection and hence, the global probability of detection and in making sure the sensed data is accurately received at the FC is proposed. One of the main advantages of using AF cooperation is the potential for reduced complexity of relay's architecture [98]. The relay is not required to decode, and is not required to know what coding strategy is employed.

Secondly, researchers have focused on sensing performance problem. An adaptive rule and a linear quadratic rule at the FC were considered in [99] and [83], respectively. However, using weighting factors [47, 100, 101] are the most popular method due to computational complexity. The weighting factor can be the credibility of each local node based on local SNR, between PU and SUs. By fusing the weighting factor at FC, the local sensing data becomes more reliable and gives a greater contribution to the overall global decision. As a result, an improved detection performance can be achieved. Deriving from this idea, in chapter 4, A novel evidence-based decision fusion scheme CSS for CR networks that uses both a credibility of SUs sensing data evidence and dissociability degree measure of SUs sensing data evidence, in the form of a weighted averaging factor that is then taken into account when making the final decision at the FC was proposed.

The final issue considered in CSS was to reduce the bandwidth of the reporting sensing data from the SUs to the FCs. Reducing the bandwidth decreases the sensing time hence increasing detection probability, increasing through put and reducing interference. This problem is crucial in a soft decision based CSS scheme. A lot of research focuses on quantisation of the soft sensing data [12, 102-104] to reduce the bandwidth of the reporting channel. Nevertheless, more or less these works have drawback. As a result, the problem of quantisation for CSS is investigated in chapter 5.

2.17 General System Model

To investigate, design and analyse the problems mentioned in section 2.16, a general system model which will be used in the next chapters of this thesis, unless stated otherwise, is described in this section.

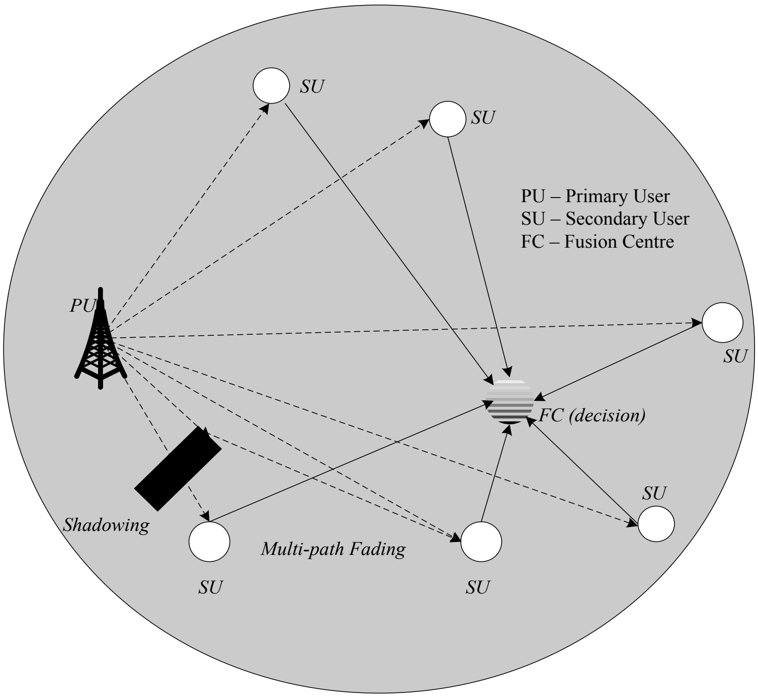

Figure 2.12 General system model: cooperative spectrum sensing

The CSS scheme considered for detecting PU's signal is shown Figure 2.12. Each SU performs a local sensing process and subsequently reports the sensing data to the FC. The global decision on the occupation of the PU signal is made at the FC. The spectrum sensing frame in Figure 2.13 describes the process.

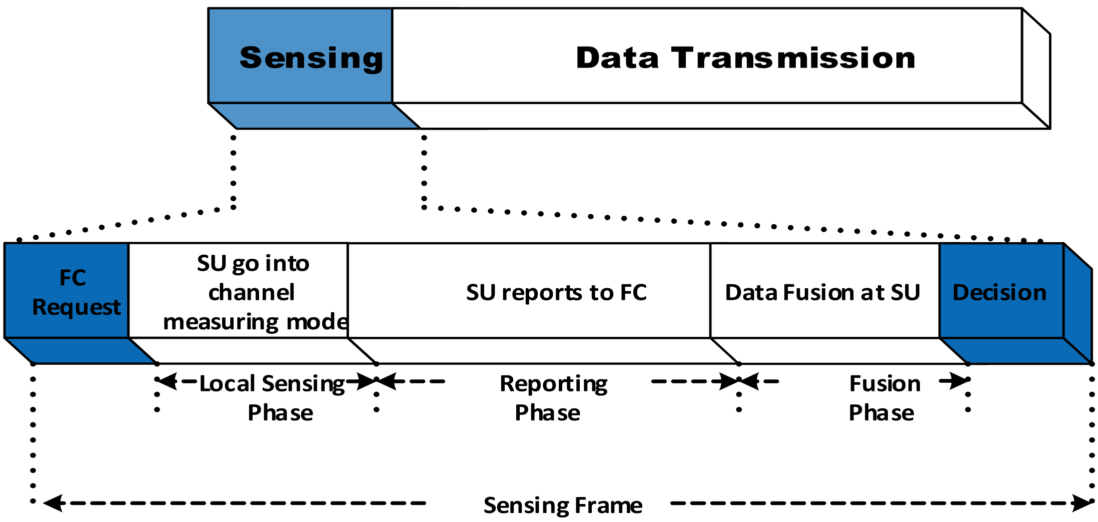

Figure 2.13 System model cooperative spectrum sensing frame.

The sensing frame starts with the FC sending a sensing request message to the SUs. All the individual SUs enter into a quiet mode i.e. none utilise the channel and perform local spectrum sensing in the sensing phase. Each SU using a reporting mechanism then sends their sensing data to the FC in the reporting phase. Hence, the SUs send their local sensing information in intervals of one's per sensing frame.

2.17.1 Local Spectrum Sensing Algorithm

Individual SUs perform local spectrum sensing in a distributed manner for detecting the PU signal. Local sensing is in effect a binary hypotheses testing predicament as described in section (2.6.1). Comparing the different algorithms for spectrum sensing, energy detection has been established to be the least complex one that reduces overhead, and is quickly able to detect the PU signal, even if the PU signal is unknown [49]. In this thesis, energy measure detection is considered for local spectrum sensing in all chapters unless otherwise stated.

2.17.2 Energy Measure

To measure the value of a single power in a practical frequency band in time domain, a band pass filter is applied to the received primary signal at the SUs and the power of the signal samples is subsequently measured as shown in Figure 2.14

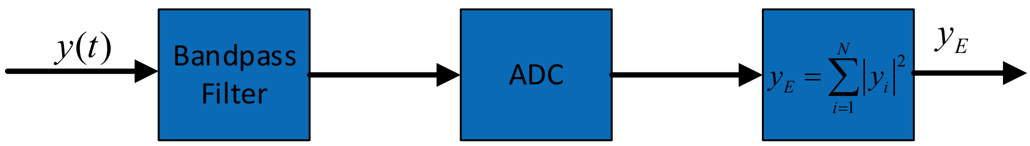

Figure 2.14 Block Diagram of an energy detection scheme.

The decision statistic is an estimation of the received signal power which is given at each SU by the sensing matrix:

$$y_E = \sum_{i=1}^{N} |y_i|^2 \tag{2.64}$$

where y_i is the i-th sample of received signal and $N = 2TW$, where T and W are correspondent to detection time and signal bandwidth in Hz, respectively. It was proved in [77] that the probability density function of the received PUs signal energy at an SU y_E, is a Chi-square distribution such that

$$f(Y_E) = \begin{cases} \chi_N^2, & H_0 \\ \chi_N^2(N\gamma), & H_1 \end{cases} \tag{2.65}$$

where χ_N^2 is the central Chi-square distribution with N degree of freedom, and $\chi_N^2(N\gamma)$ is a non-central Chi-square distribution with N degree of freedom and a non-centrality parameter $N\gamma$. γ is the SNR of the PU signal at the SUs. In the absence of knowledge of the PU signal, when the number of required samples N is relatively large, y_E can be approximated a Gaussian random variable under both hypotheses H_0 and H_1, with mean μ_1, μ_0 and variance σ_1^2, σ_0^2, respectively, such that [49]:

$$\begin{cases} \mu_0 = N, & \sigma_0^2 = 2N \\ \mu_1 = N(\gamma+1), & \sigma_1^2 = 2N(2\gamma+1) \end{cases} \tag{2.66}$$

where the SNR γ is a constant in a non-fading AWGN environment. However, in a fading channel scenario, the SNR γ is a random variable [49, 79, 105, 106].

2.17.3 Physical phenomena for fading channels

In this section, various fading channels are considered. Multipath fading is due to the constructive and destructive combination of randomly delayed, reflected, scattered, and diffracted signal components. This type of fading is relatively fast and is therefore responsible for the short-term signal variations. Depending on the nature of the radio propagation environment, there are different models describing the statistical behaviour of the multipath fading envelope.

When fading affects narrowband systems, the received carrier amplitude is modulated by the fading amplitude α, where α is a random variable with mean-square value $\Omega = \overline{\alpha^2}$ and probability density function (PDF) $f_\alpha(\alpha)$, which is dependent on the nature of the radio propagation environment. The received instantaneous signal power is modulated by α^2. Thus we define the instantaneous SNR per symbol by $\gamma = \alpha^2 E_s/N_0$ and the average SNR per symbol by $\overline{\gamma} = \Omega E_s/N_0$, where E_s is the energy per symbol. In addition, the PDF of γ is obtained by introducing a change of variables in the expression for the fading PDF $f_\alpha(\alpha)$ of α, yielding [107]:

$$f_\gamma(\gamma) = \frac{f_\alpha\left(\sqrt{\Omega\gamma/\overline{\gamma}}\right)}{2\sqrt{\gamma\overline{\gamma}/\Omega}}. \tag{2.67}$$

In this thesis, for Shadowing, Rayleigh fading, Nakagami fading and Rican fading the following assumption are made below:

Shadow fading: In terrestrial and satellite land-mobile systems, the link quality is also affected by slow variation of the mean signal level due to the shadowing from terrain, buildings, and trees. Based on empirical measurements, there is a general consensus that shadowing can be modelled by a log-normal distribution for various outdoor and indoor environments in which case the path SNR γ of the PU signal at the i-th SU has a PDF given by the standard log-normal expression [107]:

$$f_{\gamma}(\gamma)=\frac{\xi}{\sqrt{2\pi}\sigma\gamma}\exp\left(-\frac{(10\log_{10}\gamma-\mu)^2}{2\sigma^2}\right) \tag{2.68}$$

where $\xi = 10/\ln 10$, $\mu(dB)$ and $\sigma(dB)$ are the mean and standard deviation of $10\log_{10}\gamma$, respectively.

Rayleigh fading: The Rayleigh channel model is a fading channel model, which is often used to describe propagation where there is no line-of-sight (LOS) from the PU to the SUs, such as in mobile links, ionospheric and tropospheric scattering, and ship to ship radio links. The amplitude of the signal follows a Rayleigh distribution. In this case the channel fading amplitude, is distributed according to [107]:

$$f_{\alpha}(\alpha)=\frac{2\alpha}{\alpha}\exp\left(-\frac{\alpha^2}{\alpha}\right), \qquad \alpha \geq 0 \tag{2.69}$$

and hence, following (2.67), the instantaneous SNR γ of the PU signal at the i-th SU follows an exponential distribution [105] whose PDF is given by:

$$f_{\gamma}(\gamma)=\frac{1}{\bar{\gamma}}\exp\left(\frac{-\gamma}{\bar{\gamma}}\right), \qquad \gamma \geq 0 \tag{2.70}$$

Nakagami-*m* fading: The Nakagami-*m* channel model is a general multipath fading model. It is used to model attenuation of signals traversing multiple paths. It is often used to describe fading in both indoor and outdoor mobile radio links as well as in ionospheric radio links. The Nakagami-*m* PDF is in essence a central chi-square distribution given by [107]:

$$f_\alpha(\alpha) = \frac{2m^m \alpha^{2m-1}}{\Omega^m \Gamma(m)} \exp\left(-\frac{m\alpha^2}{\Omega}\right), \quad \alpha \geq 0 \tag{2.71}$$

where m is the Nakagami-*m* fading parameter which ranges from $\frac{1}{2}$ to ∞ and measures the severity of the effect of multipath fading. Applying (2.67) the SNR γ of the PU signal at the *i*-th SU, is distributed according to a gamma distribution given by [107]:

$$f_y(\gamma) = \frac{m^m \gamma^{m-1}}{\bar{\gamma}^m \Gamma(m)} \exp\left(-\frac{m\gamma}{\bar{\gamma}}\right), \quad \gamma \geq 0 \tag{2.72}$$

Smaller values of m indicate more severe fading, while larger values indicate less severe fading.

Rician fading: The Rician distribution, also known as the Ricean, Rice or Nakagami-*n* distribution, is a further general model describing the effects of multipath fading. It is often used to model propagation paths consisting of one strong direct LOS component and many random weaker components. It finds most use in the analysis of urban and suburban mobile radio links, pico-cellular indoor radio links, satellite links and ship to ship radio links. The channel fading amplitude follows the distribution [107]:

$$f_\alpha(\alpha) = \frac{2(1+n^2)e^{-n^2}\alpha}{\Omega} \exp\left[-\frac{(1+n^2)\alpha^2}{\Omega}\right] I_0\left(2n\alpha\sqrt{\frac{1+n^2}{\Omega}}\right), \quad \alpha \geq 0 \tag{2.73}$$

where n is the Nakagami-n fading parameter which ranges from 0 to ∞ and which is related to the Rician K factor by $K = n^2$. K measures the severity of the effects of the multipath fading. Applying (2.67) the SNR γ of the PU signal at the i-th SU, is distributed according to a non-central chi-square distribution given by [107]:

$$f_\gamma(\gamma) = \frac{(1+n^2)e^{-n^2}}{\bar{\gamma}} \exp\left[-\frac{(1+n^2)\gamma}{\bar{\gamma}}\right] I_0\left(2n\sqrt{\frac{(1+n^2)\gamma}{\bar{\gamma}}}\right), \qquad \gamma \geq 0 \tag{2.74}$$

where $I_0(z)$ represents the zeroth order modified Bessel function of the first kind.

2.18 Conclusion

This chapter presented the concept of spectrum sensing which is one of the fundamental prerequisites for the successful deployment of CR networks. Reviews have been presented on different problems related to the DSA and standardisation efforts. Several important aspects of spectrum sensing schemes have been reviewed such as detection strategies, performance parameters and test statistics. State-of-the-art sensing algorithms were reviewed and is seen that several tools from diverse fields like spectrum estimation, compressive sensing, MIMO systems, etc., have been applied to design the sensing schemes for CRs.

The most common spectrum sensing techniques with which the SUs are able to monitor the activities of the PU were discussed. Various spectrum sensing techniques are used in the literature depending on how much knowledge about the primary signal is available to the SUs. In general, the spectrum sensing techniques can be classified as energy-based sensing, feature-based sensing, matched filter-based sensing and other sensing techniques. It is assumed that the probability of detection can be improved with the increase in the knowledge of the PU signal and noise at the cost of complexity.

Physical characteristics of a DVB-T2 signal which is one of the most important types used by PUs in TV bands and which will be used for as the PU signal network for the rest of the thesis have been presented. It is clear from the simulated performance comparison and discussion on the pros and cons of the detectors that no one detector has the best performance for all scenarios. Energy detection is the most commonly used technique for spectrum sensing since it has low computational and implementation complexities and prior knowledge of the PUs signal is not needed. However it has the serious issue of SNR walls in the presence of noise uncertainty. Autocorrelation detectors have advantages of reasonable performance, low complexity and robustness to most of the non-idealities. However they cannot be used to detect PU signals other than OFDM. An added advantage of the energy and autocorrelation detector is that they do not often need any extra hardware as the functions used by these two detectors are very basic and incorporated in almost every radio receiver. The matched filter detector has the best performance to detect a known PU signal in AWGN. However it is computationally costly and sensitive to synchronisation errors and frequency selective fading channels. Cyclostationary detectors have several advantages like good performance, robustness and can detect and distinguish any PU or SU signals. If complexity is not an issue, they are the best choice.

Even though there has been a lot of research on sensing, and many algorithms have been proposed for the local detector, there is performance degradation caused by the hidden terminal problem which was presented. Therefore, single user detection may not be sufficient to achieve the desired performance and cooperation between different SUs may be needed. Moreover, each individual detector can be simpler with cooperative detection while maintaining the overall detection performance at a desired level. CSS schemes have been discussed. Different cooperation models such as the centralised, distributed and relay-assisted have been presented. Several fusion rules are discussed such as LRT, MRC, EGC, Chair-Varshney, and K-out-of-N. Based on the quality of decisions, the fusion rules can be classified as hard combining and soft combining. The choice of a fusion rule depends on various performance criteria such as the detection performance, false alarm control, sensing efficiency, available information, complexity, energy consumption e.t.c. The Chair-Varshney fusion rule performs best among hard decision combining schemes under the assumptions that the local false alarm and missed detection probabilities are known. CSS techniques such as the voting based sensing and eigenvalue based sensing are presented. There are several performance parameters that are discussed, like probability of detection, probability of false alarm, sensing time, cooperation delay, SNR, cooperation footprint, number of SUs, robustness against non-idealities and computational complexity. The general system model and fundamentals, such as the local detection session and sensing frame used in the rest of the thesis have also been presented.

Literature reviews about the current research problem were discussed. The research challenges and unresolved issues in CSS have been identified such as sensing accuracy, sensing efficiency, power, overhead, security, numbers of SU and reporting channels. In the next chapter, the problem of sensing accuracy and sensing efficiency in CSS is focused on. An amplify-and-forward relay-based CSS using an improved threshold energy detector is proposed.

3 Relay-Based Cooperative Spectrum Sensing with Improved Energy Detection in Cognitive Radio Networks

Cognitive radio has become a promising technique to solve the underutilisation problem of the spectrum as discussed in chapter 2. In this chapter an amplify-and-forward relay-based cooperative spectrum sensing (CSS) using an improved threshold energy detector was proposed. In this improved detector, each SU makes a local decision on spectrum occupancy based on two energy detection thresholds. If an SU detects the value out of both thresholds, it makes a decision first, amplifies and forwards the local result to the FC. If the detected value is between both thresholds, it amplifies and forwards this detected value to the FC. Finally, energy fusion and decision fusion are conducted at the FC using a "soft 1-bit" combination scheme to determine the PU's status. Cooperative probability of detection, probability of missed detection and probability of false alarm expressions are derived with and without direct communication between the PU and FC. Simulation results presented, show that the proposed algorithm achieves a good sensing performance when compared to traditional schemes. The effects of different parameters on the proposed algorithm were examined, such as the number of SUs, channel type, channel availability and different values of the SNR.

3.1 Introduction

Spectrum sensing is essentially a fundamental technique in cognitive radio (CR) networks [7] that enables CR systems adapt to the environment by sensing and detecting spectrum holes i.e. portions of the licensed spectrum unused by the primary users (PU) [15]. However, it is difficult in reality, for a CR to have a direct measure of the channel between the PU's receiver and a transmitter. As a consequence, the most recent research works focus on primary transmitter detection based on local observations of secondary cognitive users [2, 14, 33, 108-110]. The number of SUs in a CR network that partakes in spectrum sensing enables classification of SS into non-cooperative and cooperative techniques. Non-cooperative SS is usually associated with poor spectrum utilisation caused by severe multi-path fading and shadowing effects that eventually lead to the hidden terminal problem (discussed in chapter 2). In cooperative spectrum sensing (CSS), a number of secondary users (SU) coordinate to perform spectrum sensing by each individually performing SS and reporting their observations to a fusion centre (FC), in order to achieve improved sensing and detection performance [35, 80, 81, 111-113]. The work done in [23] also provided another method of increasing detection performance. Interestingly, [23] showed that when one SU acts as a relay for another SU, detection probability increases.

In this chapter, a relay based amplify-and-forward (AF) CSS using an improved cooperative energy detection was proposed. Among the traditional methods used to perform spectrum sensing [5, 90, 114]: energy detection has been widely applied for its low complexity and feasibility, hence its relevance also in this work. It also does not require prior knowledge of the unknown signal. Typically, energy detection works by measuring the energy associated with the received signal over a specified time duration and bandwidth and comparing this measured value with an appropriately selected threshold to determine the presence or the absence of the PU signal. In [97, 115-117], a censoring method using double thresholds in energy detection was proposed to reduce the communication traffic at the expense of some loss in sensing performance. In contrast, the proposed method was designed to improve the local probability of detection and hence the global probability of detection, exploiting all the observed information from local SUs. In the proposed system, the relay nodes (SUs) convey sensing information to the FC. By combining the primary and relay transmissions, SUs can achieve diversity against fading. One of the main advantages of using AF cooperation was the potential of reduced complexity of the relay's architecture. In this case, the relay was not required to decode, and was not required to know what coding strategy was employed.

The main contributions of this chapter can be described as follows:

- Designing a novel relay-based AF CSS architecture for CR networks using an improved cooperative ED to achieve high sensing efficiency and sensing accuracy of PUs.
- Combining the PU and relay (SUs) transmissions to achieve diversity against fading using AF cooperation which has the potential of reduced complexity and cost.
- Analytically derive expressions for a "soft 1-bit" double threshold combination scheme to reduce the communication overhead, improve the local probability of detection and hence the global probability of detection taking into account all sensing performance to exploit all the observed information from local SUs.
- Derive the CRs network cooperative probabilities of detection, false alarm and missed detection for the relay-based AF CSS scheme over AWGN and Rayleigh fading channels.

- Examine, evaluate and discuss the effect of different key parameters such as the PU signal type, the number of SUs, channel type and the signal-to-noise ratio on the performance of the proposed relay-based AF CSS algorithm.

The rest of this chapter is organised as follows: A non-cooperative and a CSS with an improved ED are presented in section 3.2 and 3.3, respectively. In section 3.4 the proposed relay-based AF CSS system model are presented and analysed in detail. Performance analysis and simulation results are presented in section 3.5 and 3.6, respectively. Finally, conclusions are drawn in section 3.7.

3.2 Double Threshold Energy Detector

In the following section, a CR network that includes *M* SUs and a common receiver that functions as a FC, and manages the CR network as well as all the associated SUs is considered. It is assumed that each SU performs energy detection independently during the sensing period. For local detection, SUs have to distinguish between the following two hypotheses [79]

$$y(t) = \begin{cases} n(t) & , \quad H_0 \\ s(t) + n(t), & \quad H_1 \end{cases} \tag{4.1}$$

where $y(t)$ is the signal received by SU, $s(t)$ is the received PU signal and $n(t)$ is additive Gaussian noise (AWGN) with zero mean and variance σ_n^2. Hypotheses H_0 and H_1 represent absence and presence of the PU, respectively.

According to energy detection theory [49] under AWGN channel, the energy observed (E_i) by the *i*-th SU has the following distribution:

$$E_i \sim \begin{cases} \chi^2_{2u} & , H_0 \\ \chi^2_{2u}(2\gamma) & , H_1 \end{cases} \tag{4.2}$$

where u is the time bandwidth product of the energy detector, γ denotes the instantaneous signal-to-noise-ratio (SNR), χ^2_{2u} and $\chi^2_{2u}(2\gamma)$ are central and non-central chi-square distribution respectively, each with $2u$ degrees of freedom and a non-centrality parameter of 2γ for the latter one.

In conventional energy detection theory, each SU makes its local decisions by comparing its observational value with a pre-determined threshold, as shown in Figure 3.1(a) [49],

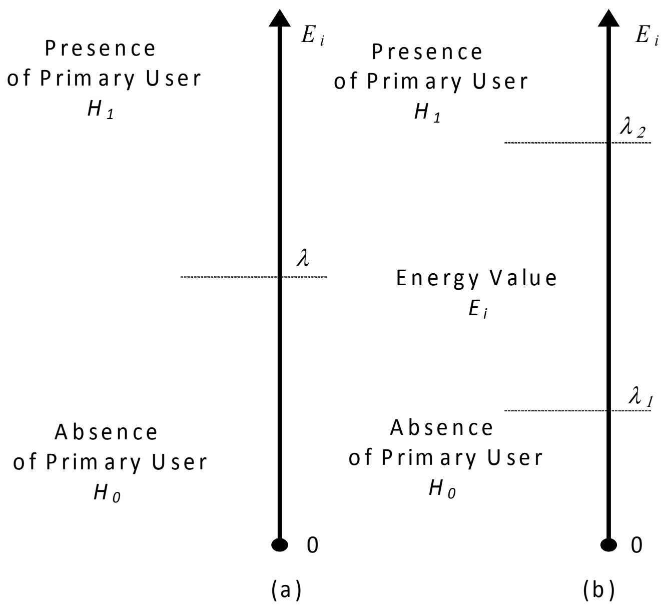

Figure 3.1 (a) Conventional energy detection and (b) Double threshold energy detection.

where E_i denotes the collected energy measurement of the *i-th* SU, H_0 and H_1 are correspondent to hypotheses of absence and presence of PU's signal respectively. Decision H_0 and H_1 is made when E_i is less or greater than the threshold value λ respectively. A double threshold scheme is shown in Figure 3.1(b), where two thresholds are utilised to assist the statistical choice of the SU. If the energy value is greater than λ_2, then the user reports H_1. If E_i is less than λ_1, decision H_0 is made. Otherwise, if E_i is between λ_1 and λ_2, then the SU reports its observational energy value i.e. E_i. Hence, the FC receives two different kinds of data; a local binary data and observational value of the SU.

3.3 Double Threshold Energy Detector Based Cooperative Spectrum Sensing

Each SU_i, for $i = 1, 2, \ldots, M$, performs energy detection individually. It is assumed that each SU has identical threshold values. If E_i satisfies $\lambda_1 \le E_i < \lambda_2$, subsequently the i-th SU sends the measured energy value E_i to the FC. If not, it reports its local decision L_i according to E_i. Let R_i denote the information that the FC receives from the i-th SU. Then it can be given by

$$R_i = \begin{cases} E_i, & \lambda_1 \le E_i < \lambda_2 \\ L_i, & Otherwise \end{cases} \tag{4.3}$$

where

$$L_i = \begin{cases} H_0, & E_i < \lambda_1 \\ H_1, & E_i \ge \lambda_2 \end{cases} \tag{4.4}$$

Consequently, the SUs make two kinds of decisions, which are the local decisions and the observed energy value. Without loss of generality, it is assumed that the FC receives K_1 and K_2 local decisions that support H_0 and H_1 respectively, and $M - K_1 - K_2$ energy values from M SUs. The FC then makes a final decision with the received information. First, a hard combination D_1 by using 'n-ratio' rule [118] is made as follows

$$D_1 = \begin{cases} H_0, & \mathrm{K}_1 \geq n * K_2 \\ H_1, & \mathrm{K}_1 < n * K_2 \end{cases} \tag{4.5}$$

let *n* be a rational number such that $1 \leq n \leq M$ and then using a soft combination rule, all energy value are combined to make a final energy decision D_2 as follows

$$D_2 = \begin{cases} H_0, & 0 \ \leq \sum_{i=1}^{M-K_1-K_2} E_i < \lambda_{FC} \\ H_1, & \sum_{i=1}^{M-K_1-K_2} E_i \geq \lambda_{FC} \end{cases} \tag{4.6}$$

where λ_{FC} is the fixed threshold value of the FC according to an appropriate false alarm probability. The FC makes a final decision F according to the following rule

$$F = \begin{cases} H_0, & \mathrm{D}_1 + D_2 > 0 \\ H_1, & Otherwise \end{cases} \tag{4.7}$$

3.4 System Model: Amplify and Forward Cooperation

In this section, the system models are described, and the AF-CSS schemes to improve the detection performance of cognitive radio networks are proposed.

3.4.1 Single Cognitive Relay

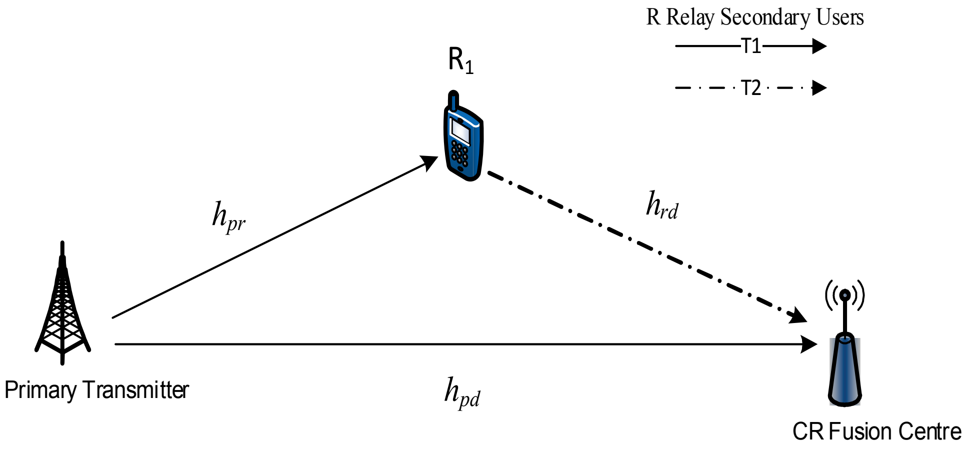

Figure 3.2 Relay based cooperative spectrum sensing.

Firstly, taking into consideration a single relay system as shown in

Figure 3.2 without the direct link h_{pd}, there are three nodes: the PU, the cognitive relay (SU) denoted by R_1 and the FC. The SUs continuously monitors the signal from the PU as described in the general system model in chapter 2. The received signal at the cognitive relay is given by:

$$y_{pr} = \theta x h_{pr} + n_r \tag{4.8}$$

where x is the transmitted signal from the PU at time T1, θ denotes the presence of the PU. θ is equal to 1 when the PU is present or 0 when PU is absent if the energy detector value E_i satisfies (4.3), otherwise the local decision value L_i replaces θ. h_{pr} is the channel gain between the PU and relay, and n_r is the noise signal at the cognitive relay. The cognitive relay acts as a variable gain AF relay, which is more practical than the decode-and-forward relay operation [119]. The relay uses a variable gain AF scheme to forward the local decision to the FC. The cognitive relay has a transmission power constraint. To remain within its power constraint the amplifying relay must use a amplification factor (gain) β_r [82], given by the formula:

$$\beta_r = \sqrt{\frac{E_r}{\theta^2 E_p \left|h_{pr}\right|^2 + N_0}} \tag{4.9}$$

where E_p is the transmitted signal power from the PU, E_r is the transmit power of the relay and N_0 the noise. Thus, at time T2 the received signal at the FC, denoted y_{rd}, is given as

$$\begin{aligned} y_{rd} &= \sqrt{\beta_r}\, y_{pr} h_{rd} + n_d \\ &= \theta\sqrt{\beta_r}\, h_{pr} h_{rd} x + \sqrt{\beta_r}\, h_{rd} n_r + n_d \end{aligned} \tag{4.10}$$

where h_{rd} is the channel gain between the relay and the FC, n_d is the noise signal at the FC. The received signal at the FC follows a binary hypothesis:

$$y_{rd} = \begin{cases} n & , \quad H_0 \\ hx + n & , \quad H_1 \end{cases} \tag{4.11}$$

As described in [41] using an ED (described in section 2.9.2)., the received signal is first pre-filtered by an ideal band pass filter with centre frequency f_c and bandwidth W to normalise the noise variance. The filter output is squared and integrated over a time interval T, to subsequently produce a measure of the energy of the received waveform. The integrator outputs act as the test statistic [41]. The total received end-to-end SNR using MRC at the FC is given by:

$$\gamma_{d\_s} = \frac{\gamma_{pr}\gamma_{rd}}{\gamma_{pr} + \gamma_{rd} + 1} \tag{4.12}$$

where $\gamma_{pr} = \left|h_{pr}\right|^2 E_p / N_0$ and $\gamma_{rd} = \left|h_{rd}\right|^2 E_r / N_0$ are SNRs from the PU to the cognitive relay and from the cognitive relay to the FC, respectively.

3.4.2 Multiple Cognitive Relays

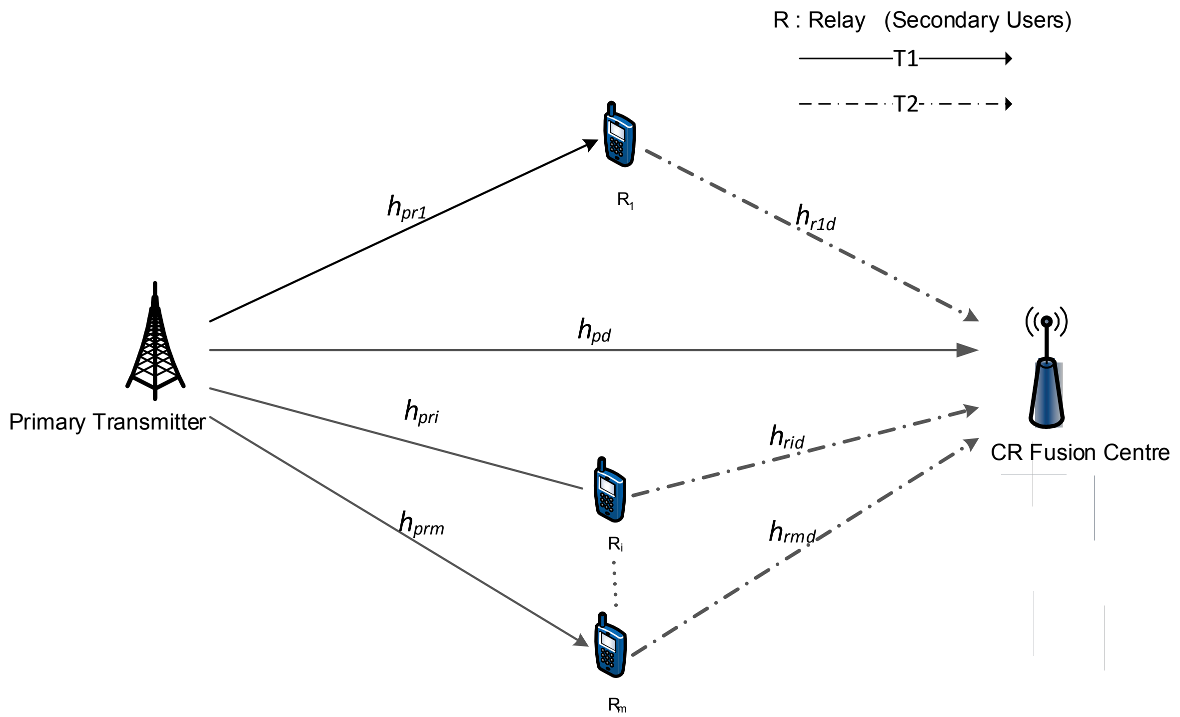

Figure 3.3 Multiple relay based cooperative spectrum sensing

With multiple cognitive relays, it is assumed that there are M SUs between the PU and the FC, as shown in Figure 3.3, h_{pri}, h_{rdi} and h_{pd} denote the channel gains between the PU and the SU R_i at time T1, between the i-th SU and the FC at time T2, and between the PU and the FC at time T1, respectively. All SUs simultaneously receive PU signal through independent fading channels. Each SU amplifies the received primary signal by an amplification factor:

$$\beta_{ri} = \sqrt{\frac{E_{ri}}{\theta^2 E_p \left|h_{pri}\right|^2 + N_0}} \tag{4.13}$$

and forwards to the FC. The SUs use orthogonal channels to forward the received primary signal. The received signal at the FC can then be considered as independent copies through orthogonal channels. After an integrator, the final test statistic is obtained. Without taking into consideration the direct link h_{pd}, the total end-to-end SNR using MRC is given by:

$$\gamma_{d\_m} = \sum_{i=1}^{M} \frac{\gamma_{pri}\gamma_{rdi}}{\gamma_{pri} + \gamma_{rdi} + 1} \tag{4.14}$$

where γ_{pri} and γ_{rdi} are SNRs of the links from the PU to the cognitive relay R_i and from the cognitive relay R_i to the FC, respectively.

3.4.3 Direct Link

In sections 3.4.1 and 3.4.2, transmission from the PU to the FC takes place through relays. However, the FC can also receive the signal of the PU through a direct link from PU to FC when the PU is closer to the FC. Therefore, the total SNR at the FC for a single relay and direct link as shown in Figure 3.3 given by

$$\gamma_{dd\_s} = \gamma_{pd} + \gamma_{d\_s} \tag{4.15}$$

where the SNR from the PU to the FC $\gamma_{pd} = \left|h_{pd}\right|^2 E_p / N_0$. The total SNR at the FC for multiple relays and direct link is given by

$$\gamma_{dd\_m} = \gamma_{pd} + \gamma_{d\_m} \tag{4.16}$$

3.5 Performance Analysis

In this section, the spectrum sensing performance of the proposed scheme is analysed. In the case of a single threshold, the probability of false alarm P_f can be expressed as [49]:

$$P_f = \frac{\Gamma(u, \lambda_0 / (2\sigma_n^2))}{\Gamma(u)} \tag{4.17}$$

where $\Gamma(.)$ is the gamma function and $\Gamma(.,.)$ is the incomplete gamma function. Given the target false probability $\overline{P}_f$, the threshold λ_0 can be determined by:

$$\lambda_0 = 2\sigma_n^2 \Gamma^{-1}(u, \overline{P}_f \Gamma(u)) \tag{4.18}$$

where $\Gamma^{-1}(.,.)$ denotes the inverse of the incomplete gamma function. It is assumed that the noise uncertainty in the wireless environment is described as $[1/\rho\sigma_n^2, \rho\sigma_n^2]$, where $\rho > 1$ is a parameter that quantifies the size of the uncertainty. In the proposed double threshold decision, the lower threshold λ_1 is selected according to the minimum noise variance, and the upper threshold λ_2 is selected according to the maximum noise variance. Therefore,

$$\lambda_1 = 2 / \rho\sigma_n^2 \Gamma^{-1}(u, \overline{P}_f \Gamma(u)) \tag{4.19}$$

$$\lambda_2 = 2 / \rho\sigma_n^2 \Gamma^{-1}(u, \overline{P}_f \Gamma(u)) \tag{4.20}$$

The local decision L_i will be made by following the logic rule in (3.1). It is assumed $P_{d1,i}$ and $P_{f1,i}$ denotes the detection and false alarm probability of the *i*-th SU corresponding to the lower threshold λ_1, while $P_{d2,i}$ and $P_{f2,i}$ denote the detection and false alarm probability of the *i*-th SU corresponding to the upper threshold λ_2. For convenience, it is assumed the noise is a unit variance [49], then

$$P_{d1,i} = P\{E_i \geq \lambda_1 \mid H_1\} = Q_u(\sqrt{2\gamma}, \sqrt{\lambda_1}) \tag{4.21}$$

$$P_{f1,i} = P\{E_i \geq \lambda_1 \mid H_0\} = \frac{\Gamma(u, \lambda_1 / 2)}{\Gamma(u)} \tag{4.22}$$

$$P_{d2,i} = P\{E_i \geq \lambda_2 \mid H_1\} = Q_u(\sqrt{2\gamma}, \sqrt{\lambda_2}) \tag{4.23}$$

$$P_{f2,i} = P\{E_i \geq \lambda_2 \mid H_0\} = \frac{\Gamma(u, \lambda_2 / 2)}{\Gamma(u)} \tag{4.24}$$

where $Q_u(.,.)$ is the generalized Marcum Q-function, let $\Delta_{0,i}, \Delta_{1,i}$ denote the probability of $\lambda_1 \leq E_i < \lambda_2$ for the *i*-th SU under hypothesis H_0 and H_1, the following can be derived

$$\Delta_{1,i} = P\{\lambda_1 \leq E_i < \lambda_2 \mid H_1\} = P_{d1,i} - P_{d2,i} \tag{4.25}$$

$$\Delta_{0,i} = P\{\lambda_1 \leq E_i < \lambda_2 \mid H_0\} = P_{f1,i} - P_{f2,i} \tag{4.26}$$

Let $P_{d,i}, P_{m,i}, P_{f,i}$ denote the probabilities of detection, missed and false alarm, respectively, at the *i*-th SU respectively, then it can be derived that

$$P_{d,i} = P\{E_i \geq \lambda_2 \mid H_1\} = P_{d2,i} \tag{4.27}$$

$$P_{m,i} = P\{E_i < \lambda_1 \mid H_1\} = 1 - \Delta_{1,i} - P_{d2,i} \tag{4.28}$$

$$P_{f,i} = P\{E_i \geq \lambda_2 \mid H_0\} = P_{f2,i} \tag{4.29}$$

The FC receives two kinds of information: $K_1 + K_2$ local decisions and $M - K_1 - K_2$ energy values, which have to be fused to make the final decision. As shown in (4.5) an 'n-ratio' rule is used to combine the local decision. There are $M - K_1 - K_2$ observed energy values that fall between the two thresholds. It shows that these $M - K_1 - K_2$ SUs could not distinguish between the absence and presence of the PU, thus the FC makes a soft combination of the observation. Form [49], it can be derived that $\Omega = \sum_{i=1}^{M-K_1-K_2} E_i$ follows the distribution:

$$\Omega \sim \begin{cases} \chi_2^2(M - K_1 - K_2)u \quad , & H_0 \\ \chi_2^2(M - K_1 - K_2)u^{(2\gamma_0)}, & H_1 \end{cases} \tag{4.30}$$

where $\gamma_0 = \sum_{i=1}^{M-k_1-k_2} \gamma_i$ is the sum of SNR form (4.16)

Hence, the probability of detection and false alarm with Ω corresponding to a threshold λ can be expressed as

$$P_{D_2 d} = Q_{(M-K_1-K_2)u}(\sqrt{2\gamma_0}, \sqrt{\lambda}) \tag{4.31}$$

$$P_{D_2 f} = \frac{\Gamma((M - K_1 - K_2)u, \lambda / 2)}{\Gamma((M - K_1 - K_2)u)} \ . \tag{4.32}$$

Now for a target false alarm probability $\overline{P}_f$ based on (4.32), the threshold can easily be obtained as

$$\lambda = 2\Gamma^{-1}((M - K_1 - K_2)u, \overline{P}_f \Gamma((M - K_1 - K_2)u)) \tag{4.33}$$

Finally, the FC makes a final decision according to (4.7), either the soft combination or the hard combination is '1' the FC will decide H_1 and vice versa. Based on the detection method discussed above, if Q_d is used to denote the cooperative probability of detection and Q_f to denote false alarm, then the overall sensing performance derivation can be obtained.

3.5.1 Probability of Detection

The cooperative probability of detection Q_{d_n} for the 'n-ratio' is derived. First, the expression for "1–ratio" is derived. Then subsequently the 'n-ratio' expression is derived. For "1-ratio", under H_1 when $K_1 < K_2$ according to (4.5), the FC will decide H_1. When $K_2 = 0$, for detection $K_1 \leq 1$

$$Q_{d\_n} = \sum_{K_1=1}^{M} \binom{K_2}{M} \binom{K_1}{M} \Delta_1^{M-K_1} P_{d,1}^{K_1} \tag{4.34}$$

when $K_2 = 1$, for detection $K_1 \leq 2$

$$Q_{d\_n} = \sum_{K_1=2}^{M-K_2} \binom{K_2}{M} \binom{K_1}{M-K_2} \Delta_1^{M-K_1-K_2} P_{d,1}^{K_1} P_m^{K_2} \tag{4.35}$$

and so on and so forth.

When $K_2 > (\lfloor M/2 \rfloor - 1)$, K_1 will always be less than or equal to K_1, and in this case contributions to the probability of detection will be zero. Hence, the Q_d expression for "1-ratio" logic is given as follows:

$$Q_{d\_n} = \sum_{K_2=0}^{\lfloor M/2 \rfloor - 1} \left[\sum_{K_1=K_2+1}^{M-K_2} \binom{K_2}{M} \binom{K_1}{M-K_2} \Delta_1^{M-K_1-K_2} P_{d,1}^{K_1} P_m^{K_2} \right] \tag{4.36}$$

for the 'n-ratio', when $K_2 > \lfloor n(M-1)/(n+1 \rfloor$, K_1 will be less than or equal to $\lfloor K_2/n \rfloor$, and in this case contribution to the probability of detection will be zero. For the 'n-ratio', the summation of K_1 will change from $(\lfloor K_1/n \rfloor + 1)$ to $(M - K_2)$. The final 'n-ratio', expression is given by:

$$Q_{d\_n} = \sum_{K_2=0}^{\lfloor n(M-1)/(n+1) \rfloor - 1} \left[\sum_{K_1=\lceil K_2/n \rceil}^{M-K_2-1} \binom{K_2}{M} \binom{K_1}{M-K_2} \Delta_1^{M-K_1-K_2} P_{d,1}^{K_1} P_m^{K_2} \right] \tag{4.37}$$

Substituting the 'n-ratio' and soft fusion into (4.7), the overall sensing performance expression can be given as:

$$Q_d = 1 - \sum_{K_2=0}^{\lfloor n(M-1)/(n+1) \rfloor - 1} \left[\sum_{K_1=\lceil K_2/n \rceil}^{M-K_2-1} \binom{K_2}{M} \binom{K_1}{M-K_2} \prod_{i=1}^{K_2} P_{d,i} \prod_{i=K_2+1}^{K_2+K_1} P_{m,i} \prod_{i=K_1+K_2+1}^{N} \Delta_{1,i}(1-P_{D_2d}) \right] - \sum_{K_2=0}^{\lfloor M/(n+1) \rfloor} \binom{K_2}{M} \prod_{i=1}^{K_2} P_{d,i} \prod_{i=K_2+1}^{N} P_{m,i}$$

(4.38)

3.5.2 Probability of False Alarm

Under H_0 when $(n*K_2) > K_1$, the FC will decide H_1. Similar to Q_d, Q_f can be expressed as

$$Q_f = 1 - \sum_{K_2=0}^{\lfloor n(M-1)/(n+1) \rfloor - 1} \left[\sum_{K_1=\lceil K_2/n \rceil}^{M-K_2-1} \binom{K_2}{M} \binom{K_1}{M-K_2} \prod_{i=1}^{K_2} P_{f,i} \prod_{i=K_2+1}^{K_2+K_1} (1-\Delta_{0,i}-P_{f,i}) \prod_{i=K_1+K_2+1}^{M} \Delta_{0,i}(1-P_{D_2f}) \right] - \sum_{K_2=0}^{\lfloor M/(n+1) \rfloor} \binom{K_2}{M} \prod_{i=1}^{K_2} P_{f,i} \prod_{i=K_2+1}^{M} (1-\Delta_{0,i}-P_{f,i})$$

(4.39)

The probability of missed detection can be expressed as

$$Q_d = 1 - Q_m \tag{4.40}$$

3.5.3 Performance over fading channel

In this section, the average detection probabilities over Rayleigh channels are derived. The same double thresholds models are used for flat fading Rayleigh channel. Under Rayleigh fading channel, probability of false alarm P_f will remain the same as in the case of AGWN channel, as it depends only on the distribution of the noise. Since under the Rayleigh channel, the signal amplitude follows a Rayleigh distribution [49]. The SNR γ follows an exponential PDF given by [49]:

$$f(\gamma) = \frac{1}{\overline{\gamma}} \exp\left(\frac{\gamma}{\overline{\gamma}}\right), \qquad \overline{\gamma} \geq 0, \tag{4.41}$$

The average P_d in this case denoted by $\overline{P}_{dRay}$ can be evaluated by averaging (4.21) over (4.41) from [49, 120] yielding:

$$\begin{aligned} \overline{P}_{dRay} &= e^{-\lambda/2} \sum_{n=0}^{u-2} \frac{1}{n!} \left(\frac{\lambda}{2}\right)^n \\ &+ \left(\frac{1+\overline{\gamma}}{\overline{\gamma}}\right)^{u-1} \left[e^{-\frac{\lambda}{2(1+\overline{\gamma})}} - e^{-\frac{\lambda}{2}} \sum_{n=0}^{u-2} \frac{1}{n!} \left(\frac{\lambda \overline{\gamma}}{2(1+\overline{\gamma})} \right) \right] \end{aligned} \tag{4.42}$$

Using equation (4.42), similar to the AWGN case, the cooperative probability of detection can be derived using the same steps and method described in section (3.5.1).

3.6 Simulation Results

In this section, to evaluate the performance of the proposed AF CSS scheme, simulation results are shown to compare the proposed approach with the tradition approaches based on the receiver operating characteristic (ROC). The effects of different parameters on the proposed algorithm were examined, such as the number of SUs and channels, channel availability and different values of the signal-to-noise-ratio. Links from the PU to the cognitive relays (SUs) and from the SUs to the FC are assumed to be independent and identical.

For the simulation in this chapter, the PU network is assumed to be a DVB-T2 signal [78], the bandwidth of the PU signal is 8 MHz, modulation type is QPSK. The average occupancy rate for the PU is set to 50%, i.e. the probability of presence and absence of the PU signal is fixed to an equal probability (0.5), respectively. The simulation is based on the Monte Carlo in MATLAB method with 50,000 iterations. The summary of the simulation parameters for analysing the developed CSS algorithm's performance evaluation is shown in Table 3.1. These simulation results are presented through receiver operating characteristics (ROC) curves and probability of detection curves in relation to SNR.

Table 3.1 Simulation parameters for the developed CSS AF algorithm

Parameter	Value
PU bandwidth	8 MHz
Local sensing	50 μs
Frame length	60
FEC blocks per frame	50
Channel condition	AWGN, Rayleigh
SNR range	-10dB to 10dB
Iterations	50,000
Number of SUs (Relay's)	1-10

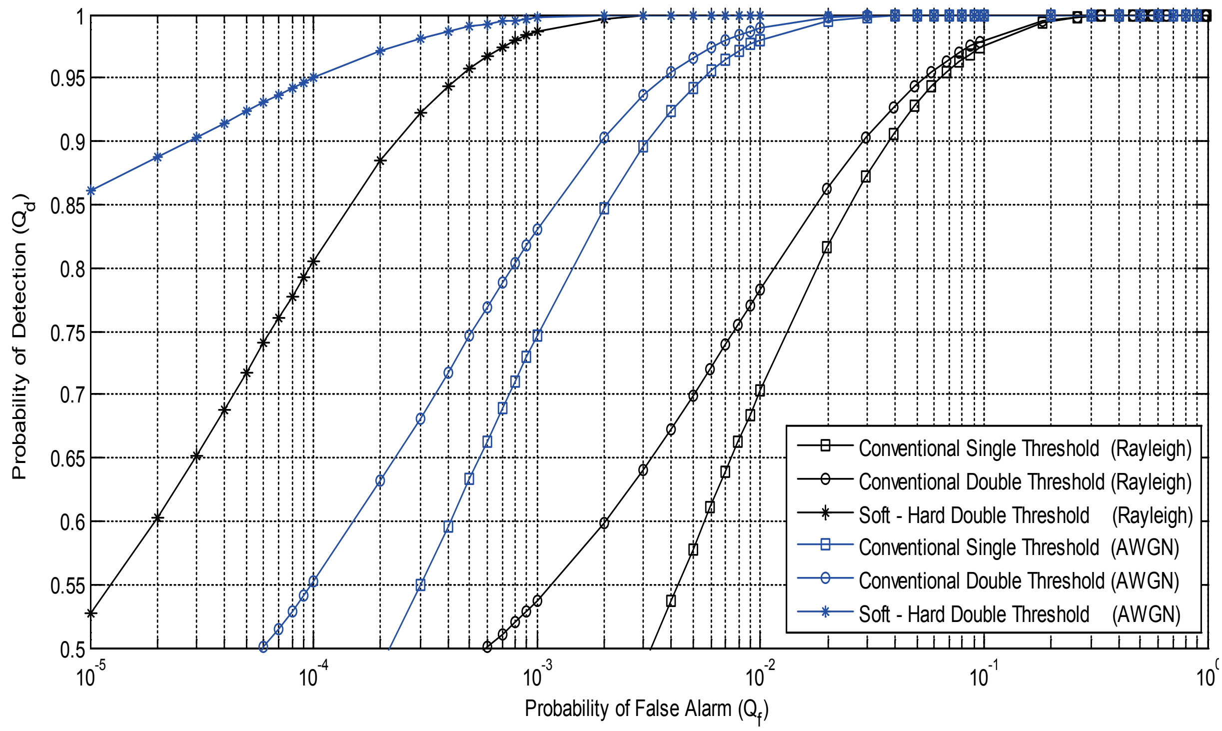

Figure 3.4 Performance comparison of a conventional single threshold, a conventional double threshold and a "soft 1-bit" double threshold energy detector with single relay AF scheme.

Figure 3.4 shows a ROC curve highlighting the performance of the conventional single threshold detection, conventional double threshold detection and a "soft 1-bit" double threshold energy detector using the proposed AF CSS algorithm under AWGN and Rayleigh fading channels, respectively. There is a single relay in the system and the SNR between the PU and SUs is 10dB. The local sensing time is 50 μs. Figure 3.4 indicates that the double threshold AF CSS method has better performance detection than the conventional cooperative method, while the proposed AF CSS "soft 1-bit" double threshold gave a better performance than the other methods. As the probability of false alarm increases, the probability of detection increases for all the algorithms, but the detection rate for the "soft 1-bit" double threshold is at a higher rate due to the higher accuracy of energy measure at the local SUs. For example, when the probability of false alarm is 10^{-3} under Rayleigh fading, the probability of detection is 0.54 for the conventional single threshold detection, 0.83 for the conventional double threshold detection and 0.99 for the "soft 1-bit" double threshold. It can be seen from the plots that there exist a particular value of Q_f that maximizes sensing performance. This value depends on the channel condition. A general observation is that spectrum sensing detection slightly decreases under Rayleigh fading channel when compared to AWGN conditions.

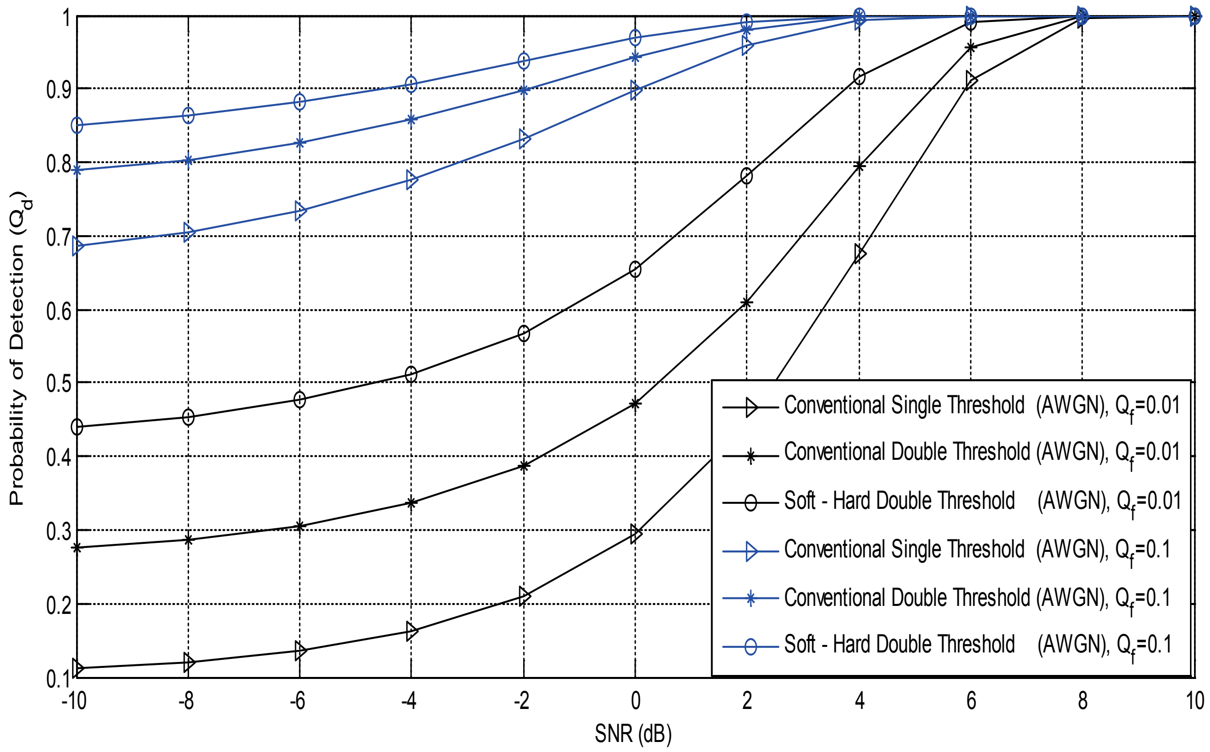

Figure 3.5 Probability of detection vs. SNR of a conventional single threshold, a conventional double threshold and a "soft 1-bit" double threshold energy detector with Q_f = 0.1 and 0.01, R = 10 AF relay scheme over AWGN channel.

Figure 3.5 and Figure 3.6 show the probability of detection in relationship to SNR (dB) with 10 AF relay nodes, using the proposed AF CSS algorithm with Q_f = 0.1 and 0.01 and SNR ranging from -10dB to 10dB for both AWGN and Rayleigh channels, respectively. The local sensing time is 50 μs.

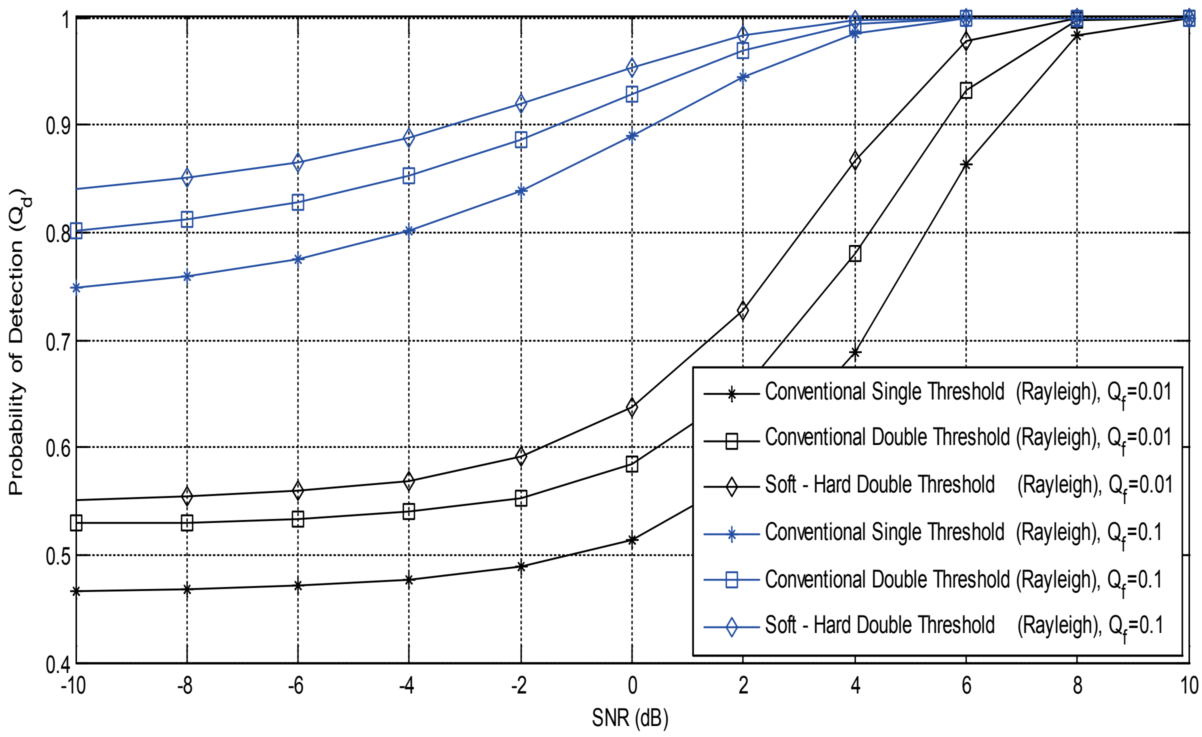

Figure 3.6 Probability of detection vs SNR of a conventional single threshold, a conventional double threshold and a "soft 1-bit" double threshold energy detector with Q_f = 0.1 and 0.01, R = 10 AF relay scheme over Rayleigh channel.

It can be observed that at a lower SNR the probability of detection for a "soft 1-bit" double threshold compared to that of the conventional ED and double threshold ED shows performance is improved, but this improvement slightly decreases as the SNR increases but is still significantly higher than the other two schemes. For example, in Figure 3.6, at an SNR of 2dB, $Q_f = 0.1$ under Rayleigh fading channel the probability of detection is 0.94 for the conventional single threshold detection, 0.96 for the conventional double threshold detection and 0.98 for the "soft 1-bit" double threshold. While at SNR of -10dB under the same conditions, the probability of detection is 0.75 for the conventional single threshold detection, 0.8 for conventional double threshold detection and 0.85 for the "soft 1-bit" double threshold. Hence, the scheme at both low and high SNR provides a significant detection performance improvement.

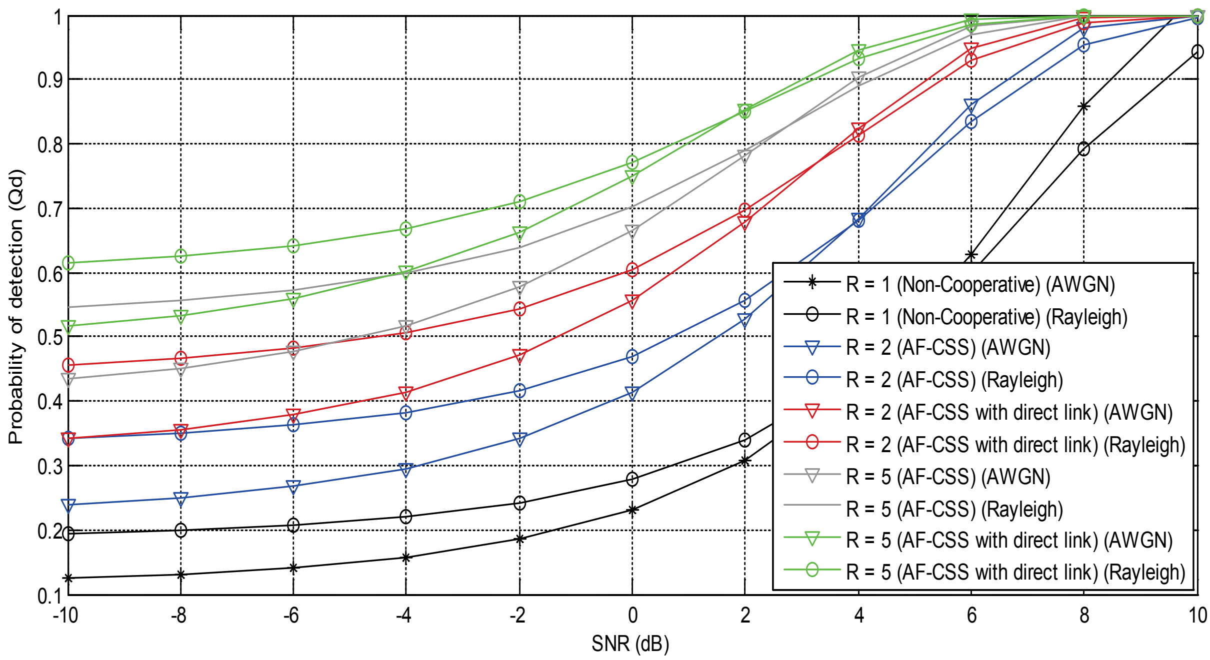

Figure 3.7 Probability of detection of the AF CSS scheme with multiple relays $Q_f = 0.1$ over AWGN and Rayleigh channels.

Figure 3.7 shows the probability of detection in relationship to SNR with different numbers of relay nodes (1, 2 and 5) using the proposed AF CSS algorithm with and without the direct link. $Q_f = 0.01$ and SNR ranging from -10dB to 10dB for both AWGN and Rayleigh fading channels. Firstly, Figure 3.7 shows that by increasing the number of SUs in the scheme the probability of detection is increased as a result of increased spatial diversity. In addition, as the SNR increases under all conditions the probability of detection increased. For example, in Figure 3.7 at 2dB when the numbers of SUs are 1, 2 and 5, the probability of detection under Rayleigh fading are 0.34, 0.56 and 0.78 respectively. When the direct link is incorporated the rate of detection increases significantly at low SNR. For example, when the SNR is -10dB and number of SUs are 5 the probability of detection difference between the non-direct link and direct link under Rayleigh channels increased by approximately 0.7dB.

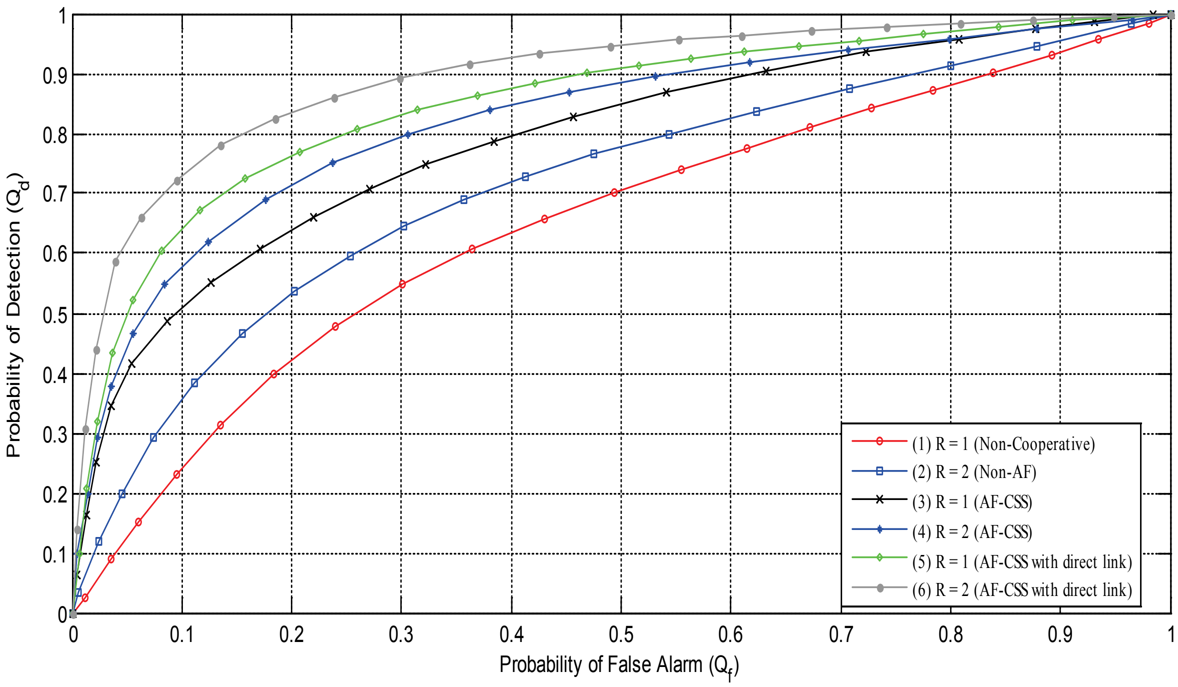

Figure 3.8 ROC curves of the AF CSS with direct link and non-cooperative schemes under Rayleigh Fading.

Figure 3.8 shows a ROC curve highlighting the detection performance probability of the proposed AF CSS scheme when a direct link is considered. A single SU and 2 SUs are spread in the network to perform local sensing. A non-cooperative scheme using different numbers of SUs are shown for comparison. The SNR between the PU and SUs is 10dB under a Rayleigh fading channel. The local sensing time is 50 μs. It can be observed that the probability of detection increased as the probably of false alarm increased in all the curves, but the detection rate for the proposed scheme with the direct link had a higher detection rate even at a higher false alarm rate. For example, when $Q_f = 0.1$, and 2 SUs are considered, the probability of detection of the proposed scheme that included a direct link increased by approximately 17% under the same conditions as compared to one without a direct link.

3.7 Conclusion

In this chapter, two important design criteria for cooperative spectrum sensing were focused on, which are the sensing accuracy and the sensing efficiency. A novel relay-based AF CSS architecture for CR networks using an improved cooperative ED has been considered. The proposed architecture combined the PU and relay (SUs) transmissions to achieve diversity against fading, using AF cooperation which has the potential of reduced complexity and cost. Analytically expressions for a "soft-1 bit" double threshold combination scheme to reduce the communication overhead, improve the local probability of detection and hence the global probability of detection were derived taking into account all sensing performance to exploit all the observed information from local secondary users. The proposed CRs network cooperative probabilities of detection, false alarm and missed detection for the proposed relay-based AF CSS scheme over AWGN and Rayleigh fading channels using multiple relays were formulated.

The effects of different parameters on the proposed algorithm were examined such as the number of SUs and channels, channel availability and different values of the signal-to-noise-ratio. Firstly, through simulation the performance of the conventional single threshold detection, conventional double threshold detection and a "soft 1-bit" double threshold energy detector using the proposed AF CSS algorithm under AWGN and Rayleigh fading channels were presented. The simulation results demonstrated the proposed AF CSS "soft 1-bit" double threshold had a much better detection performance of up to approximately 40% than the other methods. Secondly, simulation results demonstrated that at a lower SNR the probability of detection for a "soft 1-bit" double threshold, compared to that of the conventional ED and double threshold ED performance is improved under the same conditions (approximately 11% detection increase), but this improvement slightly decreases (approximately 4% detection increase) as the SNR increases but is still significantly higher than the other two schemes. Subsequently, simulation results demonstrated the probability of detection in relationship to SNR (dB) with different numbers of relay nodes using the proposed AF CSS algorithm with and without the direct links as the SNR increased under all conditions the probability of detection increases. Finally, ROC curves highlighting the detection performance probability of the proposed AF CSS scheme were presented. It was observed that the detection probability of the proposed AF CSS under Rayleigh fading scheme increased when the direct link was incorporated and also as the number of SUs increased, the detection probability increased.

In this chapter the problem of sensing accuracy and the sensing efficiency in cooperative spectrum sensing are focused on. The simulation results showed that the proposed scheme significantly reduced the error of missed detection and increased the probability of detection. Increase in detection probability is important since CRs are designed to continuously monitor spectrum and detect the presence of the PU's. However, the main drawback of the proposed scheme as well as other CSS in literature is that under practical conditions, the differences in local sensing reliability between the SUs are not considered. Hence, in the next chapter, the problem of spectrum sensing reliability and SU agility are addressed. An evidence based CSS schemes is considered which instead of treating all sensing terminals indiscriminatingly, treats each SU in the CR network in a practical independent manner by assigning a credibility value.

4 Evidence-based Decision Fusion Scheme for CSS in Cognitive Radio Networks

In this chapter, an evidence based decision fusion CSS schemes has been considered for overcoming the hidden terminal problem, improving reliability, and increasing SU agility. Under practical conditions, the combination of conflicting evidences with the classical Dempster Shafer theory (DS theory) rule may produce counter-intuitive results when combining the SUs sensing data evidence leading to poor CSS performance. In order to overcome and minimise the effect of conflicting data, and to enhance performance of the CSS system, a novel evidence-based decision fusion scheme CSS is proposed in this chapter. The approach is based on the credibility of evidence from the SUs sensing decision, which represents the similarity or the relation among the different SUs sensing data evidence, and a dissociability degree measure which indicates the quality or clarity of the SUs sensing data evidence. Furthermore, a weighted averaging factor determined by the credibility and dissociability of the SU sensing data evidence is proposed. Simulation results presented show that under practical conditions the proposed scheme enhances the performance of the CSS system when compared to traditional fusion rules such as AND rule, OR rule, that do not take into account the difference in local sensing reliability between the SUs. When compared to other fusion rules such as the Chair Varshney (CV) rule [101] and DS theory fusion [121] it also demonstrated an improved performance. The effects of different parameters such as the number of SUs, channel type, channel availability and different values of the average SNR, on the proposed algorithm were examined.

4.1 Introduction

In wireless channels, the hidden terminal problem which can lead to a very low SNR at the SUs is one of the biggest challenges of implementing spectrum sensing. In a case whereby a single SU sensing is shadowed, in severe multipath fading and shadowing effects, the SU may not reliably detect the PU signal and access the channel when there is a primary signal present causing interference to the licensed PU [2, 5]. As discussed in chapter 2, CSS is considered for overcoming the hidden terminal problem. To overcome the hidden terminal problem and increase the spectrum sensing reliability, CSS has been studied in [2, 13, 100, 109, 114, 121-126].

In general, CSS can be classified as either being centralised or distributed. Centralised CSS operates in two categorised as follows: *a)* the observations are pre-processed by the SUs to produce their measurement or test statistics. From the reported measurement, the FC makes the final judgment [14, 37, 42, 47, 79, 103, 109, 127, 128]; *b)* the FC processes the total received samples forwarded from each SU to make the final decision [47, 86, 114, 124, 125, 129]. Category *b)* requires a large portion of overhead as SUs report their collected samples. Therefore, the gain from cooperation may be exhausted by the overhead of communication. Thus, category *a)* attracts wider interest [36], hence, this chapter focuses on the fusion rule in category *a)* centralised CSS where the FC makes a final sensing decision based on the Basic Probability Assignment (BPA) of the sensing data received from each involved SU. The detection probability and false alarm probability are determined by the fusion rule.

In [100], an optimal data fusion rule, originally mentioned in [101], was applied by combining with a counting rule. Though it gave a good detection performance when the channel state changes, it required a long time period to converge which under practical condition can lead to poor performance. In [122] an optimal half voting rule was proposed, but it only gave a good performance under impractical condition i.e. when identical threshold for all SUs are considered. In [121] a method was proposed for combining all SUs spectrum decisions and their self-assessed credibility of each decision by means of Dempster Shafer theory (DS theory) of evidence, which is suitable for fast-changing radio frequency (RF) environments, due to its ability to assign uncertainty to propositions. However, under practical conditions, illogical results may be obtained by the DS theory combination rule when the conflicts between SUs sensing data are high [130-132], leading to low performance. In [123], a method was proposed to try to overcome this problem by assigning a relative relationship between SUs to adjust the credibility of the decision. It directly sets the weight for each user by assuming certain knowledge of each SUs average SNR, which is not easy to obtain, especially in low a SNR regime.

Unfortunately, the combination of conflicting evidences with the classical DS theory rule may produce counter-intuitive results when combining the SUs sensing data evidence leading to poor CSS performance. Hence, in order to minimise the effect of conflicting data along the trend of research in [131-135], a novel evidence-based decision fusion scheme CSS is proposed in this chapter. This approach is based on the credibility of evidence from the SUs which represents the similarity or the relation among different SUs sensing data evidence, and a dissociability degree measure which indicates the quality or clarity of the SUs sensing data evidence. Furthermore, a weighted averaging factor determined by the credibility and dissociability of the SU sensing data evidence is proposed.

In most of the previous work on CSS that considers weighted contribution from each user, the focus was on the following: (i) how to obtain the optimal weight for each user based on some performance criteria, by assuming knowledge of the local probabilities of false alarm and detection of each local detector which may not be known in practice, [136, 137] (ii) directly setting the weight for each user by assuming certain knowledge of each user's SNR, which is not easy to obtain, especially in low SNR a regime [123, 125, 138, 139]. Contrary to previous works, this work does not assume any knowledge of the performance of each SU detector, but rather uses the local decisions made by the SUs to estimate the BPA for each SU. The BPAs are obtained without the knowledge of each SUs SNR, which makes the proposed evidence-based scheme more practical.

In this chapter, a CR network with one PU and multiple SUs, which are operated in a time-slotted mode, have been considered. In general, the current CSS research including the hard decision fusion rule [109, 124, 128, 140] and soft decision rule [42, 141-143], assume that the received average SNRs are approximately the same at each of the SU. This assumption simplifies the calculation of the final sensing performance, including the probability of detection and probability of false alarm. On the other hand, when considering the channel shadowing effect, it cannot handle the practical inhomogeneous situations, where the average SNR varies among cooperative users. Instead of treating all sensing terminals indiscriminatingly, the proposed scheme treats each SU in the CR network in a practical independent manner by assigning a credibility value and a dissociability measure to the SUs sensing data evidence.

The main contributions of this chapter can be described as follows:

- Designing a novel evidence-based decision fusion scheme CSS for CR networks that uses both the credibility of SUs sensing data evidence and dissociability degree measure of SUs sensing data evidence, in the form of a weighted averaging factor which is then taken into account when making the final decision at the FC.

- Analytically deriving expressions for the credibility of evidence from the SUs sensing data which represents the similarity or the relation among different SUs sensing data evidence.
- Deriving the correlation coefficients between the local decisions using a distance of evidence rule and a correlation matrix (CM), this gives an insight into the agreement between the sensing decisions evidence.
- Evaluating and deriving expressions for a dissociability degree measure of evidence from the SUs sensing data which indicates the quality or clarity of the SUs sensing data evidence.
- Developing an algorithm for a weighted averaging factor and final fusion determined by the credibility value and dissociability degree measure of the SU sensing data evidence.
- Simulation and discussion of the effect of different key parameters such as the number of SUs, channel type, probability of false alarm, probability of missed detection and the average SNR on the performance of the proposed evidence-based decision fusion scheme.

The rest of this chapter is organised as follows: A CSS system model and the detection problems for local sensing at SUs are presented in section 4.2. A review of DS theory of evidence has been presented in section 4.3. In section 4.4, the proposed evidence based CSS scheme and the local SUs energy detection algorithm are introduced. In section 4.5, the BPA estimation of the SUs sensing data is presented. The evaluation of the credibility and dissociability degrees are presented in section 4.6 and 4.7, respectively. The analysis of the modified combination rule and the analysis of the final decision are detailed in section 4.8 and 4.9, respectively. In section 4.10, a summary of the proposed algorithm is outlined. Simulation results and analysis are presented through receiver operating characteristics (ROC) curves, and other performance related curves in section 4.11. Finally, conclusions are drawn in section 4.12.

4.2 System Model

A system model which is similar to the general system model described in section 2 is considered. In order to increase detection reliability of a CR network, a CSS scheme is considered instead of a single SU as illustrated in Figure 2.12. The SUs conduct local spectrum sensing by applying an energy detector to measure the PU's signal energy in each sensing frame. After the spectrum sensing process, each SU computes its own local detection and the decision along with a corresponding credibility denoted by *crd* are then transmitted to the FC, where a global decision is made. The whole CSS process can be categorised into two stages:

1. Local sensing at the SUs.
2. Final decision at the FC.

4.2.1 Local Spectrum Sensing Algorithm

Individual SUs perform local spectrum sensing in a distributed manner for detecting the PU signal. The detection problem for local sensing is in effect a binary hypotheses testing predicament that can be represented as follows [41]:

$$\begin{cases} H_0: & y(t) = n(t) \\ H_1: & y(t) = h(t)s(t) + n(t) \end{cases} \tag{4.1}$$

for $t = 1, ..., M$, where t represents the discrete time index and M denotes the number of observation, H_0 and H_1 are correspond to hypotheses of absence and presence of the PU signal, respectively, $y(t)$ represents the received data at the i-th SU, $h(t)$ represents the channel gain, $s(t)$ is the PU's transmitted signal and $n(t)$ is the additive white Gaussian noise. The following assumptions are made:

- The PU, SUs and FC are considered to be in the same region where they share a common spectrum allocation.
- The channels corresponding to the different SUs are independent.
- The noise $n(t)$ is a independent complex Gaussian random variable.
- The PU's signal $s(t)$ is an independent random process.
- The PU's signal $s(t)$ is independent of the noise $n(t)$.

Different SUs are presented with unique credibility based on its local sensing owing to changes in channel conditions between the PU and SUs. Therefore, the parameter "credibility" Crd is a variable that changes with corresponding channel condition h_i and the distance D_i between the PU and the i-th SU.

$$Crd_i = f(h_i, D_i) \tag{4.2}$$

where Crd_i represents the detection credibility from the i-th SU. Each SU has different possibilities for hypotheses H_0 and H_1, and a total credibility for its detection. Therefore, the detection result can be divided into three parts as illustrated in Figure 4.1, where $Crd(H_0)$ and $Crd(H_1)$ are the credibility for hypotheses H_0, and H_1 to be true based on local sensing at the *i*-th SU, respectively. $\Omega = \{H_1, H_2\}$ can be interpreted that either hypothesis could be true. Therefore, $Crd(\Omega)$ conveys total uncertainty of local detection at the *i*-th SU.

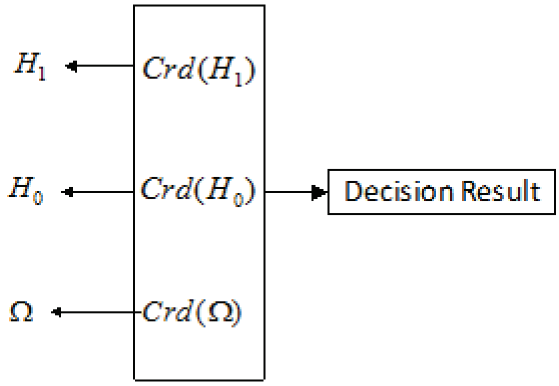

Figure 4.1. Decision Result Construction at the *i-th* SU

4.2.2 Final Decision at the Fusion Centre

Having analysed the decisions and their associated credibility Crd_i, at each *i*-th SU, the FC has the task of combining the received data using the DS theory of evidence combination which an adequate choice (see section 4.3). But the combination of conflicting evidences with the classical DS theory combination rule may produce counter-intuitive results when combining the SUs sensing data evidence. Hence, it is proposed that the FC employs an enhanced DS theory combination scheme in softly combing the two types of data, and making a final decision on whether the PU is present.

4.3 A Review of Dempster-Shafer Evidence Theory

DS theory is an approach to represent uncertain knowledge and to accomplish the uncertainty reasoning [144]. It has become an important method in data fusion [144]. DS theory of evidence has attracted much attention in a wide variety of fields such as intelligence, identification, automotive, fuzzy and wireless communication [131-134]. Due to the stochastic characteristics of wireless communication channels, there is uncertainty in local detection results at SUs. Considering that DS theory is used in managing uncertainty, it is a good choice for decision making in CR systems. In this section, a brief review of DS theory of evidence is carried out. A more complete introduction can be found in Shafer's original work [145].

4.3.1 Basic Probability Assignment (BPA)

Let $\Omega = \{A_1, A_2, ...A_n\}$ be a finite set of mutually exclusive possible hypotheses, referred to as the *frame of discernment*. The power set 2^{Ω} is the set of all subsets of Ω including itself and the null set $\varnothing$ [132].

DS theory assigns a mass (degree of belief) to each subset in the power set 2^{Ω}. While traditional probability theory employs a measure of probability to assign to each atomic hypothesis A_i in the frame of discernment, the mass in DS theory is assigned not only to each atomic hypothesis, but also to combinations of hypotheses. Hence, each subset in the power set is assigned a mass. The function m, that assigns a mass in the range of [0, 1] to each subset *A*, is called Basic Probability Assignment (BPA). This function satisfies the following conditions [132]:

$$m(\varnothing) = 0, \tag{4.3}$$

and

$$\sum_{A \subseteq \Omega} m(A) = 1. \tag{4.4}$$

The value of a mass (roughly equivalent to probability) is the belief that supports hypothesis *A*, but does not support any subsets of *A*.

Associated with m are a belief or credibility function *bel* and a plausibility function *pl* and are defined to characterise the uncertainty and the support of certain hypotheses. These two measures, derived from the mass values, are respectively defined as a map from a set of hypotheses to an interval [0, 1] for all $A \subseteq \Omega$ as follows [146]:

$$bel(A) = \sum_{B|B \subseteq A} m(B) \tag{4.5}$$

and the plausibility functions as:

$$pl(A) = 1 - bel(A) = \sum_{B|B \cap A \neq \varnothing} m(B), \tag{4.6}$$

bel(A) can be understood to be a global measure of the believe that hypothesis *A* is true, while *pl(A)* can be summarised as the amount of belief that could potentially be placed in *A*, if further information becomes available [133]. The pignistic transformation maps a belief function m to the pignistic probability function. The pignistic transformation of a belief function *m* on $\Omega = \{A_1, A_2, ...A_n\}$ is given by [130]:

$$BetP(A) = \sum_{B \subseteq \Omega} \frac{|A \cap B|}{|B|} \frac{m(B)}{1 - m(\varnothing)}, \quad \forall A \subseteq \Omega \tag{4.7}$$

where $|A|$ is the cardinality of set A. In a particular case where $m(\varnothing) = 0$ and $A \in \Omega$, i.e., A is a singleton of Ω,

$$BetP(A) = \sum_{A \in B} \frac{m(B)}{|B|}, A = A_1, ..., A_n, \quad B \subseteq \Omega \tag{4.8}$$

4.3.2 DS Theory Combination Rule

The mass function from different information sources, m_j where $(j = 1, ..., d)$ are combined with DS rule of combination, also called an orthogonal sum. The result is a new mass function [132]:

$$m(A_k) = (m_1 \oplus m_2 \oplus ... \oplus m_d)(A_k) \tag{4.9}$$

which incorporates the joint information provided by the sources, is given by [132]:

$$m(A_k) = \frac{1}{1 - K} \sum_{A_1 \cap A_2 ... A_d = A_k} \left(\prod_{1 \le j \le d} (m_j(A_j)) \right) \tag{4.10}$$

where

$$K = \sum_{A_1 \cap A_2 ... A_d = \varnothing} \left(\prod_{1 \le j \le d} (m_j(A_j)) \right) \tag{4.11}$$

K represents a measure of conflict between the different sources or contracting mass assignments, and it is introduced as a normalisation factor. In a practical system of evidence combination, the different evidence to be combined are not always concordant, there may be conflicts among them. This stems from the fact that in DS theory rule of combination, the conflicting mass assignments are discarded which may lead to counterintuitive behaviours among SUs conflicting mass assignments [132].

4.4 Cooperative Spectrum Sensing based Evidence theory

The DS combination rule is commutative and associative, and can be extended to combining multiple evidences in CSS sequentially [132]. After receiving all the sensing decisions with corresponding credibility Crd_i from the *i*-th SUs, according to DS theory of evidence combination, the FC makes a final decision on the observed band. This process can be categorised into steps, illustrated by the evidence-based decision fusion scheme for CSS block diagram in Figure 4.2.

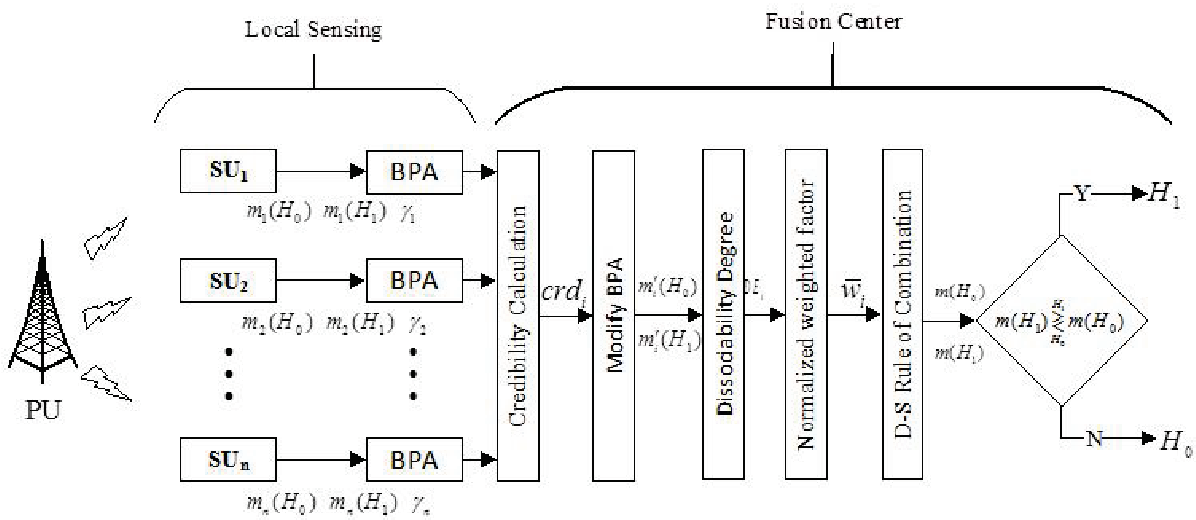

Figure 4.2. Evidence-based Decision Fusion Scheme for CSS.

4.4.1 Energy Detection

An energy detector is used to carry out the local spectrum sensing. To measure the signal power in a particular frequency region in time domain, a band-pass filter is applied to the received signal and the power of signal samples is then measured at *i*-th SU. The decision statistic is an estimation of the received signal power which, is given at each SU by the sensing matrix [41]:

$$y_E = \sum_{i=1}^{N} |y_i|^2 \tag{4.12}$$

where y_i is the *i*-th sample of received signal from the PU and $N = 2TW,$ where T and W are correspondent to the detection time and the signal bandwidth in Hz, respectively. In the absence of coherent detection, when the number of required samples N is large enough $(N > 300)$, using the CLT, y_E can be modeled as a Gaussian random variable under both hypotheses H_0 and H_1, with mean μ_0, μ_1 and variance σ_0^2, σ_1^2, respectively [49], such that

$$\begin{cases} \mu_0 = N, & \sigma_0^2 = 2N \\ \mu_1 = N(\gamma+1), & \sigma_1^2 = 2N(2\gamma+1) \end{cases} \tag{4.13}$$

where γ is the average SNR of the PU signal at the *i*-th *SU*.

4.4.2 Basic Probability Assignment (BPA) Estimation in CSS

In order to apply the DS theory of evidence to make a final decision, the frame of discernment denoted by Ω is defined as $\{H_1, H_0, \Omega\}$, where Ω denotes either hypotheses is true. After each sensing period, each SU will estimate its self-assessed decision credibility, which is equivalent to the BPA assignment for the two hypotheses H_0 and H_1, respectively.

The DS combination rule is commutative and associative hence, an appropriate BPA function is a cumulative distribution function (CDF) instead of a PDF given by [132, 134]:

$$H_0 : m_i\left(y_{E_i} \mid H_0\right) = \int_{y_{E_i}}^{+\infty} \frac{1}{\sqrt{2\pi\sigma_{0i}^2}} \exp\left(-\frac{\left(y_{E_i} - \mu_{0i}\right)^2}{\sigma_{0i}^2} \right) dy \tag{4.14}$$

$$H_1 : m_i\left(y_{E_i} \mid H_1\right) = \int_{-\infty}^{y_{E_i}} \frac{1}{\sqrt{2\pi\sigma_{1i}^2}} \exp\left(-\frac{\left(y_{E_i} - \mu_{1i}\right)^2}{\sigma_{1i}^2} \right) dy \tag{4.15}$$

where $m(.)$ is equivalent to $Crd(.)$, which is described in section 4.2.1, $m_i\left(y_{E_i} \middle| H_0\right)$ and $m_i\left(y_{E_i} \middle| H_1\right)$ are the BPAs of hypothesis H_0 and H_1 of the *i*-th SU, respectively. Using these functions, the BPA of hypotheses H_0 and H_1 are unique for each test statistics value y_{E_i} and vary in such a way that the larger y_{E_i} is the larger $m_i\left(y_{E_i} \middle| H_1\right)$ and the smaller $m_i\left(y_{E_i} \middle| H_0\right)$ are and vice versa [134]. The credibility from individual SUs and uncertainty are subject to the following constraint [121]:

$$m_i(H_1) + m_i(H_0) + m_i(\Omega) = 1 \tag{4.16}$$

4.5 Basic Probability Assignment (BPA) Credibility Degree

Instead of combining all the SUs self-assessed BPA which assumes they are all equal, the BPA of each SU should be assigned a credibility to highlight the reliability of the different SUs sensing data, for improving sensing accuracy. Subsequently, an additional stage at the FC to calculate the credibility of each BPA is proposed.

Generally, if all the self-assessed BPA evidence is assigned credibility, that piece of evidence should be more important and has more effect on the final fusion decision. On the contrary, if the self-assessed BPA evidence is highly conflicting with other bodies of evidence, this BPA should be less important and has little effect on the final fusion decision. To establish the credibility value of each self-assessed BPA, the correlation coefficients between the self-assessed BPAs are used. Using a distance of evidence rule as defined in [147], the distance of evidence between each BPA is given by:

$$d_{BPA}(m_i(H_0), m_i(H_1)) = \sqrt{\frac{1}{2}(m_i(H_0) - m_i(H_1))^T \underline{\underline{\mathbf{D}}}(m_i(H_0) - m_i(H_1))} \quad (4.17)$$

where $m_i(H_0)$ and $m_i(H_1)$ are the BPAs of the *i*-th SU and the Jaccard matrix $\mathbf{D}$ is a $2^{|\Omega|} \times 2^{|\Omega|}$ matrix to measure the conflict of the focal elements in $m_i(H_0)$ and $m_i(H_1)$, whose elements are [147]:

$$\mathbf{D}(A,B) = \frac{|A \cap B|}{|A \cup B|}, A, B \subseteq \Omega. \quad (4.18)$$

The introduction of the matrix has the advantage of taking the similarity between the BPAs into consideration. To describe the similarity between the BPAs, the correlation coefficient is defined as [148]:

$$c[m_i(H_0), m_i(H_1)] = \frac{\langle m_i(H_0), m_i(H_1) \rangle}{\|m_i(H_0)\| \cdot \|m_i(H_1)\|} , \quad (4.19)$$

where $m_i(H_0)$ and $m_i(H_1)$ have the same definition as in (4.17). Considering the similarity among the subsets of Ω, matrix $\mathbf{D}$ is used to modify the BPA from the *i*-th SU:

$$\begin{cases} m_i'(H_0) = m_i(H_0)\mathbf{D} \\ m_i'(H_1) = m_i(H_1)\mathbf{D} \end{cases}. \tag{4.20}$$

Therefore, using equation (4.19) and equation (4.20) the correlation coefficient can be redefined as:

$$c[m_i(H_0), m_i(H_1)] = \frac{\langle m_i'(H_0), m_i'(H_1) \rangle}{\| m_i'(H_0) \| \cdot \| m_i'(H_1) \|}. \tag{4.21}$$

$c[m_i(H_0), m_i(H_1)]$ satisfies the following requirement [148]:

- $0 \le c[m_i(H_0), m_i(H_1)] \le 1$
- $c[m_i(H_0), m_i(H_1)] = c[m_i(H_1), m_i(H_0)]$
- $c[m_i(H_0), m_i(H_1)] = 1 \Leftrightarrow m_i(H_0) = m_i(H_1)$
- $c[m_i(H_0), m_i(H_1)] = 0 \Leftrightarrow (\cup A_i) \cap (\cup B_j) = \varnothing$,

where A_i and B_j are focal elements of $m_i(H_0)$ and $m_i(H_1)$, respectively.

Let the number of BPAs be *n*. Subsequently, after all the degrees of similarity between the BPAs have been obtained, a correlation matrix (**CM**), which gives an insight into the agreement between the BPAs evidence is given by:

$$\mathbf{CM} = \begin{bmatrix} c[m_1(H_0), m_1(H_1)] & c[m_1(H_0), m_2(H_1)] & \cdots & c[m_1(H_0), m_n(H_1)] \\ c[m_2(H_0), m_1(H_1)] & c[m_2(H_0), m_2(H_1)] & \cdots & c[m_2(H_0), m_n(H_1)] \\ \vdots & \vdots & \ddots & \vdots \\ c[m_n(H_0), m_1(H_1)] & c[m_n(H_0), m_2(H_1)] & \cdots & c[m_n(H_0), m_n(H_1)] \end{bmatrix}, \tag{4.22}$$

where the diagonal element $c[m_i(H_0), m_i(H_1)] = 1$. The credibility degree of the BPA of $m_i(H_0)$ and $m_i(H_1)$ is given by:

$$Crd_i = \frac{1}{n-1}\sum_{i=1}^{n} c[m_i(H_0), m_i(H_1)]. \tag{4.23}$$

The credibility vector consisting of the credibility of all the BPAs from the SUs is defined by:

$$\mathbf{CRD} = [Crd_{1,} Crd_{2,} ..., Crd_{n,}]^{\mathrm{T}}, \tag{4.24}$$

therefore, the following formulation can be obtained:

$$\mathbf{CRD} = \frac{1}{n-1}(\mathbf{CM} - \mathbf{E}_{n\times n})\mathbf{I}_{n\times 1} \tag{4.25}$$

where $\mathbf{E}_{n\times n}$ and $\mathbf{I}_{n\times 1}$ are *n*-dimensional identity matrix and *n*-dimensional unit column vector, respectively.

4.6 Basic Probability Assignment (BPA) Dissociability Degree

The sensing decisions evidence dissociability denoted by *DE* is a function from a BPA *m* to $[0,1]$, it expresses the degree of the BPA focusing to the singletons of the focal elements. When the classification results are described in terms of BPAs, the BPAs dissociability can be constructed by the determined principle in multiclass classification. Generally, when the BPA from each SU to each class is nearly equal, the classification ability is poor. The greater the differences that exist among the BPA, the more reasonable decisions that can be made. Therefore, the dissociability cannot reach 1 unless the BPA is a categorical BPA, satisfying:

$$m(A) = \begin{cases} 1 & if \ A = A^*, \\ 0 & \text{otherwise.} \end{cases} \tag{4.26}$$

where A^* is one of the singletons in discriminate frame, thus $A^* \in \Omega$, Ω is the discriminate frame. If the belief function focuses on all the singletons on A equally, the dissociability is 0. Therefore, the dissociability degree *DE* can be defined as [149]:

$$DE(m) = 1 + \frac{1}{\ln(M)} \sum_{A \in A} BetP_m(A) \ln(BetP_m(A)) \tag{4.27}$$

where $BetP_m(A) = \sum_{B \subseteq A} \frac{|A \cap A|}{|B|} \frac{m(B)}{1 - m(\varnothing)}$ is the pignistic probability [149], and M is the cardinality of Ω.

4.7 Modified Combination Rule

It has been shown that credibility of evidence represents the relation among different sensing decisions evidence and the dissociability measure indicates the quality of the sensing decisions evidence. If both of the two factors are taken into consideration together, a better performance can be expected. Hence, a novel combination approach based on a modified weighted average BPA evidence is proposed.

The weighted factor is generated by the credibility and dissociability of the BPAs evidence. Both can be derived based on the BPAs, thus no extra priori knowledge is needed. The weighted factor *w* is determined by both credibility *Crd* and dissociability *DE* as follows:

$$w : (Crd, DE) \mapsto [0,1] \tag{4.28}$$

If the SUs BPA has a relatively high credibility degree, defined based on the correlation coefficient between BPAs and one of them has a higher dissociability than the others, it should be more credible. That is because such credible BPA evidence is relatively less uncertainty at the same time. Such BPAs should have a larger weight. On the contrary, suppose that the SUs BPA are relatively incredible and if one of them has lower dissociability than the others, it should be more incredible and should be assigned to a less value of weight. However, for a BPA with a higher dissociability but lower credibility, lower weighted factor should be assigned to it. This indicates that the conflict between this BPA and others may be high. On the other hand, zero dissociability reflects the probability assigned to each singleton is equal, thus its weighted factor is mainly determined by credibility. The requirements for w can be summarised as:

i. $\frac{\delta w}{\partial(Crd)} > 0, \frac{\delta w}{\partial(DE)} > 0$

ii. $0 \le w \le 1$

iii. $w(1,1) = 1$

iv. $w(0, DE) = 0$

v. $w(Crd, 0) = \lambda \cdot Crd, 0 < \lambda < 1$

Hence, the modified weights can be defined as follows:

$$w = \frac{1}{2}(Crd + crd \cdot DE^{-Crd}). \tag{4.29}$$

The factor $1/2$ is needed in equation to normalise w and to guarantee that $0 \le w \le 1$. The weighted factor w_i for each BPA can be normalised by:

$$\overline{w} = w_i / \sum_{i=1}^{n} w_i. \tag{4.30}$$

If all the BPAs evidence is available at the same time, the masses can be averaged and the combined masses calculated by combining the average values multiple times [150]. Thus, the BPA for the weighted averaged evidence $\overline{m}$ can be given by:

$$\overline{m}(A) = \sum_{i=1}^{n} \overline{w} \cdot m_i(A), \quad A \in \Omega \tag{4.31}$$

If there are n pieces of evidence, the averaged BPA must be combined $(n-1)$.

4.8 Final Decision

According to DS theory of evidence, the combination of the averaged BPA can be obtained by [145]:

$$m(H_0) = \overline{m}_1 \oplus \overline{m}_2 \oplus \ldots \oplus \overline{m}_n(H_0) = \frac{\sum_{A_1 \cap A_2 \cap \ldots A_n = H_0} \prod_{i=1}^{n} \overline{m}_i(A_i)}{1-K} \tag{4.32}$$

$$m(H_1) = \overline{m}_1 \oplus \overline{m}_2 \oplus \ldots \oplus \overline{m}_n(H_1) = \frac{\sum_{A_1 \cap A_2 \cap \ldots A_n = H_1} \prod_{i=1}^{n} \overline{m}_i(A_i)}{1-K} \tag{4.33}$$

where

$$k = \sum_{A_1 \cap A_2 \cap \ldots A_n = \varnothing} \prod_{i=1}^{n} \overline{m}_i(A_i) \tag{4.34}$$

In conclusion, the final decision computed at the FC is given as:

$$H_1 : m(H_1) > m(H_0) \tag{4.35}$$

$$H_0 : m(H_0) > m(H_1), \tag{4.36}$$

which can be expressed in a compact form as:

$$m(H_1) \underset{H_0}{\overset{H_1}{\gtrless}} m(H_0). \tag{4.37}$$

4.9 Summary of Algorithm

The proposed evidence-based decision fusion scheme for CSS can be summarised as follows:

Summary of the proposed evidence-based decision fusion scheme for CSS in CR Networks	
1.	***Step 1*****:** compute local spectrum sensing statistic (energy detector)
2.	y_{E_i} using (4.12)
3.	***Step 2*****:** compute the cumulative evidence probability
4.	$m_i\left(y_{E_i}\middle\vert H_1\right)$, $m_i\left(y_{E_i}\middle\vert H_0\right)$ and $m_i(\Omega)$ using (4.14), (4.15) and (4.16).
5.	***Step 3*****:** compute the distance of evidence between each BPA
6.	$d_{BPA}(m_i(H_0), m_i(H_1)$ using (4.17)
7.	***Step 4*****:** compute modification of BPA
8.	$m_i'(H_0)$ and $m_i'(H_1)$ using (4.20)
9.	***Step 5*****:** compute the redefinition of correlation matrix

$c[m_i(H_0), m_i(H_1)]$ using (4.21)

Step 6**:** compute the credibility vector

$\mathbf{CRD}$ using (4.22) and (4.23)

Step 7**:** compute dissociability of each BPA

$DE(m)$ using (4.27)

Step 8**:** compute weighted factor and normalised the weighted factor

w and $\overline{w}$ using (4.29) and (4.30)

Step 9**:** compute the average BPAs

$\overline{m}(A)$ using (4.31)

Step 10: compute the combination of the weighted averaged evidence

$m(H_0)$ *and* $m(H_1)$ using (4.32) and (4.33)

Step 11**:** compute final decision

If $m(H_1) > m(H_0)$ then test supports

H_1

else $m(H_0) > m(H_1)$ **test supports**

H_0

4.10 Simulation Results

This section is used to evaluate the performance of the proposed evidence based CSS scheme, where simulation results are shown to compare the proposed approach with other related approaches based on the receiver operating characteristic (ROC) and probability of detection curves in relation to SNR curves. The effects of different parameters on the proposed algorithm were examined, such as the SUs with independent channels, channel availability and different values of the SNR. For the simulation in this chapter, the PU network is assumed to be a DVB-T2 signal [78], the bandwidth of the PU signal is 8 MHz and modulation type is QPSK. The average occupancy rate for the PU is set to 50%, i.e. the probability of presence and absence of the PU signal is fixed to an equal probability (0.5), respectively. The simulation is based on the Monte Carlo method in MATLAB with 100,000 iterations. AWGN and Rayleigh channels are considered, there are six SUs spread in the network to perform local spectrum sensing. A summary of the simulation parameters for analysing the developed CSS algorithm's performance evaluation are shown in Table 4.1.

Table 4.1 Simulation parameters for the developed evidence based CSS

Parameter	Value
PU bandwidth	8 MHz
Local sensing	25 μs
Frame length	60
FEC blocks per frame	50
Channel condition	AWGN, Rayleigh
SNR range	-20dB to -8dB
Iterations	100,000
Number of SUs	6
PU average occupancy rate	0.5 (50%)

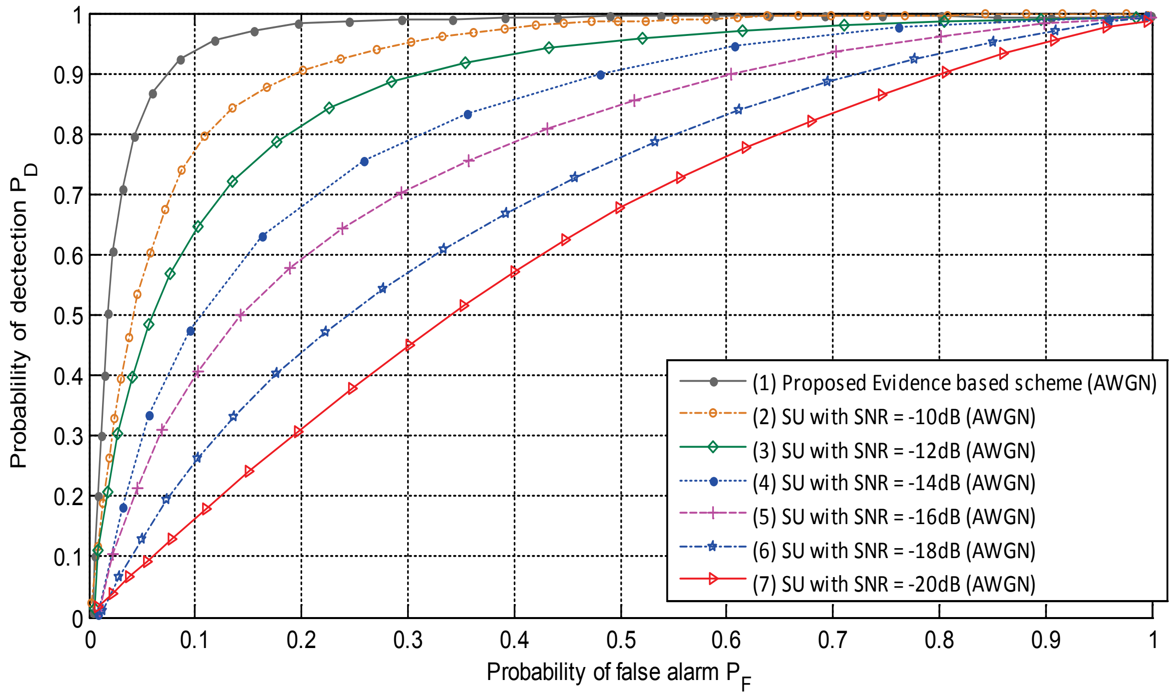

Figure 4.3. ROC curves of the proposed scheme and the local sensing results (energy detection) at each SU over AGWN channel.

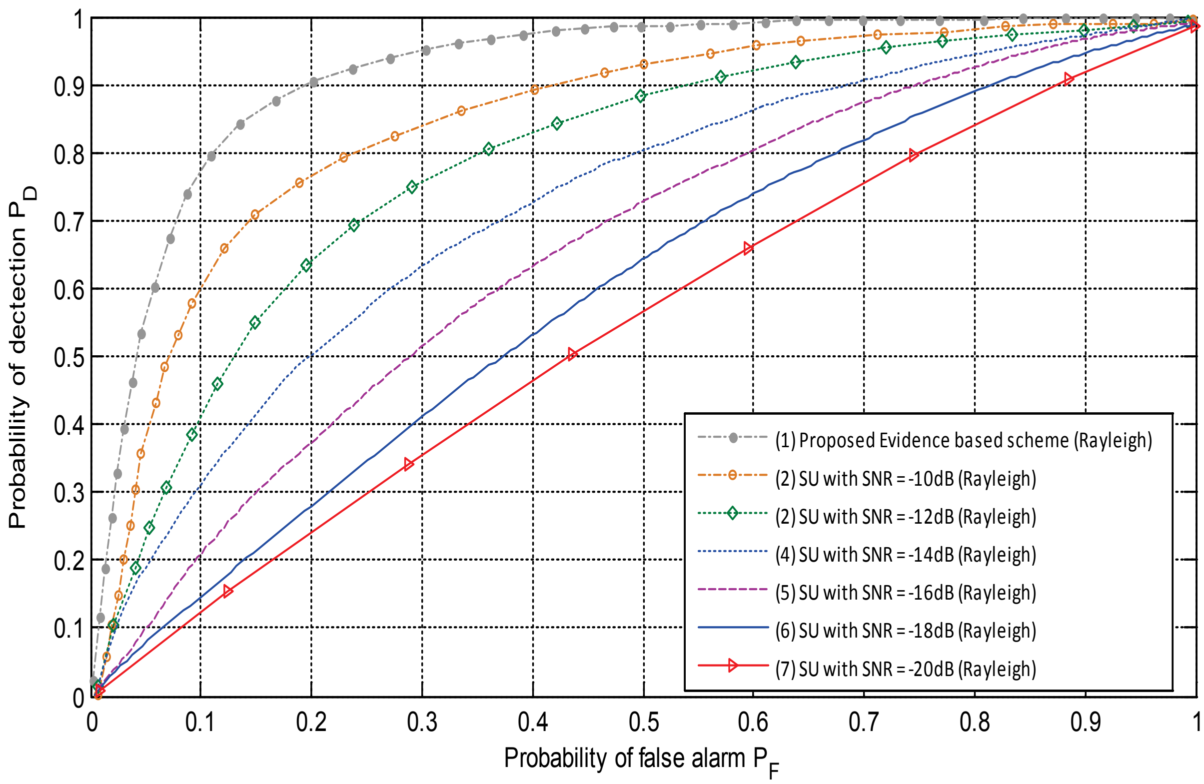

Figure 4.4. ROC curves of the proposed scheme and the local sensing results (energy detection) at each SU over Rayleigh fading.

Figure 4.3 and Figure 4.4 show the ROC curves, highlighting the performance of the proposed evidence based scheme and energy detection result at each SU under AWGN and Rayleigh fading channels, respectively. A sensing time of $25\ \mu s$ was considered. Energy detection is adopted as the local detection at the SUs. There are six SUs considered in the system. A practical scenario has been considered, where the six distributed SUs endure different channel conditions. The received signal condition at the six SUs are respectively -10 dB, -12 dB, -14 dB, -16 dB, -18 dB and -20 dB. It is shown in both Figure 4.3 and Figure 4.4 that the proposed CSS schemes which considers all the six SUs, outperforms any of the single standalone SUs. For example, when the probability of false alarm under a Rayleigh channel is 0.1, the probability of detection improves by approximately 18% considering a single SU with channel conditions of -10 dB.

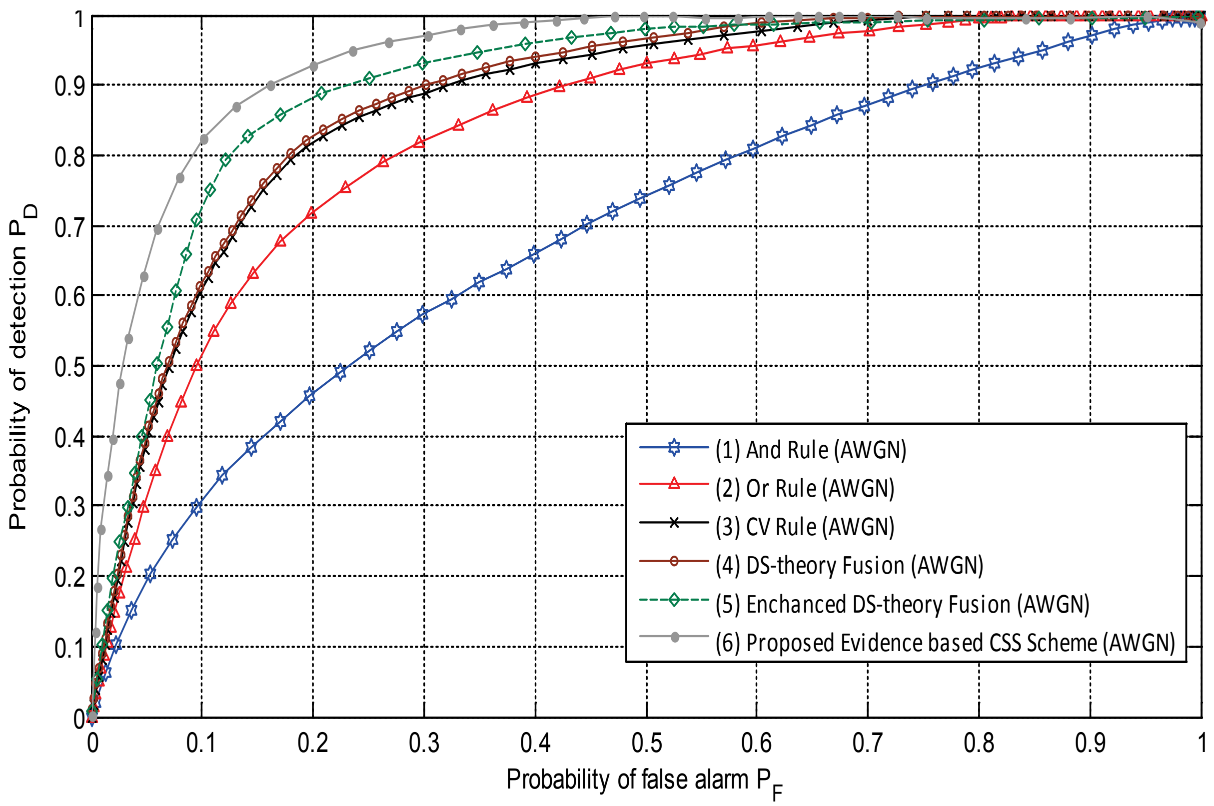

Figure 4.5. ROC comparison between the proposed scheme, AND rule, OR rule, CV rule, DS theory fusion and Enhanced DS theory fusion over AGWN channel.

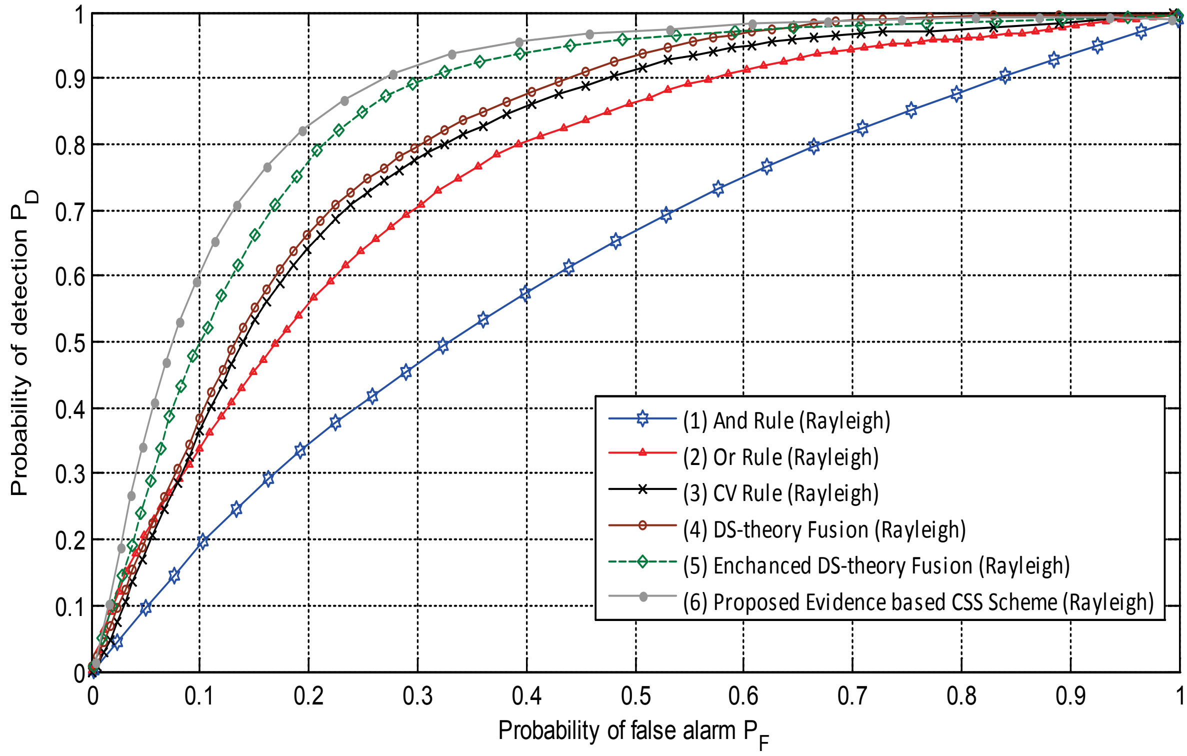

Figure 4.6. ROC comparison between the proposed scheme, AND rule, OR rule, CV rule, DS theory fusion and enhanced DS theory fusion over Rayleigh channel.

Figure 4.5 and Figure 4.6 show the ROC curves, highlighting the performance of the proposed evidence based scheme compared to the AND rule, OR rule, CV rule [101], DS theory fusion [121] and enhanced DS theory fusion [123] under AWGN and Rayleigh fading channels, respectively. Six distributed SUs with diffrent distance measures to the PU are considered. Without loss of generality, the SNRs of the received PU signals at the SUs are assumed to be - 10*dB*, -12*dB*, -14*dB*, -16*dB*, -18*dB* and -20*dB*, respectively. Under these conditions, Figure 4.5 and Figure 4.6 show the ROC curves of different fusion rules, which can be split into two groups. The first group: AND rule, OR rule, and CV rule are considered as traditional hard decision CSS schemes [42, 151]. As discussed in chapter 2, hard decision have the fewest communication overhead (1-bit hard decision for CSS), but the sensing performance are evidently worse [42, 151]. The ROC curves of the AND rule, the OR rule, and the CV rule have performances than those of the other algorithms highlighted in Figure

4.5 and Figure 4.6. For example, under AWGN conditions, when the probability of false alarm is 0.1 the probability of detection for AND rule, the OR rule, and the CV rule are approximately 0.3, 0.5 and 0.6, respectively.

The second group of CSS algorithms, DS theory fusion and enhanced DS theory fusion scheme can be considered as soft decision scheme, they utilise the BPA of the sensing data to be sent to the FC, and hence have a higher detection performance than the first group for a chosen false alarm probability value. The proposed algorithm falls under the second group, it utilises the BPA of the local sensing observation and fusion decisions are made at the FC. The results of this second group correspond with the maximum ROC curves. The proposed scheme has a better performance than both the DS theory fusion and enhanced DS theory fusion scheme. For example, under AWGN conditions, when the probability of false alarm is 0.1 the probability of detection for the DS theory fusion, enhanced DS theory fusion and the proposed scheme are approximately 0.62, 0.72 and 0.82, respectively. The improvement is approximately 10%, while a similar improvement of approximately 9% under Rayleigh conditions can be observed.

In general, it can be observed that spectrum sensing detection slightly decreases under Rayleigh channel conditions when compared to AWGN conditions. For example, in Figure 4.5 and Figure 4.6, taking the proposed scheme into consideration, when the probability of false alarm is 0.2 the probability of detection under Rayleigh channels when compared to AWGN decrease by approximately 10%.

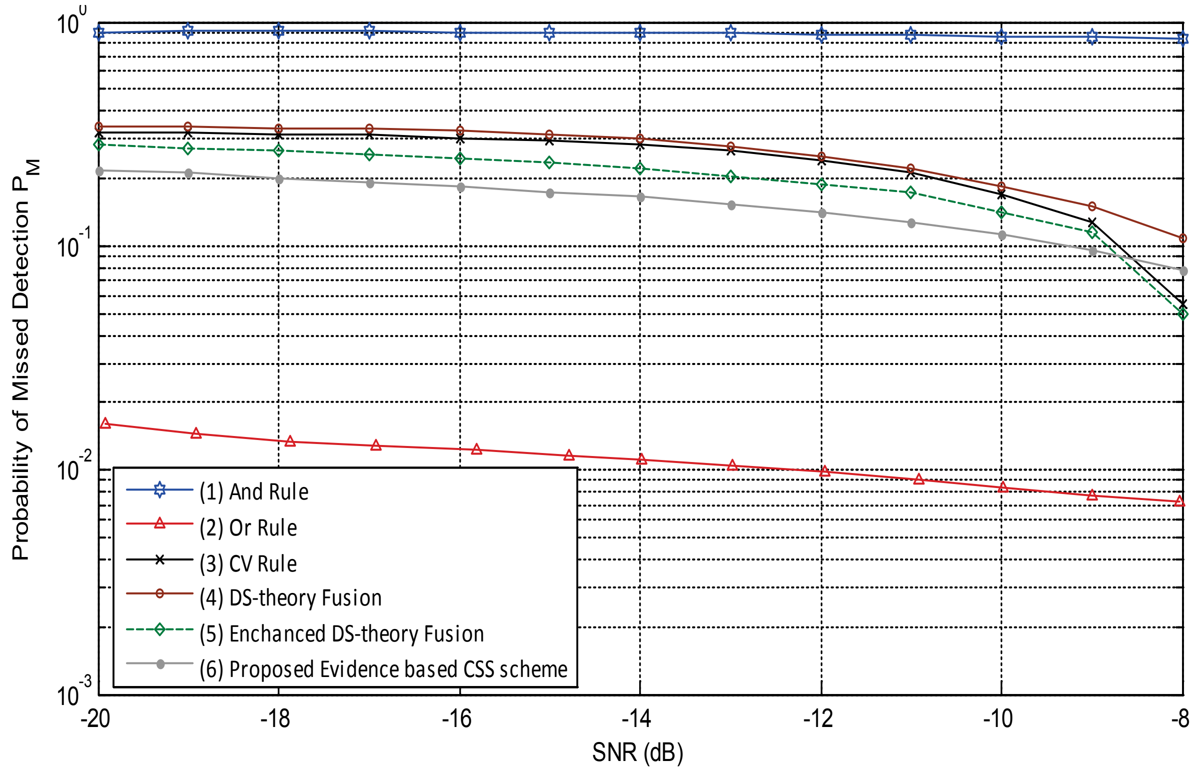

Figure 4.7. Probability of missed detection comparison between AND rule, OR rule, CV rule, DS theory fusion, Enhanced DS theory fusion and the proposed evidence based CSS scheme.

In Figure 4.7, the probability of missed detection of the AND rule, OR rule, CV rule, DS theory fusion, Enhanced DS theory fusion and the proposed scheme are highlighted. Six distributed SUs with diffrent distance measures to the PU are considered under AWGN conditions. In order to evaulate the proposed scheme in a practial situaton, it is assumed that the first SU channel conditions is changed from -20 dB to -8dB, which is representable of a CSS problem, where an SU experiences fading. The next five SUs have the same AWGN channel with SNR = - 16dB. It is shown in Figure 4.7, that under the above conditions, the probability of missed detection P_M of the OR rule is always the smallest and vice versa for the AND rule which indicates unsuitable performance in a practical scenario. The proposed scheme gives a lower probability of missed detection than the CV rule, DS theory fusion and enhanced DS theory fusion due to the effective BFA function, credibility adjustment, dissociability and weight combination algorithm among the SUs. For example, at SNR = -18 dB, the missed detection of the proposed scheme reduced by approximately 7% when compared to the enhanced DS theory fusion.

4.11 Conclusion

In this chapter, a novel evidence based decision fusion scheme CSS for CR networks that uses both a credibility of SUs sensing data evidence and dissociability degree measure has been proposed. Furthermore, a weighted averaging factor determined by the credibility and dissociability of the SU sensing data evidence has also been proposed. The proposed approach has been used to overcome and minimise the effect of conflicting SUs sensing data evidence when using a classical DS theory combination rule.

A CR network with one PU and multiple SUs, which are operated in a time-slotted mode, have been considered. Instead of treating all sensing terminals indiscriminatingly, the proposed scheme treats each SU in the CR network in a practical independent manner by assigning a credibility value and a dissociability measure to the SUs BPA evidence. Local spectrum sensing was carried out at each SU using an energy detector to estimate the received signal power. An appropriate BPA function as a form of cumulative density function (CDF) was used. Instead of combining all the SUs (self-assessed BPA which means treating all BPA's equally), the BPAs of each SU are modified by a credibility evidence to improved sensing accuracy. Subsequently, an enhanced stage to the FC was proposed.

To establish the credibility value which represents the relation among different sensing decisions evidence of each SU sensing decision, the distance of evidence between each BPA was derived using a distance of evidence rule. Afterwards, to describe the similarity between the SUs, a correlation coefficient was defined. A matrix was used to modify the BPA from each SU. Subsequently, after all the degrees of similarity between the BPAs had been obtained, a correlation matrix and credibility vectors consisting of the BPAs were expressed. To ascertain the quality of the BPA evidence a dissociability measure *DE* was formulated using a pignistic probability. Finally, weighted factor has been generated based on the credibility and dissociability of the BPAs with no extra priori knowledge needed. The combination of the averaged BPAs evidence was also obtained using the DS evidence theory combination rule.

Simulations were performed under AWGN and Rayleigh fading, respectively. The results have demonstrated that under practical condition the proposed scheme significantly improved performance for CSS when compared to the AND rule, OR rule, which do not take into account the difference in local sensing reliability between SUs. Also when comparing against the CV rule, DS theory fusion and enhanced DS theory fusion there is an improved performance in CSS. The missed detection probability of the proposed scheme decreased by approximately 7% when compared to the enhanced DS theory fusion.

In this chapter, two important design criteria for CSS were focused on, which are the sensing reliability, and SU agility. The simulation results showed that the proposed scheme yields a significant improvement in the detection probability as well as a considerable reduction in the missed detection probability without any prior knowledge of the primary system by utilising DS theory. However, the main drawback of the proposed scheme as well as other soft data fusions (including the CSS scheme used in chapter 3) are the bandwidth required for transmitting the sensing data. Hence, in the next chapter the problem of quantisation in CSS is investigated.

5 Enhanced Quantization for Cooperative Spectrum Sensing in Cognitive Radio

The transmission overhead in a CR network should be as minimal as possible, meaning that utilizing a wideband reporting channel to transmit raw sensing statistic is not efficient. A wideband reporting channel increases spectrum sensing times, which in turn reduces data transmission duration, thereby reducing the throughput of the SUs. A large overhead also increases cost and reduce spectrum efficiency. The CSS scheme in chapter 4 provided a considerable enhancement in the probability of detection and a significant reduction in the probability of false alarm without any prior knowledge of the PU signal by utilizing evidence theory. However, the main drawback of the proposed evidence based CSS scheme as well as a host of other soft data fusion schemes, is the bandwidth requirement for transmitting the sensing measurements to the FC. Hence, in this chapter, different quantization schemes for CSS are proposed to reduce the transmission overhead, increase throughput and improve the overall spectrum efficiency in a CR network which can be significant in high data rate applications. First, a Maximum Likelihood Estimation (MLE) for CSS for both a uniform and output entropy quantization schemes are proposed. Then evidence based CSS with quantization are considered. Simulation results presented, show that under practical conditions these schemes can achieve good detection performance, comparable to conventional soft decision schemes, with reduced communication overhead.

5.1 Introduction

To overcome the hidden terminal problem and increase the spectrum sensing reliability, CSS schemes have been studied in [13, 100, 109, 114, 121-124, 126]. To reduce detection time and increase SU gain, CSS was considered in [2, 13, 109, 152]. In CSS, the SUs transmit their sensing statistics to the data FC. A data fusion rule is subsequently carried out to fuse the recovered data and make a global decision [129]. Owing to the receiver diversity gain, the global decision is considered much more reliable than the local decisions. In most literatures of CSS [43, 100, 122, 143], local SUs are assumed to perform their individual decisions to decide on the presence or absence of the PU signal, which can be equivalent to a 1-bit quantization. At the FC, the quantized decisions are combined using counting rules, under such a circumstances; the optimal fusion scheme is the "*k out of n*" rule [14]. Nevertheless, the scheme is suboptimal [88] when the numbers of CR's n are not infinite. Even though the overhead communication requirements in this method are reduced, the detection performance considerably reduces. Hence leading to the motivation for using quantized soft data statistics in CSS that do not considerably reduce detection performance [2, 102, 140, 153-155].

There are a number of traditional quantization schemes in that quantize soft data statistics [104, 156, 157]. Mostly, all of these quantization schemes need some sort of prior information of the PU's signal which is not always available in a practical CR network. A two-bit hard combination which achieves a good sensing detection was proposed in [47]. However, the quantization thresholds are based on an intuitive criterion of the received signal energy at individual SUs and cannot be proven to be optimal. A multi-bit quantization scheme was proposed in [153] to apply the deflection criterion [156] however an optimal quantization was not implemented. In [12, 158], a Lloyd based LLR quantizer was proposed, but it required full knowledge of prior probability of PU's signal and it was assumed the reporting channels are perfect, this is not always practical. In [42], a soft decision based CSS algorithm for an OFDM based PU signal was designed using a quantized LLR. It was assumed that the distribution of the received signal at the individual SUs under the alternative hypothesis is known.

In this chapter, quantization methods are considered for output entropy quantization for a MLE based CSS scheme and an evidence based CSS scheme. For the MLE based CSS scheme, an output entropy quantization MLE based CSS using an estimator algorithm for the composite hypothesis testing is developed. Here, the MLE of the energy measurements are quantized to use instead of the quantized versions of LLRs used in [12] for detecting a PU signal. Contrary to [2, 12, 42], it is assumed that the PU signal is unknown. A novel uniform threshold quantization scheme and an output entropy quantization are proposed to provide less complex overhead as a potential benefit of sensing data volume that may help speed up the PU signal detection process.

For the evidence based CSS scheme, a scheme that quantizes the BPA data at each SU before sending it to the FC is developed. The proposed scheme takes into consideration the characteristics of the hypothesis distribution under diverse SNR of the PU signal. It is assumed that there is no prior knowledge of the PU signal. A novel combination scheme similar to that in chapter 4 is developed at the FC. A combination gain corresponding to that in chapter 4 is achieved, while only a minimal amount of bandwidth for the reporting channel is needed.

The main contributions of this chapter can be described as follows:

- Designing a novel optimal entropy quantization for (MLE) for CSS for CR networks using a uniform threshold quantizer (UTQ) and an output entropy quantization scheme.
    - Deriving Maximum Likelihood estimator for a CSS scheme and optimize it by adjusting the parameter associate with the threshold distribution.
    - Evaluate and deriving expressions for a proposed (UTQ) and an output entropy quantizer and evaluating their performance for a low SNR range.

- Designing a novel evidence-based decision fusion CSS quantization scheme for CR network.
    - Evaluating and deriving expressions for a proposed (UTQ) and an output entropy quantizer using LLR.
    - Developing an algorithm for the quantization of the credibility value and dissociability degree measure of the SU sensing data evidence.
    - Simulation and discussion of the effect of different key parameters such as the probability of error, channel type, probability of false alarm, probability of missed detection and the average SNR on the performance of the proposed scheme.

The rest of this chapter is organised as follows: A Lloyd-Max algorithm is described in section 5.2. In section 5.3, an optimal entropy quantization for a MLE based CSS scheme is presented. An evidence based quantization scheme is presented in section 5.4. Finally, in section 5.5 the conclusions are presented.

5.2 Lloyd-Max algorithm

Generally, all the quantization methods are primarily based on the optimal Lloyd-Max quantization scheme and will be referred to further on in this chapter. As a result, the details of these quantization methods are provided in this section. An algorithm for designing an optimal quantizer using MMSE distortion measure was presented in [159]. Assuming a *D*-level bit quantizer *Q(y)* of an input value *y* is given by a set of quantization levels $l_i, i = 1, 2, ..., D.$ and quantization boundary $t_i, i = 1, 2, ..., D$. The principle of quantization requires $-\infty = t_0 \leq t_1 \leq ... \leq t_{D-1} \leq t_D = \infty$ and takes $Q(y) = l_i \quad \text{if} \, Y \in (t_{i-1}, t_i), \quad \mathrm{i} = 1, 2, ..., D$, where $l_i \in (t_{i-1}, t_i)$. The optimal quantization in the sense of MMSE can be achieved from the following Lloyd-Max quantization criterions [12, 159]:

$$t_i = \frac{l_{i-1} + l_i}{2} \tag{5.1}$$

where

$$l_i = \frac{\int_{t_{i-1}}^{t_i} y \cdot f_Y(y) dy}{\int_{t_{i-1}}^{t_i} f_Y(y) dy} \, , \tag{5.2}$$

$f_Y(y)$ is the PDF of input Y. The quantization levels which ought to be centroid of the PDF in the quantization interval (t_{i-1}, t_i) is represented by equation (5.2), the quantization boundaries which are the middle point between two neighbouring quantization levels are represented by equation (5.1). The distortion is defined by the MSQE as follows [159]:

$$R = \sum_{i=1}^{D} \int_{t_{i-1}}^{t_i} (y - l_i)^2 f_Y \cdot (y) dy. \tag{5.3}$$

The Lloyd-Max algorithm carries out of the following operation [159]:

- Iteration 1: Guess the initial set of quantization levels l_i $i = 1, 2, ..., D$
- Iteration 2: Calculate the quantization boundaries t_i using equation (5.1).
- Iteration 3: Re-calculate the quantization levels l_i using equation (5.2).
- Iteration 4: Estimate the distortion R by (5.3) and the value of relative distortion error δ_R :

$$\delta_R = \frac{R_{R-1} - R_R}{R_{R-1}} \tag{5.4}$$

- Iteration 4: Repeat iteration 2 and iteration 3 until no further distortion reduction.

5.3 Optimal Entropy Quantization for Maximum Likelihood Estimation for Cooperative Spectrum Sensing.

A type of global decision known as hard decision in CSS facilitates easy implementation and reduces the bandwidth requirement on the reporting channel between the SUs and the FC, but these advantages come at the expense of data loss and reduction in performance [88]. The alternative soft decision fusion CSS schemes in previous research works [5, 109, 125, 143] provide a considerable enhancement in the probability of detection at the expense of increased bandwidth required for transmitting the sensing measurements to the (FC). Owing to the constraint of control of the reporting channel bandwidth, the local sensing statistic ought to be quantized before subsequently transmitting to FC. Using quantized local decision values of a local statistic or Log-Likelihood Ratio (LLR) can help reduce the required reporting channel bandwidth and improve CSS performance [42, 160].

A LLR quantizer that utilizes the distribution parameters of sensing data was proposed in [12] and [2]. However, it requires a full knowledge of prior probability of the PU's signal which is not always available. Also, it was assumed that the reporting channels are perfect, which can lead to performance losses under practical conditions. In [42], a soft decision based CSS scheme for an OFDM PU network using the quantized versions of LLR's was proposed. However, it was assumed under the alternative hypothesis that the distribution of the received signal is known, even though under practical conditions this may not be the case. Contrary to the simple hypothesis LLR test in which the PDFs under both hypotheses are completely known, a practical scheme in which a composite hypothesis test must accommodate unknown parameters is proposed. The MLE statistics are quantized and sent to the FC as an alternative of the quantized decision statistics of LLRs. Uniform and optimal entropy quantization's schemes are proposed to reduce the reporting channel overhead. The proposed scheme gives a simple and practical implementation of CSS with negligible loss as compared to the optimal case of using quantized LLRs, which can be significant in high data rate applications.

5.3.1 System Model

In this section, a system model as shown in Figure 5.1 which is similar to the general system model in section 2.9 is considered. N SUs are considered for the CSS scheme. The local SUs utilise the autocorrelation coefficients of the PU signal during each sensing period. The following assumptions are made:

- It is assumed that the sensing time is large enough, such that the PU signal can be modeled as a Gaussian distribution for a complex random variable
- Channels corresponding to individual SUs are assumed to be independent and all SUs and the PU share the same spectrum allocation.

- Both the sensing channels and reporting channels are assumed to be independent and identically distributed (i.i.d).

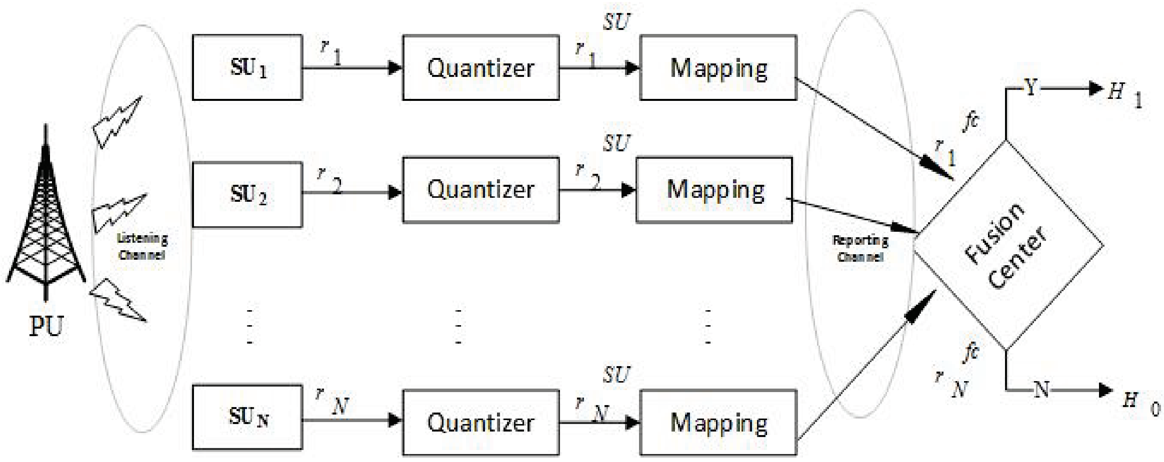

Figure 5.1 A maximum likelihood D-*level* quantizer based cooperative spectrum sensing scheme.

The PU detection problem is formulated as a composite hypothesis testing problem, where H_0 denotes the presence of the PU and H_1 denotes the absence of the PU [41]. The SUs transmit quantized values of the MLE observations to a FC to make a final decision. The essential performance criteria for CSS at the FC are the probability of detection, the probability of missed detection, and the probability of false alarm which are denoted by $P_{d,ml}$, $P_{m,ml}$ and $P_{f,ml}$, respectively. Note by definition, $P_{m,ml} = 1 - P_{d,ml}$. Let the constraints on the probability of false alarm and the probability of missed detection be denoted by α_{ml} and β_{ml}, respectively, thus, $P_{f,ml} \leq \alpha_{ml}$ and $P_{m,ml} \leq \beta_{ml}$.

5.3.2 Maximum Likelihood Estimation (MLE)

The local decisions are assumed to be the quantized values of the MLE outputs of the PU signal. As opposed to the simple hypothesis test (LLR) in which the PDFs under both hypotheses are completely known. It is assumed that the PDFs under H_0 or under H_1 or both hypotheses may not be completely known. The PU signal is assumed to be a DVB-T2 *(see section 2.12.1)* with an OFDM signal that consists of sum of narrowband subcarriers that are typically modulated by using phase shift keying (PSK) or quadrature amplitude keying (QAM). The presence of a cyclic prefix (CP) gives OFDM signals the following well-known, convenient property [161]:

- The autocorrelation coefficients are nonzero at delays $\tau = \pm T_d$, where T_d is the number of samples corresponding to useful symbol length in an OFDM block.

Without loss of generality, a sampling factor of 1 is assumed. Therefore T_d also represents the number of subcarriers for the DVB-T2 system. The OFDM signal is constructed by feeding T_d symbols to an Inverse Fast Fourier Transform (IFFT) through serial to parallel conversion [161].

The hypothesis testing problem for detecting the PU signal is giving by [41]:

$$\begin{cases} H_0: & y(t) = w(t) \\ H_1: & y(t) = s(t) + w(t) \end{cases} \tag{5.5}$$

where $y(t)$ is the received complex OFDM signal, $s(t)$ is the PU's transmitted signal and $w(t)$ is the complex circular additive white Gaussian noise. Under the assumption of a large IFFT size and using the CLT [53]:

$$\begin{aligned} s(t) &\sim \mathcal{N}_C(0, \sigma_s^2) \\ w(t) &\sim \mathcal{N}_C(0, \sigma_w^2) \end{aligned} \tag{5.6}$$

where $\mathcal{N}_{\mathcal{C}}(.)$ denotes the Gaussian distribution for a complex random variable, σ_s^2 and σ_w^2 are the variance of the $s(t)$ and $w(t)$, respectively. Therefore,

$$\begin{cases} H_0: \;\; y(t) \sim \mathcal{N}_{\mathcal{C}}(0, \sigma_w^2) \\ H_1: \;\; y(t) \sim \mathcal{N}_{\mathcal{C}}(0, \sigma_s^2 + \sigma_w^2) \end{cases} . \tag{5.7}$$

Considering $y(t) = y_r(t) + jy_i(t)$ to be circularly symmetric Gaussian random variables, the real and imaginary parts of y is given by [161]:

$$\begin{aligned} y_r(t) &\sim \mathcal{N}_{\tau}(0, \sigma_y^2 / 2) \\ y_i(t) &\sim \mathcal{N}_{\tau}(0, \sigma_y^2 / 2) \end{aligned} , \tag{5.8}$$

where $\mathcal{N}_{\tau}(.)$ denotes the Gaussian distribution for a complex random variable, σ_y^2 is the variance of the $y(t)$. For a cyclic prefix-OFDM (CP-OFDM) signal, the values of the autocorrelation coefficient $\rho(\tau) = E[y(t)y^*(t+\tau)] / E[y(t)y^*(t)]$ for lags $\tau = \pm T_d$ under the two hypotheses are given by [161]:

$$\begin{cases} H_0: \;\; \rho(\pm T_d) = 0 \\ H_1: \;\; \rho(\pm T_d) = \rho_1 \end{cases} , \tag{5.9}$$

where

$$p_1 = \frac{T_c}{T_d + T_c} \frac{\sigma_s^2}{\sigma_s^2 + \sigma_w^2} , \tag{5.10}$$

T_c is the number of samples corresponding to CP in an OFDM block. If the MLE of the autocorrelation coefficient at the *i*-th SU is denoted by r_i, the MLE of ρ can then be evaluated in terms of the received observation $[y(0),...,y(M+T_d-1)]$ by [161]:

$$r_i = \frac{\frac{1}{M}\sum_{t=0}^{M-1}\Re\{y(t)y^*(t+T_d)\}}{\frac{1}{M+T_d}\sum_{t=0}^{M+T_d-1}|y(t)|^2} \tag{5.11}$$

where $\Re\{.\}$ is the real part of a complex number, M is the number of observation, T_d denotes the number of symbols in an OFDM data block, and $M \gg T_d$. The distribution of r_i can be approximated for a low SNR in the absence of the knowledge of the true autocorrelation coefficient by [161]:

$$\begin{cases} H_0: & r_i \sim \mathcal{N}(0,\sigma^2) \\ H_1: & r_i \sim \mathcal{N}(\theta,\sigma^2) \end{cases} \tag{5.12}$$

where $\theta > 0$ and $\sigma^2 = \frac{1}{2M}$.

Subsequently, the MLE r_i needs to be quantized. Let d be the number of bits used for quantizing r_i to achieve the required local soft decision r_i^{su} and D be the corresponding number of the quantization levels, where $D = 2^d$. The *i-th* SU transmits a *d*-bit sequence S_i^{su} over a non-ideal reporting channel. Hence, due to channel errors, the received *d*-bit sequence at the FC S_i^{fc} might be different from the transmitted sequence S_i^{su}. The testing rule used to decide on the presence (H_1) or absence (H_0), of the PU signal, at the FC is based on the global test statistic [39]:

$$T = \sum_{i=1}^{N} r_n^{fc} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_{fc} \tag{5.13}$$

where the local soft decision corresponding to S_i^{fc} is the denoted by r_n^{fc} and the threshold η_{fc} is used for the global decision. The probability of detection $P_{d,ml}$ can be calculated by [50]:

$$P_{d,ml} = \mathrm{P}(T > \eta | H_1) + \gamma \mathrm{P}(T = \eta | H_1) \tag{5.14}$$

where η is local detectors threshold and γ is randomization parameter. The probability of error is given as follows [134]:

$$P_{E,ml} = \min[P_0 P_{f,ml}(\eta_{fc}) + P_1(1 - P_{d,ml}(\eta_{fc}))], \tag{5.15}$$

where P_0 and P_1 are the global probability of the PU signal absence and presence, respectively, and $P_{f,ml}$ is the global probabilities of false alarm.

5.3.3 The Optimal Entropy MLE Quantizer for CSS

The primary aim is to design an optimal quantizer that will preserve the MLE value with minimum quantization bits. Hence, the obvious choice is a quantizer that minimizes an output entropy distortion [56, 162]. The quantizers at each of the local sensors are assumed to be independent and identical. For each local SU, the thresholds for the quantization region are $t_i, i = 1, 2, ..., D$ and the quantization levels for each of the SU are denoted by $l_i, i = 1, 2, ..., D$.

5.3.4 Uniform Threshold Quantization

In general, MLE can be quantized by a uniform threshold quantization (UTQ) algorithm, which is the simplest and most commonly used quantization algorithm. It is straightforward to design and practical to implement [104].

Let a quantization region at each of the individual SUs of $(-\delta, \delta)$ be considered. The quantization interval $\Delta = \frac{2\delta}{D}$, which is the middle point between two neighbouring quantization levels. The value of δ is chosen to ensure that the decision for hypothesis H_1 is made if $r_i > \delta$ and decision for hypothesis H_0 if $r_i < -\delta$. When $\delta = 3\sigma$, the selected quantization region ensures that majority of the distribution region of r_i gets covered for hypothesis H_0. The quantization levels for the quantizer at the SUs are given by [104]:

$$l_i = -\delta + (i - 0.5)\Delta, \quad i = 1, 2, ..., D. \tag{5.16}$$

If $t_0, ..., t_D$ are the quantization region thresholds, then:

$$t_0 = -\delta, \quad t_D = \delta, \tag{5.17}$$

$$t_i = \frac{l_i + l_{i+1}}{2}, \quad i = 1, 2, ..., D\text{-}1 \tag{5.18}$$

5.3.5 Proposed Uniform Threshold Quantization

If a UTQ is considered as shown in Figure 5.2, where $D = 2$, the quantization level l_1 and l_2 each includes half of the distribution of r_i under H_0, respectively. Hence, for low values of D even at high SNR, the scheme may result in detection loss. The SUs ought to be able to keep the desired probability of false alarm even in the worst conditions. Therefore it is proposed that the quantization region is divided in such a way that the local threshold η for each local detector is the center of the quantization region. Hence, the proposed quantization region is $(-\delta, \eta)$ when taking each individual SU into consideration.

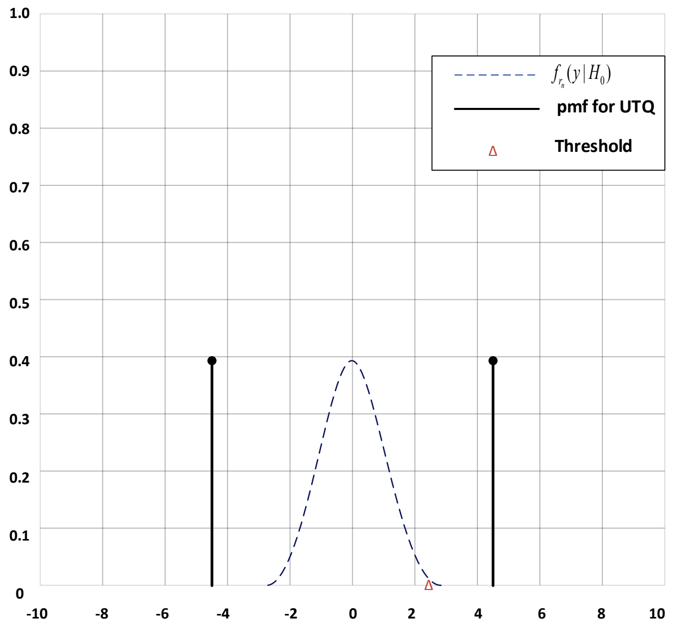

Figure 5.2 Uniform Threshold Quantization with quantization levels *D* = 2.

The quantization regions $(-\delta, \eta)$ are uniformly divided into $D/2$ regions, therefore, the quantization interval is given by:

$$\Delta = \frac{2(\eta + \delta)}{D} \tag{5.19}$$

If $t_0, ..., t_D$ are the quantization region thresholds with η as the centre, then:

$$t_0 = -\delta, \quad t_{D+1} = 2\eta + \delta, \tag{5.20}$$

$$t_i = -\delta + i\Delta \quad i = 1, 2, \ldots, D, \tag{5.21}$$

$$l_i = \frac{t_i + t_{i+1}}{2} \quad i = 1, 2, \ldots, D \tag{5.22}$$

For the proposed UTQ with $D = 2$ and $\alpha_{ml} = 0.01$ (the assumed best constraint false alarm rate), the quantization level l_i covers approximately 99% of the distribution of H_0 and l_2 covers the remaining approximately 1% of the distribution under H_0, as shown in Figure 5.3. When the proposed UTQ is compared to the original UTQ scheme there is an increase in the region of the distribution under H_1. This results in an improvement of the detection performance. The improvement depends on the choice of η.

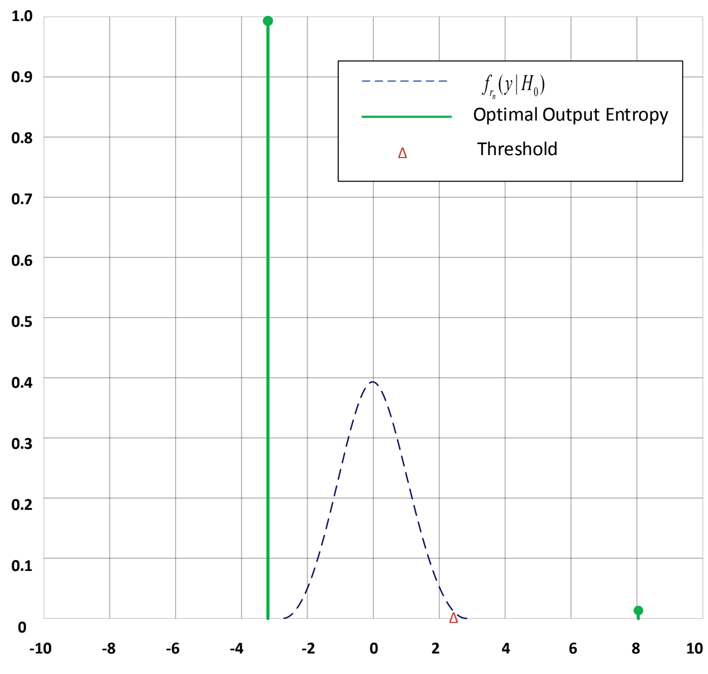

Figure 5.3 Proposed Uniform Threshold Quantization with quantization levels, $D = 2$

5.3.6 Threshold

The improvement in the probability detection lies on the selected threshold. For the proposed UTQ, the quantization regions are divided in such a way that the local threshold η for each individual SU are the centre of the quantization region. The improvement in the detection performance depends on the choice of η, The value of η can be optimized by properly formulating the optimization problem. The thresholds are chosen to preserve the required probability of false alarm α_{ml} and are given by:

$$\eta = \frac{\sqrt{2\sigma}}{erfc}(2\sigma_{ml}) \tag{5.23}$$

where *erfc* is the error function.

5.3.7 Optimal Entropy Quantizer

When considering a fixed quantization level, output entropy is a good theoretic criterion of quantizer trustworthiness [162]. In [162] a quantizer which maximizes the output entropy was proposed, it was shown to be approximately the same when compared to a minimum average entropy (MAE) quantization for certain types of signal distributions including a Gaussian distribution which is suitable in this section. The output entropy quantization scheme is less complex and more practical to implement than an optimal MAE quantization scheme [162]. For implementing an output entropy quantization, let the range of r_i under H_1 be split into D levels hence, the quantization levels have a value of $1/D$. Therefore, the probability mass function (PMF) for the quantized local soft decision r_i^{su} is given by [162]:

$$P\ (r_i^{su} = l_i) = \int_{t_{i-1}}^{t_i} f_{r_i}(y)dy = 1/D, \quad i = 1, 2, ..., D \tag{5.24}$$

where $f_{r_i}(.)$ denotes the PDF under H_0. Assuming $t_0 = -\infty$ and $t_i = \infty$, the rest of the thresholds t_i can be calculated for $i =$ 1, 2,..., $D-1$ from equation (5.24). The quantization level is the centroid region between the thresholds t_{i-1} and t_i is given by [162]:

$$l_i = \frac{\int_{t_{i-1}}^{t_i} x \cdot f_{r_i}(y)dy}{\int_{t_{i-1}}^{t_i} f_{r_i}(y)dy} \qquad i = 1,...,D \tag{5.25}$$

5.3.8 Proposed Optimal Output Entropy Quantization

The optimal output entropy, similar to the UTQ also has a poor performance for small values of D. Thus, a similar approach to the case of the UTQ is proposed. The quantization region $(-\delta, \eta)$ is split into $D/2$ levels. Each level has the same PMF value of $\frac{2F(\eta)}{D}$, where $F(.)$ is the cumulative distribution function (CDF) of r_i under H_0. Therefore, the PMF value for the quantized r_i^{su} is given as follows:

$$P\,(r_i^{su} = l_i) = \int_{t_{i-1}}^{t_i} f_{r_n}(y)dy = 2F(\eta)/D, \quad i = 1,...,D/2 \tag{5.26}$$

where $f_{r_n}(.)$ denotes the PDF under H_0. Assuming $t_0 = -\infty$ and $t_{D/2} = \eta$, the threshold $t_i, i = 1,2,...,\frac{D}{2}-1$, can be calculated from equation (5.26). The other $D/2$ levels are the mirror images of these levels with η as the center as follows:

$$t_i = 2\eta - t_{D-i}, \quad i = \frac{D}{2} + 1, 2, ..., D - 1$$
$$t_D = \infty. \tag{5.27}$$

The quantization level l_i is the centroid of the region between the thresholds t_{i-1} and t_i, which are calculated from (5.25) for $i = 1, 2, ..., D$

5.3.9 Simulation Results

This section is used to evaluate the performance of the proposed UTQ and optimal entropy quantization for MLE based CSS, where simulation results are shown to compare the proposed approach with other related approaches based on probability of detection in relation to SNR curves, and probability of error curves. The effects of different parameters on the proposed algorithms were examined, such as the quantization methods, number of quantization levels, channel availability and SNR values.

For the simulation in this chapter, the PU network is assumed to be a DVB-T2 signal [78], the bandwidth of the PU signal is 8 MHz and modulation type is QPSK. The number of samples corresponding to useful symbol length in an OFDM block $T_d = 32$ and CP length $T_c = 8$. The simulation is based on the Monte Carlo method in MATLAB with 100,000 iterations. AWGN and Rayleigh fading environments are considered. There are six SUs spread in the network to perform local spectrum sensing. Gray mapping is used between the *D* quantization levels and the *d*-bit sequences while the constraints on the probability of false alarm and the probability of missed detection for the CSS are $\alpha_{ml} = 0.01$ and $\beta_{ml} = 0.01$. A summary of the simulation parameters for analysing the proposed CSS algorithm's performance are outlined in Table 5.1.

Table 5.1 Simulation parameters for the MLE based CSS scheme.

Simulation Parameter	Value
PU bandwidth	8 MHz
Local sensing	25 μs
T_d	32
T_c	8
Channel condition	AWGN, Rayleigh
SNR range	-25dB to 0dB
Iterations	100,000
Number of SUs (N)	6
α_{ml}	0.01
β_{ml}	0.01
Mapping	Gray Mapping

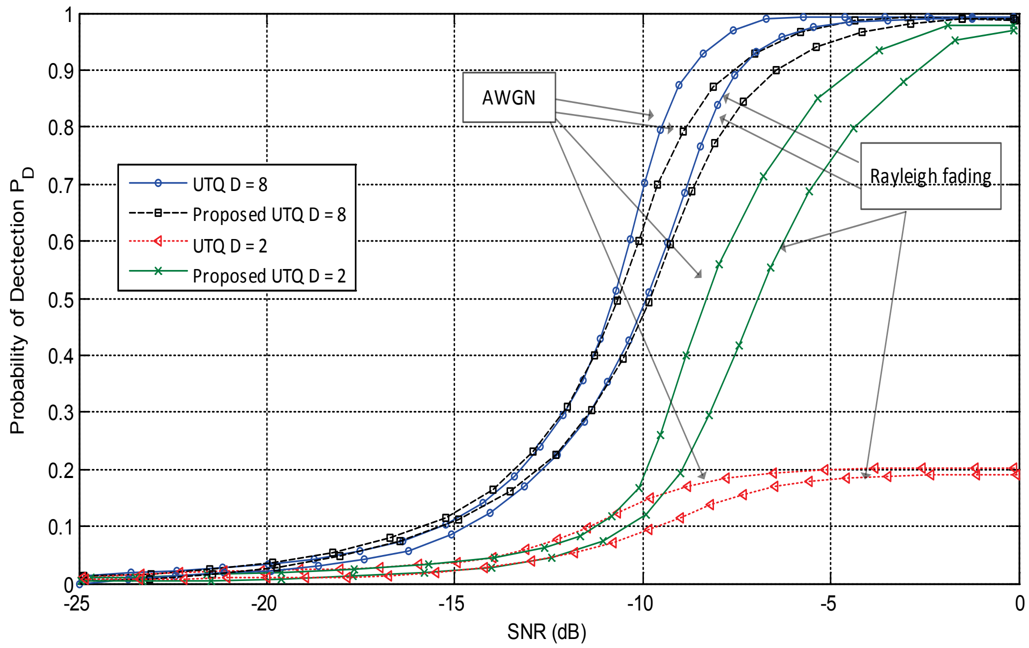

Figure 5.4 Probability of detection with different quanitization level values when SNR values at the SUs are changed from -25dB to 0 dB for a UTQ quantisation scheme.

Figure 5.4 presents probability of detection curves for a MLE based CSS as a function of SNR. The performance of a UTQ and the proposed UTQ quantisation scheme when the quantization levels D = 2 and D = 8 in are presented under AWGN and Rayleigh fading environments. The average SNR values at the six SUs are changed from -25dB to 0 dB. It can be observed that the detection performance for both the UTQ and the proposed UTQ quantisation schemes are similar when D = 8. However, at a lower value, when D = 2, there is a significant gain in the detection performance of the proposed scheme. For example, when the average SNR in the AWGN environments is -8dB and D = 8, the probability of detection of the UTQ scheme and the proposed scheme are approximately 0.89 and 0.95, respectively. However, when D = 2 under the same conditions the probability of detection of the UTQ scheme and the proposed scheme are approximately 0.18 and 0.52, respectively leading to an improvement of approximately 34%. A similar improvement of approximately 15% under Rayleigh fading conditions can be observed. Even for high SNRs, a probability of detection of 0.99 under the UTQ scheme cannot be achieved under the simulated conditions.

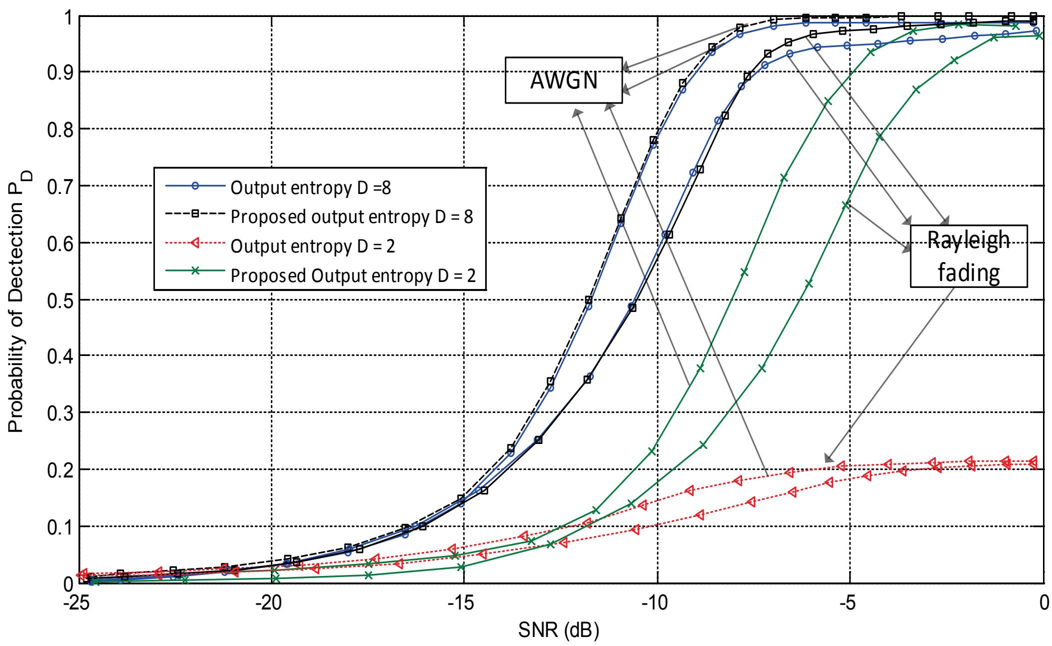

Figure 5.5 Probability of detection with different quantisation bits levels when SNR values at the SUs are changed from -25dB to 0 dB for an output entropy quantisation scheme.

In Figure 5.5, probability of detection curves for a MLE based CSS as a function of SNR are presented highlighting the performance of an output entropy quantisation and the proposed output entropy quantisation scheme, when the quantization levels D = 2 and D = 8 in both AWGN and Rayleigh fading environments. It can be observed that the detection performance for both the quantisation schemes are similar when D = 8. However, at a lower value, when D = 2, there is a significant gain in the detection performance of the proposed scheme. The observations are similar to that made regarding the quantisation schemes in Figure 5.4. When when D = 2 and the average SNR is -8dB, there is an improvement of approximately 20% and 14% under AWGN and Rayleigh fading conditions, respectively.

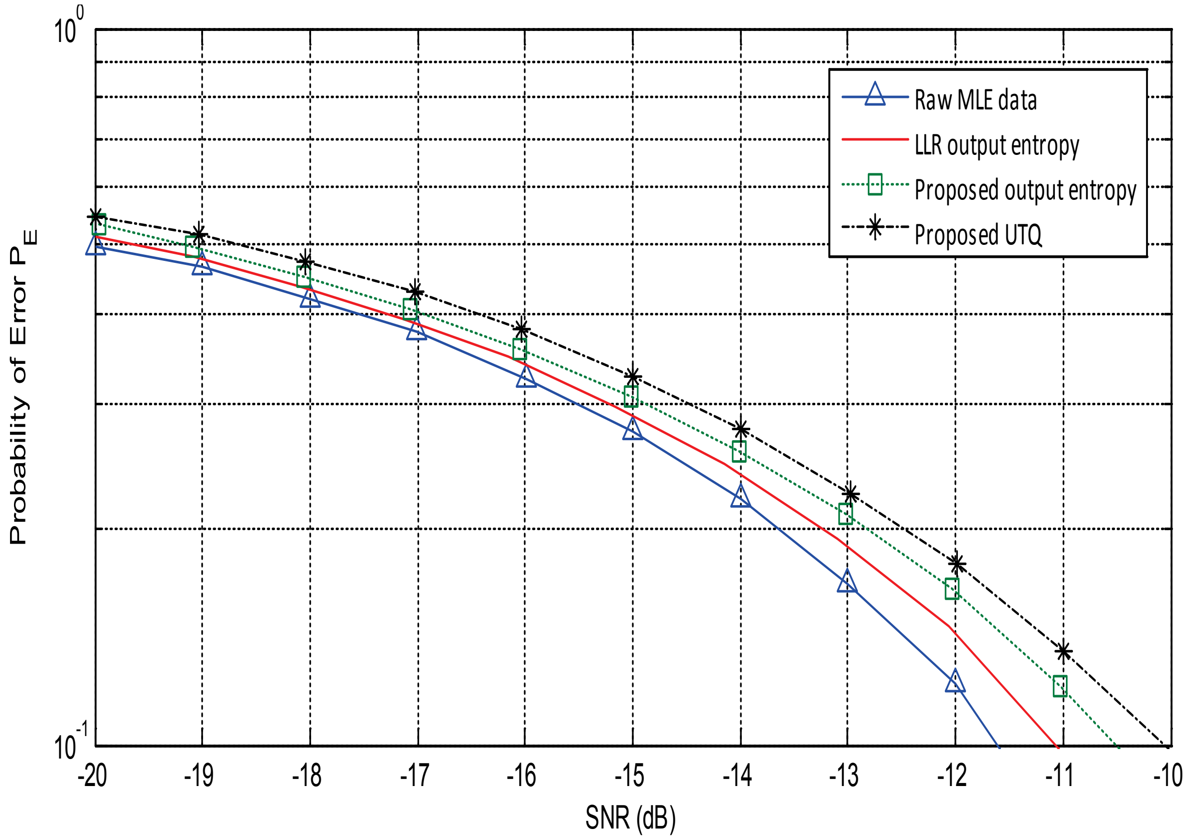

Figure 5.6 Probability of error for different quantisation based CSS schemes when values of SNR are changed from = -20 dB to-10 dB.

Figure 5.6 presents the probability of error curves for different quantisation based CSS schemes as function of SNR. The quantisation schemes considered are the proposed MLE based CSS using UTQ, the proposed MLE CSS using output entropy and a CSS LLR output entropy. The non-quantised MLE data are presented for comparison. Six different SUs are considered and the SNR values are changed from -20 dB to -10 dB. It is observed that the choice of quantization scheme affects the probability of error of the different CSS schemes. The proposed UTQ had the least performance. When compared to the LLR output entropy scheme the proposed output entropy performed slightly less. However, the proposed scheme gives a simple and practical implementation of CSS with negligible loss as compared to the optimal case of using quantized LLRs, which is vital in a practical scenario where the PU signal statistics are unavailable.

5.4 Evidence Theory based Cooperative Spectrum Sensing with Quantization in Cognitive Radio Networks.

An evidence based CSS quantisation scheme was proposed in chapter 4, however, the main drawback of the proposed scheme as well as other evidence based schemes such as [121] and [123] are the bandwidth required for transmitting the sensing data to the FC. The schemes transmit not just the sensing results but also the credibility and other related information to the FC. Thus, the bandwidth requirement will be extremely large when the number of SU increase leading to longer sensing times. It is advantageous to have shorter sensing and longer data times [29], if the sensing time is too long, the data transmission duration reduces thereby reducing the throughput of the SUs and underutilising the frequency spectrum. Evidence based CSS quantisation scheme increase sensing reliability and SU agility hence, in this section a quantization method to reduce the transmission data using evidence theory is proposed to reduce the transmission data from the SUs to the FC using a LLR output entropy quantisation scheme similar to the MLE output entropy scheme in section 5.3.

5.4.1 System Model

A CSS scheme which is similar to that in section 2.18 is considered, where the average SNR of the PU signals received at the SUs are assumed to be identical. The Evidence-based CSS scheme shown in Figure 5.7 which is similar to that in Figure 4.2 is considered. The CSS process can be categorised into two stages: Local sensing at the SUs and final decision at the FC.

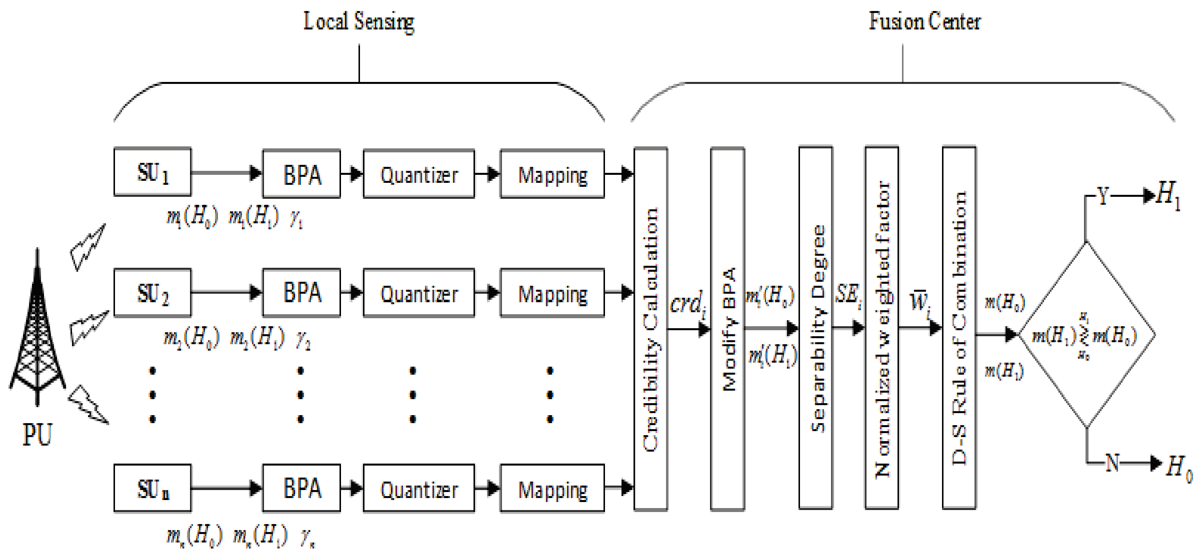

Figure 5.7. Evidence-based Decision Fusion Scheme for CSS with quantisation.

In the local sensing phase, each SU listens for the PU signal and measures the SNR of the channel using an energy detector as described in section (2.18.2). The received PU signal and the measured average SNR are used to estimate the BPA values as described in chapter 4. The BPA functions are defined as a form of a CDF equations (similar to equation (4.14), (4.15) and (4.16) :

$$H_0 : m_i\left(y_{E_i} \mid H_0\right) = \int_{y_{E_i}}^{+\infty} \frac{1}{\sqrt{2\pi\sigma_{0i}^2}} \exp\left(-\frac{\left(y_{E_i} - \mu_{0i}\right)^2}{\sigma_{0i}^2}\right) dy \tag{5.28}$$

$$H_1 : m_i\left(y_{E_i} \mid H_1\right) = \int_{-\infty}^{y_{E_i}} \frac{1}{\sqrt{2\pi\sigma_{1i}^2}} \exp\left(-\frac{\left(y_{E_i} - \mu_{1i}\right)^2}{\sigma_{1i}^2}\right) dy \tag{5.29}$$

$$m_i(H_1) + m_i(H_0) + m_i(\Omega) = 1 \tag{5.30}$$

where H_0 and H_1 are correspond to hypotheses of absence and presence of the PU signal, y_E can be modeled as a Gaussian random variable under both hypotheses H_0 and H_1, with mean μ_0, μ_1 and variance σ_0^2, σ_1^2, respectively and $m_i\left(y_{E_i}\middle|H_0\right)$ and $m_i\left(y_{E_i}\middle|H_1\right)$ are the BPAs of hypothesis H_0 and H_1 of the i-th SU, respectively. Ω denotes either hypotheses is true.

The estimated BPAs are then transmitted to the FC where the credibility of SUs BPAs evidence (equation 4.24) and dissociability degree measure (equation 4.27) of the SUs are calculated, in the form of a weighted averaging factor (equation 4.31) which is then taken into account when making the final decision at the FC. According to the modified combination rule as described in section (4.7), the combination of the BPAs can be obtained by [145]:

$$m(H_0) = \overline{m}_1 \oplus \overline{m}_2 \oplus \ldots \oplus \overline{m}_n(H_0) = \frac{\sum_{A_1 \cap A_2 \cap \ldots A_n = H_0} \prod_{i=1}^{n} \overline{m}_i(A_i)}{1-K} \tag{5.31}$$

$$m(H_1) = \overline{m}_1 \oplus \overline{m}_2 \oplus \ldots \oplus \overline{m}_n(H_1) = \frac{\sum_{A_1 \cap A_2 \cap \ldots A_n = H_1} \prod_{i=1}^{n} \overline{m}_i(A_i)}{1-K} \tag{5.32}$$

$$k = \sum_{A_1 \cap A_2 \cap \ldots A_n = \varnothing} \prod_{i=1}^{n} \overline{m}_i(A_i) \tag{5.33}$$

where A_i is one element of the set $\{H_1, H_0, \Omega\}$. The final decision equation (4.35) can be formulated by:

$$\eta_{fc} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \tag{5.34}$$

where $\eta_{\text{total}} = \frac{m(H_1)}{m(H_0)}$ is the global combination ratio and λ is a threshold that enables control of the false alarm and detection probability according to the requirements of the FC.

5.4.2 Local Soft Decision Log Likelihood Ratio

In the evidence based CSS scheme described in chapter 4, the SUs send their BPA values of their hypotheses to the FC instead of making a local hard decision. At least two elements have to be transmitted to the FC. After combining all of the BPAs from the SUs by the combination rule, the FC makes a decision based on the ratio between $m(H_1)$ and $m(H_0)$. Therefore, the ratio plays a very important role in the global decision. Therefore, the ratio

$$\eta_i = \frac{m_i(H_1)}{m_i(H_0)} \tag{5.35}$$

is assumed to be the local soft decision of the *i*-th SU. For computational convenience and the overall bandwidth reduction it is proposed to use a log likelihood ratio hypothesis testing at the SU as presented in section 5.4. The likelihood ratio is given by:

$$\eta_i^{\log} = \log \frac{m_i(H_1)}{m_i(H_0)} \tag{5.36}$$

is the local soft decision or the decision credibility of the *i*–th SU.

5.4.3 Local decision Quantization

The major drawback of an evidence based CSS data fusion is the bandwidth required for the reporting channel when the number of SUs are large, the bandwidth for reporting their sensing results to the FC will be huge and with an increase in bandwidth of the reporting reduces the utilizing of the spectrum because the sensing time increases. Hence, in order to reduce the overhead of the network, a local decision quantization methods are proposed here that enable the SU to only send a minimal amount of bits to the local sensing decision to the FC. The quantizers at each of the local sensors are assumed to be independent and identical. For each local SU, the thresholds for the quantization region are $t_i, i = 1, 2, ..., D$ and the quantization levels for each of the SU are denoted by $l_i, i = 1, 2, ..., D$.

5.4.4 Uniform threshold Quantization for LLR

The LLR can be quantized by a UTQ algorithm, which is the simplest and most commonly used quantization algorithm. It is straightforward to design and practical to implement [104]. Similarly to section (5.2), where a UTQ scheme was proposed to quantizer a general MLE statics, a similar scheme is employed. Instead of the MLE statics, the LLR of the local credibility in a logarithmic value $\eta_i^{\log} = \log(\eta_i)$ is quantized to a multi-bit level. Let *d* be the number of bits used for quantizing $\eta_i^{\log}$ and D be the corresponding number of the quantization levels, where $D = 2^d$. For simplicity, let $\eta_i^{\log} \in \Re_i$ and $\Re_i$ denotes the quantization region.

Instead of using a normal UTQ which suffers from detection loss at low values of D even at high SNR, the proposed UTQ (section 5.3.5) is considered, that is, the quantization region is divided in such a way that the local threshold η_{LT} for each local detector is the center of the quantization region.

Hence, the proposed quantization region is $(-\delta, \eta_{LT})$ when taking each individual SU into consideration. The quantization regions $(-\delta, \eta_{LT})$ are uniformly divided into $D/2$ regions, therefore, the quantization interval is given by:

$$\Delta = \frac{2(\eta_{LT} + \delta)}{D} \tag{5.37}$$

If $t_0, ..., t_D$ are the quantization region thresholds with η_{LT} as the centre, then:

$$t_0 = -\delta, \quad t_{D+1} = 2\eta_{LT} + \delta, \tag{5.38}$$

$$t_i = -\delta + i\Delta \quad i = 1, 2, ..., D, \tag{5.39}$$

$$l_i = \frac{t_i + t_{i+1}}{2} \qquad i = 1, 2, ..., D \tag{5.40}$$

The value of δ is chosen to ensures that the decision for hypothesis H_1 is made if $\Re_i > \delta$ and decision for hypothesis H_0 if $R_i < -\delta$. When $\delta = 3\sigma$, the selected quantization region ensures that majority of the distribution region of R_i gets covered for hypothesis H_0.

5.4.5 Output Entropy quantization for LLR

Designing an optimal quantizer that will preserve the MLE value with minimum quantization bits is imperative to minimize overhead bandwidth while getting detection performance high. Hence, the obvious choice is a quantizer that minimizes an output entropy distortion [56, 162]. The output entropy quantization scheme is less complex and more practical to implement than an optimal MAE quantization scheme [162]. Hence, similar to section (5.4.2) an output entropy scheme is used to quantize the LLR.

The optimal output entropy, similar to the UTQ also has a poor performance for small values of D. Thus, a similar approach to the case of the UTQ is proposed. That is, the quantization region is divided in such a way that the local threshold η_{LT} for each local detector is the center of the quantization region. The quantization region $(-\delta, \eta_{LT})$ is split into $D/2$ levels. Each level has the same PMF value of $\frac{2F(\eta_{LT})}{D}$, where $F(.)$ is the cumulative distribution function (CDF) of $\Re_i$ under H_0. Therefore, the PMF value for the quantized $\Re_i$ is given follows:

$$P\ (\Re_i = l_i) = \int_{t_{i-1}}^{t_i} f_{R_i}(y)dy = 2F(\eta_{LT}) / D, \quad i = 1,...,D/2 \tag{5.41}$$

where $f_{\Re_i}(.)$ denotes the PDF under H_0 . Assuming $t_0 = -\infty$ and $t_{D/2} = \eta_{LT}$, the threshold $t_i, i = 1, 2, ..., \frac{D}{2} - 1$, can be calculated from equation (5.26). The other $D/2$ levels are the mirror images of these levels with η_{LT} as the center as follows:

$$\begin{aligned} & t_i = 2\eta_{LT} - t_{D-i}, \quad i = \frac{D}{2} + 1, 2, ..., D - 1 \\ & t_D = \infty. \end{aligned} \tag{5.42}$$

The quantization level l_i is the centroid of the region between the thresholds t_{i-1} and t_i, which are calculated by:

$$l_i = \frac{\int_{t_{i-1}}^{t_i} x \cdot f_{R_i}(y)dy}{\int_{t_{i-1}}^{t_i} f_{R_i}(y)dy} \qquad i = 1, ..., D \tag{5.43}$$

A summary of the steps required to quantizer the LLR of the evidence based CSS is shown in

Table 5.2 Summary of steps for quantization the LLR statistic.

Summary of the steps for quantization the LLR statistic	
***Step 1*:**	Choose between a UTQ or an output entropy quantizer based on the CR network requirements.
***Step 2*:**	Compute local spectrum sensing statistic using energy detector.
***Step 3*:**	SUs compute the BPAs of H_0 , H_1 and the decisions credibility $\eta_i^{\log}$.
***Step 4*:**	The decisions credibility $\eta_i^{\log}$ is quantized based on the quantizer chosen in ***Step 1.***
***Step 5*:**	The output which is a the multi-bit local decision will be transmitted to the FC.
***Step 6*:**	The value of the decisions credibility $\eta_i^{\log}$ is retrieved.

5.4.6 Data Fusion centre

The entire system of the proposed CSS utilizing quantization data is shown in Figure 5.7, the proposed scheme included two phases, the local sensing phase and the fusion phase. The main difference is that the SUs will report to the FC a quantized decision credibility ratio instead of transmitting raw BPAs as in the chapter 4. This evidently reduces the reporting channel transmission overhead. In the fusion phase at FC, it is assumed that the decision credibility values of each SU will be retrieved by a de-quantization process. Similar to sections (4.3) and (4.4), the next step is to calculate the credibility degree of the de-quantized data using equations (5.44) - (5.45). The BPAs dissociability degree can then be calculate using equation (4.27). The weight factor using equation (4.29) is determined. Finally, combination using DS theory rule of combination decision is made equations (5.31) – (5.33) and a final decision is made by equation (5.34).

5.4.7 Simulation Results

This section is used to evaluate the performance of the proposed evidence based CSS quantization scheme, where simulation results are shown to compare the proposed approach with other related approaches based on the receiver operating characteristic (ROC) and probability of error curves in relation to SNR curves. The effects of different parameters on the proposed algorithm were examined, such as the SUs with independent channels, channel availability and different values of the SNR. For the simulation in this chapter, the PU network is assumed to be a DVB-T2 signal [78], the bandwidth of the PU signal is 8 MHz and modulation type is QPSK. The average occupancy rate for the PU is set to 50%, i.e. the probability of presence and absence of the PU signal is fixed to an equal probability (0.5), respectively. The simulation is based on the Monte Carlo method in MATLAB with 100,000 iterations. Rayleigh fading channels are considered, there are six SUs spread in the network to perform local spectrum sensing. A summary of the simulation parameters for analysing the developed CSS algorithm's performance evaluation are shown in Table 4.1

Table 5.3 Simulation parameters for the evidence based CSS quantization

Parameter	Value
PU bandwidth	8 MHz
Local sensing	25 μs
Frame length	60
FEC blocks per frame	50
Channel condition	Rayleigh
SNR range	-10dB to -20dB
Iterations	100,000
Number of SUs	6
PU average occupancy rate	0.5 (50%)

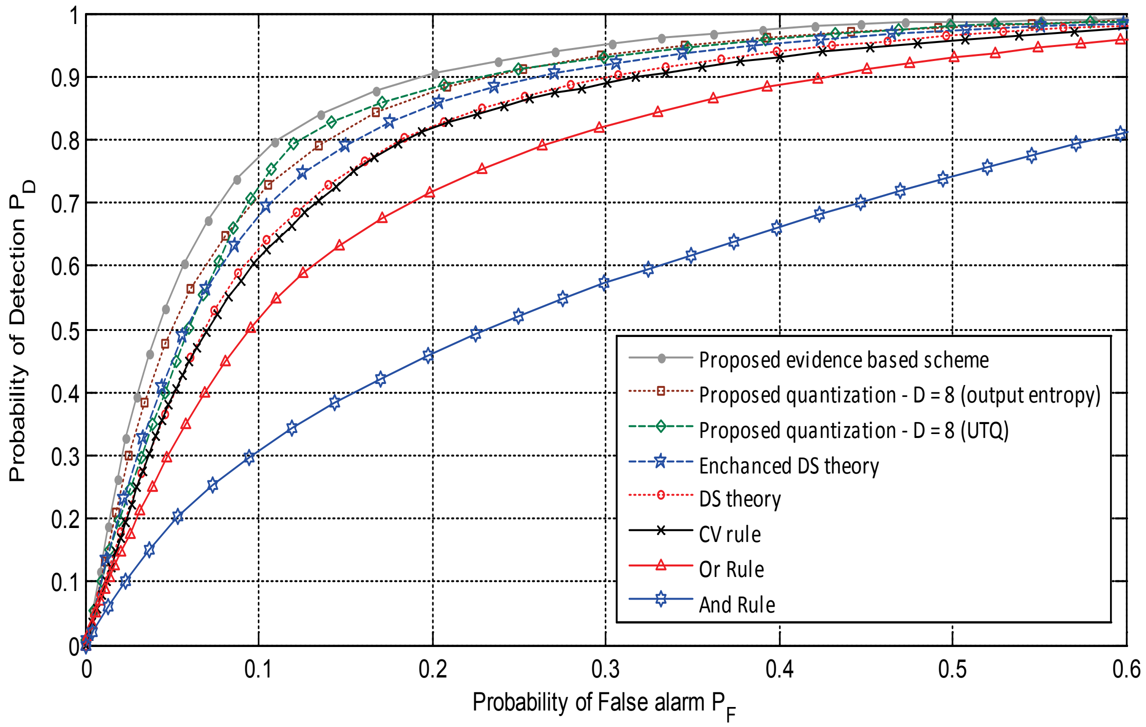

Figure 5.8 ROC of different CSS Schemes under with various channel conditions with different average SNR over Rayleigh fading.

Figure 5.9 show the ROC curves, highlighting the performance of the proposed evidence based CSS UTQ output entropy and UTQ schemes under Rayleigh fading channels. A sensing time of 25 μs was considered. There are six SUs considered in the system. A practical scenario has been considered, where the six distributed SUs endure different channel conditions. The average received signal condition at the six SUs are respectively -10 dB, -12 dB, -14 dB, -16 dB, -18 dB and -20 dB. Figure 5.9 show the ROC curves of the AND rule, OR rule, CV rule [101] which are considered for reference purposes as conventional traditional as hard decision CSS scheme. The sensing performance of these convention group is obviously the lowest one, because they have the lowest communication overhead requirement, i.e., only 1-bit hard decision for CSS. The ROC curves of the AND rule, OR rule are lower than the CV rule [101], which is the optimal 1-bit hard decision fusion rule. The proposed evidence based CSS (in chapter 4), DS theory fusion [121] and enhanced DS theory fusion [123], require raw sensing data to be sent to the FC and hence, have higher values of the detection probability for a specific value of the false alarm probability. The ROC curves for the UTQ and the output entropy quantization CSS scheme show a minimal quantization degradation in respect to the evidence based CSS, but they outperform the other schemes. The observations indicate the effectiveness of the proposed evidence based method in chapter 4.

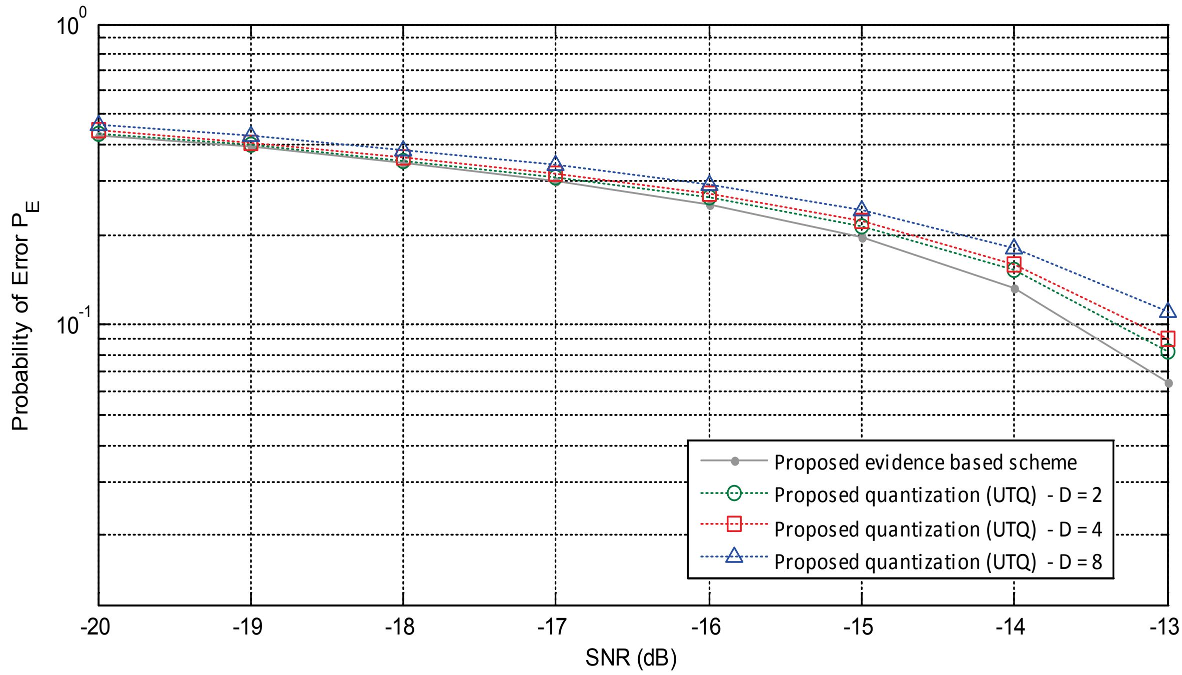

Figure 5.9 Probability of Error performances for evidence based CSS UTQ for different *D* values

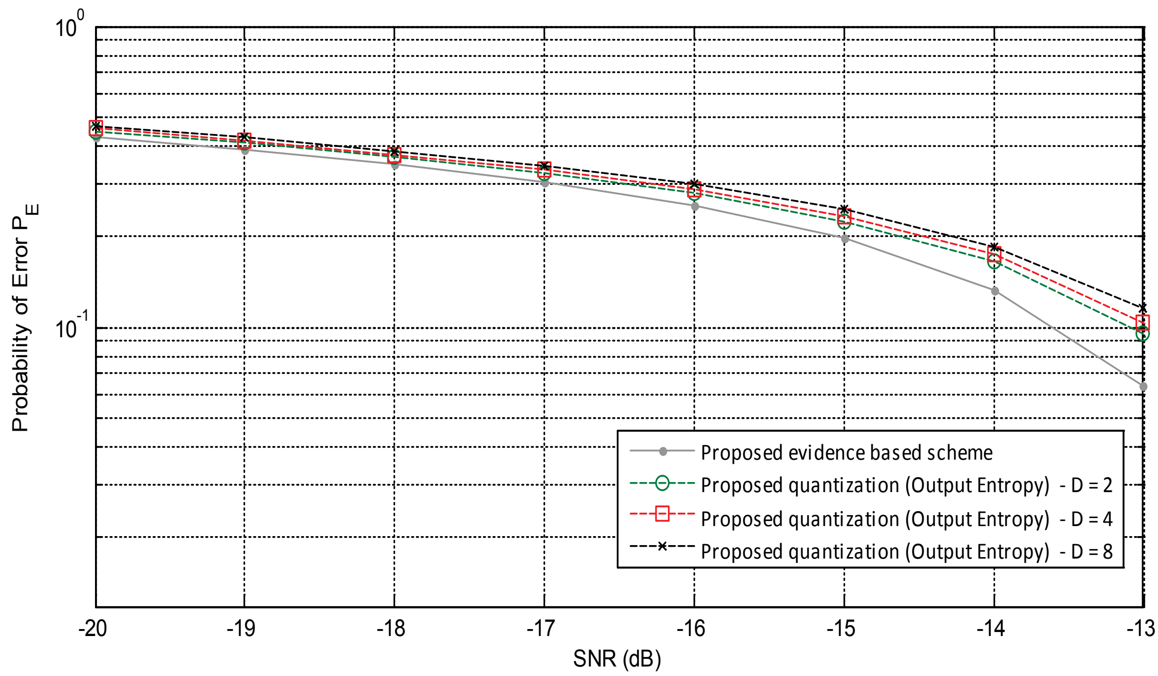

Figure 5.10 Probability of Error performances for evidence based CSS output entropy quantization for different *D* values

Figure 5.9 and Figure 5.10 presents the probability of sensing errors for bot the UTQ and the output entropy quantization scheme for CSS different number of quantization levels *D*. Six SUs are considered in the system, with a sensing time of 25 μs. To observe the effect of the SNR on the sensing performance of the proposed scheme, the six SUs in the CR network are assumed to have an identical value of PU's signal SNR which is changed from -20 dB to -13 dB. The probability of error is computed by [134]

$$P_E = \min[P_0 P_f(\eta_{fc}) + P_1(1 - P_d(\eta_{fc}))] \tag{5.46}$$

Where η_{fc} is the global threshold, P_0 and P_1 are the probability of the PU signal absence and presence, respectively, and $P_{f,ml}$ is the global probabilities of false alarm. Figure 5.9 and Figure 5.10 show that the as expected that the error probabilities of the proposed quantization based CSS schemes decrease along with the increase of quantization levels. It is observed that the sensing error probabilities decrease as the signal SNR values increase. When comparing Figure 5.9 to Figure 5.10, it can be observed that at a low quantisation level *D*, the probability of error of the UTQ is slightly less than the output entropy.

5.5 Conclusion

In this chapter, quantization enhancement schemes for CSS for CR networks have been proposed. The first scheme proposed was a MLE based CSS scheme using a UTQ and an output entropy quantisation scheme.

For the MLE based CSS, the local decisions are assumed to be the quantized values of the MLE outputs of the PU signal, as opposed to the simple hypothesis test (LLR) in which the PDFs under both hypotheses are completely known. Hence the designed scheme could be used in a practical environment where there is knowledge of the PU signal. The primary aim was to design an optimal quantizer that will preserve the MLE value with minimum quantization bits. Hence, the obvious choice was a quantizer that minimizes an output entropy distortion. For low values of quantization levels even at high SNR, the scheme may results in detection loss. The SUs ought to be able to keep the desired probability of false alarm even in the worst conditions. Therefore it was proposed that the quantization region is divided in such a way that the local threshold η for each local detector is the center of the quantization region. A quantizer which maximizes the output entropy was proposed, the output entropy quantization scheme is less complex and more practical to implement than an optimal MAE quantization scheme. The optimal output entropy, similar to the UTQ also had a poor performance for small quantization levels values. Thus, a similar approach to the case of the UTQ was proposed. Simulation results showed that the proposed scheme had significant improvement on detection performance at low quantization levels, and there were improvements of approximately 15% under Rayleigh fading conditions could be observed. When compared to the LLR output entropy scheme the proposed output entropy performed slightly less. However, the proposed scheme gives a simple and practical implementation of CSS with negligible loss as compared to the optimal case of using quantized LLRs

The next quantization scheme proposed was an evidence based CSS quantization scheme. It incorporated the proposed UTQ and output entropy quantization algorithm. The proposed scheme included two phases, the local sensing phase and the fusion phase. The main difference with chapter 4 was that the SUs will report to the FC a quantized decision credibility ratio instead of transmitting raw BPAs. This evidently reduced the reporting channel transmission overhead. In the fusion phase at FC, it was assumed that the decision credibility values of each SU were retrieved by a de-quantization process. A credibility and dissociability degree of the BPAs were calculated and the weight factor determined. Finally, DS theory rule of combination was used to combine the final decisions. The simulation results illustrated that the scheme can obtain high detection rate combination as well as a reduced reporting channel bandwidth. The ROC curves for the UTQ and the output entropy quantization CSS scheme showed minimal quantization degradation in respect to the evidence based CSS, but they outperform the other schemes such as the AND rule, OR rule, CV rule, DS theory fusion and enhanced DS theory. In this chapter, quantisation soft decision in CSS was focused on to reduce the demand on the reporting channel. The simulation results showed that the proposed scheme yields a significant improvement in the detection probability as well with minimal loss of information.

6 Conclusion and Future work

This chapter summarizes the main contributions of this thesis and discusses interesting and important future research directions.

6.1 Conclusion

The rapid increasing interest in wireless communication has led to the continuous development of wireless devices and technologies. The modern convergence and interoperability of wireless technologies has further increased the amount of services that can be provided leading to the substantial demand for access to the radio frequency spectrum in an efficient manner. With this growth, the accessibility of high quality wireless frequency spectrum has become severely limited. This has led to a widespread belief that the spectrum frequency is a scarce resource and it is difficult to allocate spectrum frequency for new applications. However, real-time spectrum measurements have shown that the frequency spectrum is inefficiently utilised consequently, the real challenge is not the frequency spectrum scarcity but the inefficient spectrum utilization. CR a new concept of reusing licensed spectrum in an unlicensed manner promises to overcome over the evident spectrum underutilised caused by the inflexible spectrum allocation. However, a single sensing node in facing propagation environments may lead to the hidden terminal problem. When such a situation occurs a SU has to differentiate between a spectrum hole, where there is no primary signal, and a deep fade, where it is difficult to detect the PU signal. In order to minimise the hidden terminal problem, research efforts have concentrated on CSS where different SU work in partnership to detect the presence of a PU and provides diversity gains to tackle the fading and shadowing effects.

This thesis is devoted to the optimization of CSS schemes in CR. Overviews were presented on different formulate problems related to the DSA in CR. A review of the fundamentals of spectrum sensing and state of the art spectrum sensing algorithms such as matched filter, energy detection and feature detection were analysed systematically and their performance criteria discussed. An energy detection sensing algorithm due to its low complexity was used in most parts of this thesis. CSS i.e. collaboration between multiple SU was discussed and has been shown as a way to improve the underutilization of the frequency spectrum when the hidden terminal problem occurs. This approach led to the problem formulation of the thesis and the general system model and fundamentals used in the thesis were presented.

An AF based cooperative sensing scheme with double energy thresholds was proposed in order to improve local sensing performance as well as global sensing performance. It was identified that most works do not consider a direct link between the PU and FC. Thus they ignore the benefits that can be extracted when the PU is involved in cooperation. It was shown that combining an AF protocol and double threshold detector, the performance of the probability of detection was increased both in a single relay and multiple relay scenario compared to that of conventional energy detection. The results indicated that the proposed AF double threshold CSS scheme has a significant improvement in terms of required average SNR for detection which increased as the number of relays increased. It was observed that the detection probability of the proposed AF double threshold CSS scheme increased when the direct link was incorporated and also as the number of cognitive relays increased, the detection probability increased. The scheme significantly reduced the error of missed detection and increased the probability of detection. The simulation results demonstrated the proposed AF CSS “soft 1-bit” double threshold had a much better detection performance of up to approximately 40% than the other methods. Also, simulation results demonstrated that at a lower SNR the probability of detection for a "soft 1-bit" double threshold, compared to that of the conventional ED and double threshold ED performance improved under the same conditions (approximately 11% detection increase), but this improvement slightly decreases (approximately 4% detection increase) as the SNR increases but is still significantly higher than the other two schemes.

However, the main drawback of the proposed scheme as well as other CSS in literature is that under practical conditions, the differences in local sensing reliability between the SUs are not considered. The next part of the thesis aimed to sensing reliability and increase detection performance. Therefore, an evidence based CSS scheme was presented. Under practical conditions, the combination of conflicting evidences with the classical Dempster Shafer theory (DS theory) rule may produce counter-intuitive results when combining the SUs sensing data evidence leading to poor CSS performance. In order to overcome and minimise the effect of conflicting data, and to enhance performance of the CSS system, a novel evidence-based decision fusion scheme CSS is proposed in this chapter. The approach is based on the credibility of evidence from the SUs sensing decision, which represents the similarity or the relation among the different SUs sensing data evidence, and a dissociability degree measure which indicates the quality or clarity of the SUs sensing data evidence. Furthermore, a weighted averaging factor determined by the credibility and dissociability of the SU sensing data evidence is proposed. Results have shown that the proposed scheme utilises the advantages of evidence which does not requires cohrent detection of the PU signal. It also showed that the proposed scheme can achive an improved gain of combination for CSS than other rules such as the "Or"rule, And" rule, and the "CV" rule during specific practical cases. Simulation results showed that the missed detection probability of the proposed scheme decreased by approximately 7% when compared to the enhanced DS theory fusion. Two important design criteria for CSS were focused on, which are the sensing reliability, and SU agility. The simulation results showed that the proposed scheme yields a significant improvement in the detection probability as well as a considerable reduction in the missed detection probability without any prior knowledge of the primary system by utilising DS theory. However, the main drawback of the proposed scheme as well as other soft data fusions (including the CSS scheme used in chapter 3) are the bandwidth required for transmitting the sensing data. Hence, in the next part of the thesis of quantisation in CSS is investigated.

The final part of this thesis focused on the quantization to reduce the reporting bandwidth channel of a CSS scheme. For the MLE based CSS, the local SU decisions are quantized and used as the soft decision statistic for CSS. It is a simple non-complex scheme with minimal loss as compared to the optimal Lloyd-Max based LLR. This is vital in a practical scenario when the PU signal information is unknown. Simulation results showed that the proposed scheme had significant improvement on detection performance at low quantization levels, and there were improvements of approximately 15% under Rayleigh fading conditions could be observed. When compared to the LLR output entropy scheme the proposed output entropy performed slightly less. However, the proposed scheme gives a simple and practical implementation of CSS with negligible loss as compared to the optimal case of using quantized LLRs. The evidence based scheme used the output entropy quantization algorithm to quantize the local sensing decision and send the decision to the FC to be combined using the proposed evidence based CSS scheme from chapter 4. The simulation results showed that the proposed scheme yields a significant improvement in the detection probability as well with minimal loss of information.

6.2 Future work

CR offers the promise of being a disruptive technology innovation that will enable the future wireless world. The rapid increase of wireless technologies is expected to increase the demand for radio spectrum by a large scale over the next decade. This quandary must be addressed through technology and regulatory innovations for significant improvements in spectrum efficiency and increased robustness of wireless devices. CR network represent a hypothesis shift in both radio and networking technologies, with the possibility to provide major gains in performance and spectrum efficiency. On the other hand, even as cognitive radio platforms have started to emerge, significant innovative research work is required to address the many technical challenges of CR networking. These include spectrum sensing, cooperative communications, incentive mechanisms, CR architecture and protocol design, CR security, CR system adaptation algorithms and emergent system behaviour.

In this thesis, the focus was on four CSS problems which were diversity performance, detection accuracy performance, low computational complexity, and channel bandwidth. There are other research problems in CSS which are covered in the chapter 2 such as security, delay, optimal SU number, energy saving and detection range. The research was investigated for a relay assisted cooperation and a centralised cooperative model. Also, other models mentioned in chapter 2 can also be researched on the formulated problems in this thesis. The spectrum sensing technique focused on was energy detection due to its low computational complexity. However, all the schemes developed can be implemented with other sensing techniques such as match filter, autocorrelation etc. Research in wireless communications is huge and has endless possibilities. Focusing on the major problem issues covered in this thesis. There are other research problems which can be achieved in various interesting ways.

6.2.1 Space-Time Coding for Cooperative Spectrum Sensing

In this thesis, a low complex cooperative transmission protocol was used in a relay based CSS scheme to transfer the sensing information to the FC to obtain diversity gain and improve sensing detection. To further improve the diversity gain of a relay-based CSS different diversity schemes such as space-time coding can be used to achieve spatial diversity. Assuming the local spectrum has been completed at the two relays described in chapter 3 and the local sensing decision are denoted by X_1 and X_2. Instead of transmitting D_1 and D_2 to the destination, the two SU coordinated to form a transmit cluster in which space-time block coding can be applied to form a transmit cluster. To carry out this research, it has to be assumed that the two SU send their information to each other. Other space-time block codes such as distributed spaced time block codes can also be researched to increase diversity. Another research area to be considered in this area is censor and relay scheme.

6.2.2 Evidence based Weighted Local Sensing

In this thesis, the work focused on optimising a DS-theory based CSS. In order to overcome and minimise the effect of conflicting data, and to enhance performance of the CSS system, a novel evidence-based decision fusion scheme CSS was proposed. The approach is based on the credibility of evidence from the SUs sensing decision, which represents the similarity or the relation among the different SUs sensing data evidence, and a dissociability degree measure which indicates the quality or clarity of the SUs sensing data evidence. An evidence fusion scheme was used to find the conflicting data at the FC redistribute and combine the conflicting mass based on weights. One combination rule cannot be said to be the best one. All alternative combination rules are rational and depend on the specific application and environment. The work can be further extended by using the evidence based scheme to generate the weight factors in the discounting of sources of evidence at the local SUs to derive more reasonable combined evidences.

6.2.3 Adaptive and Prior Quantisation for Cooperative Spectrum Sensing

In this thesis, the three quantisation methods designed where applied for MLE and the BPA ratio. Further research can be considered to quantize the actual sensing data measurement level. In this thesis, only the SU data being forwarded to the FC was quantised. The information sent form the FC to SU can also be quantized to reduce the time it takes to report to the SU hence increasing sensing time. Adaptive quantization method can be designed so that the SU can send prior information about the channel state to each SU before transmission. In the evidence based quantisation scheme, a LLR was used which assumed all the information about the PU was known. A MLE used in section 5.2 can be implemented in the evidence based scheme using a composite hypothesis.

6.2.4 Security: Primary User Emulation Attack

Sensing a frequency band requires energy, time and financial cost. Hence, SU have a motivation to sense for a shorter duration. The resource allocation of the vacant frequency bands is based on SU sensing quality. Therefore, there is an incentive for malicious users to fake the detection results. The presence of un-trusted SU has been shown to degrade cooperative sensing performance. PU emulation attack, i.e., the attacker emulates the primary user for resisting the secondary access of SU is an area that needs to be researched. This kind of attack will reduce the exploitation of the vacant spectrum band. However, it can be detected by the combination of a spectrum sensing scheme and localization algorithm. Consequently, this can be a future research direction. A secure CSS sensing scheme based on chapter 4 taking advantage of the reliability statistic assigned to each SU can be researched.

REFERENCES

[1] ITU World Telecommunication/ICT Indicators database, "ICT Facts and Figures (2015)," *International Telecommunication Union*, April 2015.

[2] G. Yang *et al.*, "Cooperative Spectrum Sensing in Heterogeneous Cognitive Radio Networks Based on Normalized Energy Detection," *IEEE Transactions on Vehicular Technology*, Vol. 65, No. 3, pp. 1452-1463, March 2016.

[3] Roke Manor Research Limited. "United Kingdom Frequency Allocation Chart," January 2015. [Online]. http://www.extremetech.com/wpcontent/uploads/2013/01/uk-spectrum-allocation-chart1.jpg. [Accessed: 7 July, 2016].

[4] Federal Communications Commission Spectrum Policy Task Force, *"Report of the Spectrum Efficiency Working Group,"* Technical Report, Rep. ET Docket 02-135, November 2002.

[5] D. Cabric *et al.*, "Implementation Issues in Spectrum Sensing for Cognitive Radios," in *Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers*, pp. 772-776, November 2004.

[6] V. Valenta *et al.*, "Survey on Spectrum Utilization in Europe: Measurements, Analyses and Observations," in *Cognitive Radio Oriented Wireless Networks & Communications (CROWNCOM), 2010 Proceedings of the Fifth International Conference on*, pp. 1-5, June 2010.

[7] J. Mitola III, and G. Q. Maguire, Jr., “Cognitive Radio: Making Software Radios More Personal,” *IEEE Personal Communications*, Vol. 6, No. 4, pp. 13-18, August 1999.

[8] J. Mitola III, “Cognitive Radio: An Integrated Agent Architecture for Software Defined Radio,” Royal Institute of Technology (KTH), Stockholm, Sweden, 2000.

[9] L. Korowajczuk, “LTE, WiMAX and WLAN Network Design, Optimization and Performance Analysis,” pp. 782 Chicester, UK: Wiley, 2011.

[10] M. Mouly, and M. Pautet, “The GSM System for Mobile Communications,” pp. 704 Telecom Publishing, 1992.

[11] S. Haykin, “Cognitive Radio: Brain-Empowered Wireless Communications,” *IEEE Journal on Selected Areas in Communications*, Vol. 23, No. 2, pp. 201-220, February 2005.

[12] N.-T. Nhan, and K. Insoo, “Log-Likelihood Ratio Optimal Quantizer for Cooperative Spectrum Sensing in Cognitive Radio,” *IEEE Communications Letters*, Vol. 15, No. 3, pp. 317-319, January 2011.

[13] G. Ganesan, and L. Ye, “Agility Improvement through Cooperative Diversity in Cognitive Radio,” in *Proceedings of IEEE Global Telecommunications Conference, GLOBECOM '05*, St. Louis, Missouri, pp. 2505- 2509, December 2005.

[14] L. Ying-Chang *et al.*, “Sensing-Throughput Tradeoff for Cognitive Radio Networks,” *IEEE Transactions on Wireless Communications*, Vol. 7, No. 4, pp. 1326-1337, April 2008.

[15] I. F. Akyildiz *et al.*, “Next Generation Dynamic Spectrum Access Cognitive Radio Wireless Networks: A Survey,” *Computer Networks Journal (Elsevier)*, Vol. 50, No. 13, pp. 2127-2159, September 2006.

[16] I. F. Akyildiz *et al.*, “Crahns: Cognitive Radio Ad Hoc Networks,” *Ad Hoc Networks, Special Issue on Social-Based Routing in Mobile and Delay-Tolerant Networks*, Vol. 10, No. 8, pp. 1517-1646, July 2009.

[17] M. A. McHenry, “NSF Spectrum Occupancy Measurements Project Summary,” *Shared Spectrum Company*, August 2005.

[18] A. Shukla *et al.*, *"Cognitive Radio Technology: A Study for Ofcom – Summary Report,"* QinetiQ Proprietary, December 2006.

[19] J. Mitola, III, “Software Radios-Survey, Critical Evaluation and Future Directions,” in *National Telesystems Conference*, pp. 13/15-13/23, May 1992.

[20] E. Larsson, and M. Skoglund, “Cognitive Radio in a Frequency-Planned Environment: Some Basic Limits,” *IEEE Transactions on Wireless Communications*, Vol. 7, No. 12, pp. 4800-4806, December 2008.

[21] A.Sahai *et al.*, “Some Fundamental Limits on Cognitive Radio,” in *Proceedings of Allerton Conference on Communication, Control and Computing*, pp. 1662-1671, October 2004.

[22] G. Ganesan, and L. Ye, “Cooperative Spectrum Sensing in Cognitive Radio, Part I: Two User Networks,” *IEEE Transactions on Wireless Communications*, Vol. 6, No. 6, pp. 2204-2213, June 2007.

[23] G. Ganesan, and L. Ye, "Cooperative Spectrum Sensing in Cognitive Radio, Part II: Multiuser Networks," *IEEE Transactions on Wireless Communications*, Vol. 6, No. 6, pp. 2214-2222, June 2007.

[24] D. Gesbert, "From Theory to Practice: An Overview of MIMO Space–Time Coded Wireless Systems," *IEEE Journal on Selected Areas in Communications*, Vol. 3, No. 3, pp. 85-97, April 2003.

[25] Z. Tian, "Compressed Wideband Sensing in Cooperative Cognitive Radio Networks," *IEEE GLOBECOM 2008 - 2008 IEEE Global Telecommunications Conference*, pp. 1-5, Nov. 30 2008-Dec. 4 2008, November 2008.

[26] A. B. Flores *et al.*, "IEEE 802.11af: A Standard for TV White Space Spectrum Sharing," *IEEE Communications Magazine*, Vol. 51, No. 10, pp. 92-100, October 2013.

[27] M. Sherman *et al.*, "IEEE Standards Supporting Cognitive Radio and Networks, Dynamic Spectrum Access, and Coexistence," *IEEE Communications Magazine*, Vol. 46, No. 7, pp. 72-79, July 2008.

[28] B. Fette, "Cognitive Radio Technology," pp. 882: Elsevier, 2009.

[29] S. Chaudhari, "Spectrum Sensing for Cognitive Radios: Algorithms, Performance, and Limitations," Ph.D dissertation, School of Electrical Engineering, Aalto University, Finland, November 2012.

[30] T. X. Brown, "An Analysis of Unlicensed Device Operation in Licensed Broadcast Service Bands," in *Proceedings of the First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN'05)*, pp. 11-29, November 2005.

[31] C. Stevenson *et al.*, “IEEE 802.22: The First Cognitive Radio Wireless Regional Area Network Standard,” *IEEE Communications Magazine*, Vol. 47, No. 1, pp. 130-138, January 2009.

[32] “IEEE Standard for Information Technology--Telecommunications and Information Exchange between Systems Wireless Regional Area Networks (Wran)--Specific Requirements - Part 22: Cognitive Wireless Ran Medium Access Control (Mac) and Physical Layer (Phy) Specifications: Policies and Procedures Foroperation in the Tv Bands Amendment 1: Management and Control Plane Interfaces and Procedures and Enhancement to the Management Information Base (Mib),” *IEEE Std 802.22a-2014 (Amendment to IEEE Std 802.22-2011)*, pp. 1-519, May 2014.

[33] "Dyspan Standards Committee," [Online]. http://grouper.ieee.org/groups/. [Accessed: 1 june, 2016].

[34] A. Wald, “Sequential Tests of Statistical Hypothesis,” *The Annals of Mathematical Statististics*, Vol. 16, No. 2, pp. 117-186, April 1945.

[35] "IEEE 802.19 Wireless Coexistence Working Group (WG)," [Online]. http://ieee802.org/19/. [Accessed: 1 june, 2016].

[36] I. F. Akyildiz *et al.*, “Cooperative Spectrum Sensing in Cognitive Radio Networks: A Survey,” *Physical Communication*, Vol. 4, No. 1, pp. 40-62, December 2011.

[37] D. Guoru *et al.*, “Robust Spectrum Sensing with Crowd Sensors,” *IEEE Transactions on Communications*, Vol. 62, No. 9, pp. 3129-3143, August 2014.

[38] M. Subhedar, and G. Birajdar, “Spectrum Sensing Techniques in Cognitive Radio Networks: A Survey,” *International Journal of Next-Generation Networks (IJNGN)* Vol. Vol.3, No. 2, pp. 37-51, June, 2011.

[39] P. K. Varshney, “Distributed Detection and Data Fusion,” Springer-Verlag New York, 1996.

[40] M. I. Skolnik, “Introduction to Radar Systems,” Singapore: McGraw-Hill, 1980.

[41] H. Urkowitz, “Energy Detection of Unknown Deterministic Signals,” in *Proceedings of the IEEE*, pp. 523-531, April 1967.

[42] S. Chaudhari *et al.*, “Cooperative Sensing with Imperfect Reporting Channels: Hard Decisions or Soft Decisions?,” *IEEE Transactions on Signal Processing*, Vol. 60, No. 1, pp. 18-28, October 2012.

[43] S. Junyang *et al.*, “Maximum Channel Throughput Via Cooperative Spectrum Sensing in Cognitive Radio Networks,” *IEEE Transactions on Wireless Communications*, Vol. 8, No. 10, pp. 5166-5175, October 2009.

[44] S. K. Jayaweera, “Signal Processing for Cognitive Radios,” John Wiley & Sons, Inc., 2014.

[45] Z. Zhenghao *et al.*, “Belief Propagation Based Cooperative Compressed Spectrum Sensing in Wideband Cognitive Radio Networks,” *IEEE Transactions on Wireless Communications*, Vol. 10, No. 9, pp. 3020-3031, September 2011.

[46] R. S. Blum *et al.*, “Distributed Detection with Multiple Sensors I. Advanced Topics,” *Proceedings of the IEEE*, Vol. 85, No. 1, pp. 64-79, January 1997.

[47] M. Jun *et al.*, “Soft Combination and Detection for Cooperative Spectrum Sensing in Cognitive Radio Networks,” *IEEE Transactions on Wireless Communications*, Vol. 7, No. 11, pp. 4502-4507, Novemeber 2008.

[48] S. Chaudhari *et al.*, "Autocorrelation-Based Decentralized Sequential Detection of OFDM Signals in Cognitive Radios," *IEEE Transactions on Signal Processing*, Vol. 57, No. 7, pp. 2690-2700, March 2009.

[49] F. F. Digham *et al.*, "On the Energy Detection of Unknown Signals over Fading Channels," *IEEE Transactions on Communications*, Vol. 55, No. 1, pp. 21-24, January 2007.

[50] D. Cabric *et al.*, "Spectrum Sensing Measurements of Pilot, Energy, and Collaborative Detection," in *IEEE Military Communications Conference*, pp. 1-7, October 2006.

[51] H. Tang, "Some Physical Layer Issues of Wide-Band Cognitive Radio Systems," *First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 151-159, 8-11 Nov. 2005, 2005.

[52] V. I. Kostylev, "Energy Detection of a Signal with Random Amplitude," in *IEEE International Conference on Communications (ICC)*, pp. 1606-1610 vol.1603, May 2002.

[53] J. S. Rosenthal, "A First Look at Rigorous Probability Theory," Singapore: World Scientific, 2000.

[54] N. S. Shankar *et al.*, "Spectrum Agile Radios: Utilization and Sensing Architectures," in *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 160-169, November 2005.

[55] A. Sahai *et al.*, "Cognitive Radios for Spectrum Sharing [Applications Corner]," *IEEE Signal Processing Magazine*, Vol. 26, No. 1, pp. 140-145, January 2009.

[56] C. Xiaofei, and S. Nagaraj, “Entropy Based Spectrum Sensing in Cognitive Radio,” in *Wireless Telecommunications Symposium*, pp. 57-61, April 2008.

[57] M. Jun *et al.*, “Signal Processing in Cognitive Radio,” *Proceedings of the IEEE*, Vol. 97, No. 5, pp. 805-823, April 2009.

[58] W. A. Gardner, “Exploitation of Spectral Redundancy in Cyclostationary Signals,” *IEEE Signal Processing Magazine*, Vol. 8, No. 2, pp. 14-36, April 1991.

[59] S. Kapoor, and G. Singh, “Non-Cooperative Spectrum Sensing: A Hybrid Model Approach,” *Devices and Communications (ICDeCom), 2011 International Conference on*, pp. 1-5, 24-25 Feb. 2011, February 2011.

[60] S. Kozłowski, "Implementation and Verification of Cyclostationary Feature Detector for DVB-T signals," *IET Signal Processing*, vol. 10, no. 2, pp. 162-167, 4 2016.

[61] W. Lu *et al.*, “Combating Hidden and Exposed Terminal Problems in Wireless Networks,” *IEEE Transactions on Wireless Communications*, Vol. 11, No. 11, pp. 4204-4213, October 2012.

[62] P. Jallon, “An Algorithm for Detection of DVB-T Signals Based on Their Second-Order Statistics,” *EURASIP Journal on Wireless Communications and Networking*, Vol. 2008, pp. 38-39, December 2007.

[63] J. Lunden *et al.*, “Collaborative Cyclostationary Spectrum Sensing for Cognitive Radio Systems,” *IEEE Transactions on Signal Processing*, Vol. 57, No. 11, pp. 4182-4195, June 2009.

[64] C. K. Tan, and W. K. Lim, “Reliable and Low-Complexity Wavelet-Based Spectrum Sensing for Cognitive Radio Systems at Low Snr Regimes,” *IEEE Electronics Letters*, Vol. 48, No. 24, pp. 1565-1567, November 2012.

[65] G. W. Wornell, "Emerging Applications of Multirate Signal Processing and Wavelets in Digital Communications," *Proceedings of the IEEE*, Vol. 84, No. 4, pp. 586-603, April 1996.

[66] L. Khaled, and Z. Wei, "Cooperative Communications for Cognitive Radio Networks," *Proceedings of the IEEE*, Vol. 97, No. 5, pp. 878-893, April 2009.

[67] E. J. Candes *et al.*, "Robust Uncertainty Principles: Exact Signal Reconstruction from Highly Incomplete Frequency Information," *IEEE Transactions on Information Theory*, Vol. 52, No. 2, pp. 489-509, Febuary 2006.

[68] D. L. Donoho, "Compressed Sensing," *IEEE Transactions on Information Theory*, Vol. 52, No. 4, pp. 1289-1306, April 2006.

[69] T. Zhi, and G. B. Giannakis, "Compressed Sensing for Wideband Cognitive Radios," in *Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on*, pp. IV-1357-IV-1360, 2007.

[70] R. S. Blum *et al.*, "Distributed Detection with Multiple Sensors I. Advanced Topics," *Proceedings of the IEEE*, Vol. 85, No. 1, pp. 64-79, 1997.

[71] H. Poor and O. Hadjiliadis, "Quickest Detection," pp. 229 New York: Cambridge University Press, 2009.

[72] E. Lehmann, "Testing Statistical Hypotheses," New York: Wiley, 1959,.

[73] A. Taherpour *et al.*, "Multiple Antenna Spectrum Sensing in Cognitive Radios," *IEEE Transactions on Wireless Communications*, Vol. 9, No. 2, pp. 814-823, February 2010.

[74] Z. Rui *et al.*, “Multi-Antenna Based Spectrum Sensing for Cognitive Radios: A GLRT Approach,” *IEEE Transactions on Communications*, Vol. 58, No. 1, pp. 84-88, January 2010.

[75] I. Eizmendi *et al.*, “DVB-T2: The Second Generation of Terrestrial Digital Video Broadcasting System,” *IEEE Transactions on Broadcasting*, Vol. 60, No. 2, pp. 258-271, April 2014.

[76] D. Danev, “On Signal Detection Techniques for the DVB-T Standard,” in *4th International Symposium on Communications, Control and Signal Processing (ISCCSP)*, pp. 1-5, March 2010.

[77] H. Urkowitz, “Energy Detection of a Random Process in Colored Gaussian Noise,” *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-5, No. 2, pp. 156-162, March 1969.

[78] European Telecommunications Standards Institute, *"Digital Video Broadcasting (DVB); Frame Structure Channel Coding and Modulation for a Second Generation Digital Terrestrial Television Broadcasting System (DVB-T2),"* September 2009.

[79] A. Ghasemi, and E. S. Sousa, “Collaborative Spectrum Sensing for Opportunistic Access in Fading Environments,” in *Proceedings of the First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN'05)*, pp. 131-136, November 2005.

[80] Y. Abdulkadir *et al.*, “A Differential Space-Time Coding Scheme for Cooperative Spectrum Sensing in Cognitive Radio Networks,” *2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pp. 1386-1391, Aug. 30 2015-Sept. 2 2015, September 2015.

[81] O. Simpson *et al.*, “Optimal Entropy Quantization for Maximum Likelihood Estimation Based Cooperative Spectrum Sensing,” *2016 Wireless Telecommunications Symposium (WTS)*, pp. 1-5, 18-20 April 2016, April 2016.

[82] O. Simpson *et al.*, “Relay-Based Cooperative Spectrum Sensing with Improved Energy Detection in Cognitive Radio,” *10th International Conference on Broadband and Wireless Computing, Communication and Applications (BWCCA)*, pp. 227-231, 4-6 Nov. 2015, November 2015.

[83] J. Unnikrishnan, and V. V. Veeravalli, “Cooperative Sensing for Primary Detection in Cognitive Radio,” *IEEE Journal of Selected Topics in Signal Processing*, Vol. 2, No. 1, pp. 18-27, February 2008.

[84] Z. Qing, and B. M. Sadler, “A Survey of Dynamic Spectrum Access,” *IEEE Signal Processing Magazine*, Vol. 24, No. 3, pp. 79-89, May 2007.

[85] T. Yucek, and H. Arslan, “A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications,” *IEEE Communications Surveys & Tutorials*, Vol. 11, No. 1, pp. 116-130, March 2009.

[86] Q. Zhi *et al.*, “Optimal Linear Cooperation for Spectrum Sensing in Cognitive Radio Networks,” *IEEE Journal of Selected Topics in Signal Processing*, Vol. 2, No. 1, pp. 28-40, February 2008.

[87] E. Hossain, and B. Bhargava, “Cognitive Wireless Communication Networks,” pp. 440: New York: Springer, 2007.

[88] R. Viswanathan, and V. Aalo, “On Counting Rules in Distributed Detection,” *IEEE Transactions on Acoustics, Speech and Signal Processing*, Vol. 37, No. 5, pp. 772-775, May 1989.

[89] S. M. Mishra *et al.*, “Cooperative Sensing among Cognitive Radios,” in *Procedings of in IEEE International Conference on Communications. (ICC '06)*, pp. 1658-1663, June 2006.

[90] S. Chunhua *et al.*, “Cooperative Spectrum Sensing for Cognitive Radios under Bandwidth Constraints,” in *IEEE Wireless Communications and Networking Conference (WCNC '07)*, pp. 1-5, March 2007.

[91] Z. Yonghong, and L. Ying-Chang, “Eigenvalue-Based Spectrum Sensing Algorithms for Cognitive Radio,” *IEEE Transactions on Communications*, Vol. 57, No. 6, pp. 1784-1793, June 2009.

[92] Y. Zeng, and Y. C. Liang, “Spectrum-Sensing Algorithms for Cognitive Radio Based on Statistical Covariances,” *IEEE Transactions on Vehicular Technology*, Vol. 58, No. 4, pp. 1804-1815, April 2009.

[93] S. Althunibat *et al.*, “On the Trade-Off between Security and Energy Efficiency in Cooperative Spectrum Sensing for Cognitive Radio,” *IEEE Communications Letters*, Vol. 17, No. 8, pp. 1564-1567, July 2013.

[94] C. Chao *et al.*, “Cooperative Spectrum Sensing in Cognitive Radio Networks in the Presence of the Primary User Emulation Attack,” *IEEE Transactions on Wireless Communications,*, Vol. 10, No. 7, pp. 2135-2141, April 2011.

[95] S. Thomopoulos, and L. Zhang, “Distributed Decision Fusion in the Presence of Networking Delays and Channel Errors,” *Information Sciences*, Vol. 66, No. 1-2, pp. 91–118, December 1992.

[96] Z. Jiang *et al.*, "Double Threshold Energy Detection of Cooperative Spectrum Sensing in Cognitive Radio," in *International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, pp. 1-5, May 2008.

[97] S. Atapattu *et al.*, "Energy Detection Based Cooperative Spectrum Sensing in Cognitive Radio Networks," *IEEE Transactions on Wireless Communications*, Vol. 10, No. 4, pp. 1232-1241, April 2011.

[98] L. Jun *et al.*, "On the Throughput-Reliability Tradeoff for Amplify-and-Forward Cooperative Systems," *IEEE Transactions on communications*, Vol. 61, No. 4, pp. 1290-1303, February 2013.

[99] C. Yunfei, "Optimum Number of Secondary Users in Collaborative Spectrum Sensing Considering Resources Usage Efficiency," *IEEE Communications Letters*, Vol. 12, No. 12, pp. 877-879, December 2008.

[100] C. Lei *et al.*, "An Adaptive Cooperative Spectrum Sensing Scheme Based on the Optimal Data Fusion Rule," in *4th International Symposium on Wireless Communication Systems*, pp. 582-586, October 2007.

[101] Z. Chair, and P. K. Varshney, "Optimal Data Fusion in Multiple Sensor Detection Systems," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-22, No. 1, pp. 98-101, January 1986.

[102] S. Chaudhari, and V. Koivunen, "Effect of Quantization and Channel Errors on Collaborative Spectrum Sensing," in *Conference Record of the Forty-Third Asilomar Conference on Signals, Systems and Computers*, pp. 528-533, Novermber 2009.

[103] P. Kaligineedi, and V. K. Bhargava, “Distributed Detection of Primary Signals in Fading Channels for Cognitive Radio Networks,” in *Proceedings of IEEE Global Communications Conference*, pp. 1-5, November 2008.

[104] S. A. Kassam, “Optimum Quantization for Signal Detection,” *IEEE Transactions on Communications*, Vol. 25, No. 5, pp. 479-484, May 1977.

[105] F. F. Digham *et al.*, “On the Energy Detection of Unknown Signals over Fading Channels,” in *IEEE International Conference on Communications (ICC '03)*, pp. 3575-3579 vol.3575, May 2003.

[106] F. E. Visser *et al.*, “Multinode Spectrum Sensing Based on Energy Detection for Dynamic Spectrum Access,” in *IEEE Vehicular Technology Conference*, pp. 1394-1398, May 2008.

[107] J. G. Proakis, “Digital Communications,” 3rd ed.: McGraw-Hill, 1995.

[108] H. Xiaolei *et al.*, “Hedonic Coalition Formation Game for Cooperative Spectrum Sensing and Channel Access in Cognitive Radio Networks,” *IEEE Transactions on Wireless Communications*, Vol. 11, No. 11, pp. 3968-3979, October 2012.

[109] D. Hamza *et al.*, “Equal Gain Combining for Cooperative Spectrum Sensing in Cognitive Radio Networks,” *IEEE Transactions on Wireless Communications*, Vol. 13, No. 8, pp. 4334-4345, August 2014.

[110] H. Hu *et al.*, “Location-Information-Assisted Joint Spectrum Sensing and Power Allocation for Cognitive Radio Networks with Primary-User Outage Constraint,” *IEEE Transactions on Vehicular Technology*, Vol. 65, No. 2, pp. 658-672, February 2016.

[111] W. Han *et al.*, “Efficient Soft Decision Fusion Rule in Cooperative Spectrum Sensing,” *IEEE Transactions on Signal Processing*, Vol. 61, No. 8, pp. 1931-1943, February 2013.

[112] Y. J. Choi *et al.*, “Throughput Analysis of Cooperative Spectrum Sensing in Rayleigh-Faded Cognitive Radio Systems,” *IET Communications*, Vol. 6, No. 9, pp. 1104-1110, June 2012.

[113] G. Ding *et al.*, “Spectrum Sensing in Opportunity-Heterogeneous Cognitive Sensor Networks: How to Cooperate?,” *IEEE Sensors Journal*, Vol. 13, No. 11, pp. 4247-4255, November 2013.

[114] Z. Hongting *et al.*, “Analysis and Algorithm for Robust Adaptive Cooperative Spectrum-Sensing,” *IEEE Transactions on Wireless Communications,*, Vol. 13, No. 2, pp. 618-629, January 2014.

[115] A. Bhowmick *et al.*, “Double Threshold-Based Cooperative Spectrum Sensing for a Cognitive Radio Network with Improved Energy Detectors,” *IET Communications*, Vol. 9, No. 18, pp. 2216-2226, December 2015.

[116] A. Bagwari *et al.*, “Cooperative Spectrum Sensing Based on Two-Stage Detectors with Multiple Energy Detectors and Adaptive Double Threshold in Cognitive Radio Networks,” *Canadian Journal of Electrical and Computer Engineering*, Vol. 36, No. 4, pp. 172-180, March 2013.

[117] Q. T. Vien *et al.*, “Double-Threshold Based Cooperative Spectrum Sensing over Imperfect Channels,” in *2015 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 293-298, March 2015.

[118] S. K. Srivastava, and A. Banerjee, "'N-Ratio' Logic Based Cooperative Spectrum Sensing Using Double Threshold Energy Detection," in *4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, pp. 1-6, June 2009.

[119] K. Ben Letaief, and Z. Wei, "Cooperative Communications for Cognitive Radio Networks," *Proceedings of the IEEE*, Vol. 97, No. 5, pp. 878-893, May 2009.

[120] A. Nuttall, "Some Integrals Involving the Qm," *IEEE Transactions on Information Theory*, Vol. 21, No. 1, pp. 95-96, November 1975.

[121] Q. Peng *et al.*, "A Distributed Spectrum Sensing Scheme Based on Credibility and Evidence Theory in Cognitive Radio Context," in *IEEE 17th International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 1-5, Septmber 2006.

[122] Z. Wei *et al.*, "Cooperative Spectrum Sensing Optimization in Cognitive Radio Networks," in *IEEE International Conference on Communications (ICC '08)*, pp. 3411-3415, May 2008.

[123] N.-T. Nhan, and K. Insoo, "An Enhanced Cooperative Spectrum Sensing Scheme Based on Evidence Theory and Reliability Source Evaluation in Cognitive Radio Context," *IEEE Communications Letters*, Vol. 13, No. 7, pp. 492-494, July 2009.

[124] P. Salvo Rossi *et al.*, "Orthogonality and Cooperation in Collaborative Spectrum Sensing through MIMO Decision Fusion," *IEEE Transactions on Wireless Communications*, Vol. 12, No. 11, pp. 5826-5836, September 2013.

[125] Y. Zhou *et al.*, "Sensing Nodes Selection and Data Fusion in Cooperative Spectrum Sensing," *IET Communications*, Vol. 8, No. 13, pp. 2308-2314, September 2014.

[126] S. Srinu, and S. L. Sabat, “Optimal Multinode Sensing in a Malicious Cognitive Radio Network,” *IEEE Systems Journal*, Vol. 9, No. 3, pp. 855-864, June 2015.

[127] Z. Wei *et al.*, “Optimization of Cooperative Spectrum Sensing with Energy Detection in Cognitive Radio Networks,” *IEEE Transactions on Wireless Communications*, Vol. 8, No. 12, pp. 5761-5766, December 2009.

[128] H. Weijia *et al.*, “Efficient Cooperative Spectrum Sensing with Minimum Overhead in Cognitive Radio,” *IEEE Transactions on Wireless Communications*, Vol. 9, No. 10, pp. 3006-3011, August 2010.

[129] Q. Zhi *et al.*, “Optimal Linear Fusion for Distributed Detection Via Semidefinite Programming,” *IEEE Transactions on Signal Processing*, Vol. 58, No. 4, pp. 2431-2436, December 2010.

[130] H. Deqiang *et al.*, “A Modified Evidence Combination Approach Based on Ambiguity Measure,” in *11th International Conference on Information Fusion*, pp. 1-6, June 2008.

[131] Y. Sun *et al.*, “Full Diversity Reception Based on Dempster-Shafer Theory for Network Coding with Multiple-Antennas Relay,” *China Communications*, Vol. 12, No. 10, pp. 76-90, November 2015.

[132] K. Nguyen *et al.*, “Score-Level Multibiometric Fusion Based on Dempster-Shafer Theory Incorporating Uncertainty Factors,” *IEEE Transactions on Human-Machine Systems*, Vol. 45, No. 1, pp. 132-140, October 2015.

[133] Z. Tian *et al.*, “A Digital Evidence Fusion Method in Network Forensics Systems with Dempster-Shafer Theory,” *China Communications*, Vol. 11, No. 5, pp. 91-97, May 2014.

[134] N. T. Nhan, and K. Insoo, "Evidence-Theory-Based Cooperative Spectrum Sensing with Efficient Quantization Method in Cognitive Radio," *IEEE Transactions on Vehicular Technology*, Vol. 60, No. 1, pp. 185-195, October 2011.

[135] D. M. Weeraddana *et al.*, "Dempster-Shafer Information Filtering Framework: Temporal and Spatio-Temporal Evidence Filtering," *IEEE Sensors Journal*, Vol. 15, No. 10, pp. 5576-5583, October 2015.

[136] E. C. Y. Peh *et al.*, "Cooperative Spectrum Sensing in Cognitive Radio Networks with Weighted Decision Fusion Schemes," *IEEE Transactions on Wireless Communications*, Vol. 9, No. 12, pp. 3838-3847, December 2010.

[137] D. C. Oh *et al.*, "Linear Hard Decision Combining for Cooperative Spectrum Sensing in Cognitive Radio Systems," *Vehicular Technology Conference Fall (VTC 2010-Fall), 2010 IEEE 72nd*, pp. 1-5, September 2010.

[138] W. Zhang *et al.*, "Distributed Consensus-Based Weight Design for Cooperative Spectrum Sensing," *IEEE Transactions on Parallel and Distributed Systems*, Vol. 26, No. 1, pp. 54-64, December 2015.

[139] X. Xu *et al.*, "Energy-Efficiency-Based Optimal Relay Selection Scheme with a BER Constraint in Cooperative Cognitive Radio Networks," *IEEE Transactions on Vehicular Technology*, Vol. 65, No. 1, pp. 191-203, January 2016.

[140] B. A. Bastami, and E. Saberinia, "A Practical Multibit Data Combining Strategy for Cooperative Spectrum Sensing," *IEEE Transactions on Vehicular Technology*, Vol. 62, No. 1, pp. 384-389, September 2013.

[141] S. Maleki *et al.*, "Energy-Efficient Distributed Spectrum Sensing for Cognitive Sensor Networks," *IEEE Sensors Journal*, Vol. 11, No. 3, pp. 565-573, June 2011.

[142] Z. Zhenghao *et al.*, "Belief Propagation Based Cooperative Compressed Spectrum Sensing in Wideband Cognitive Radio Networks," *IEEE Transactions on Wireless Communications*, Vol. 10, No. 9, pp. 3020-3031, July 2011.

[143] N. Nguyen-Thanh *et al.*, "How Many Bits Should Be Reported in Quantized Cooperative Spectrum Sensing?," *IEEE Wireless Communications Letters*, Vol. 4, No. 5, pp. 465-468, October 2015.

[144] T. Denoeux, "A Neural Network Classifier Based on Dempster-Shafer Theory," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, Vol. 30, No. 2, pp. 131-150, March 2000.

[145] G. Shafer, "A Mathematical Theory of Evidence," Princeton, NJ: Princeton Univ. Press, 1976.

[146] D. M. Weeraddana *et al.*, "Dempster-Shafer Information Filtering Framework: Temporal and Spatio-Temporal Evidence Filtering," *Sensors Journal, IEEE*, Vol. 15, No. 10, pp. 5576-5583, October 2015.

[147] A. L. Jousselme *et al.*, "A New Distancebetween Two Bodies of Evidence," *Information Fusion*, Vol. 2, pp. 91-101, June 2001.

[148] Y. F. Song *et al.*, "Measurement of Evidence Conflict Based on Correlation Coefficient," *Journal on Communications*, Vol. 35, No. 5, pp. 95-100, April 2014.

[149] P. Smets, "The Combination of Evidence in the Transferable Belief Model," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 12, No. 5, pp. 447-458, May 1990.

[150] C. K. Murphy, "Combining Belief Functions When Evidence Conflicts," *Decision Support Systems*, Vol. 29, No. 1, pp. 1-9, December 2000.

[151] K. Umebayashi *et al.*, "Efficient Decision Fusion for Cooperative Spectrum Sensing Based on or-Rule," *IEEE Transactions on Wireless Communications*, Vol. 11, No. 7, pp. 2585-2595, June 2012.

[152] S. Jana *et al.*, "Trusted Collaborative Spectrum Sensing for Mobile Cognitive Radio Networks," *IEEE Transactions on Information Forensics and Security*, Vol. 8, No. 9, pp. 1497-1507, August 2013.

[153] C. Lei *et al.*, "Cooperative Spectrum Sensing with Multi-Bits Local Sensing Decisions in Cognitive Radio Context," in *IEEE Wireless Communications and Networking Conference*, pp. 570-575, March 2008.

[154] Z. Qian, and P. K. Varshney, "Diversity Signal Reception Via Soft Decision Combining," in *Proceedings on IEEE International Conference on Acoustics, Speech, and Signal Processing*, pp. 2937-2940 vol.2935, May 2001.

[155] W. Han *et al.*, "Efficient Soft Decision Fusion Rule in Cooperative Spectrum Sensing," *IEEE Transactions on Signal Processing*, Vol. 61, No. 8, pp. 1931-1943, March 2013.

[156] B. Picinbono, and P. Duvaut, "Optimum Quantization for Detection," *IEEE Transactions on Communications*, Vol. 36, No. 11, pp. 1254-1258, November 1988.

[157] R. S. Blum, and M. C. Deans, "Distributed Random Signal Detection with Multibit Sensor Decisions," *IEEE Transactions on Information Theory*, Vol. 44, No. 2, pp. 516-524, March 1998.

[158] S. A. Alvi *et al.*, "A near-Optimal LLR Based Cooperative Spectrum Sensing Scheme for Crahns," *IEEE Transactions on Wireless Communications*, Vol. 14, No. 7, pp. 3877-3887, 2015.

[159] S. Lloyd, "Least Squares Quantization in PCM," *IEEE Transactions on Information Theory*, Vol. 28, No. 2, pp. 129-137, March 1982.

[160] C. C. Lee, and J. J. Chao, "Optimum Local Decision Space Partitioning for Distributed Detection," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 25, No. 4, pp. 536-544, July 1989.

[161] S. Chaudhari *et al.*, "Autocorrelation-Based Decentralized Sequential Detection of OFDM Signals in Cognitive Radios," *IEEE Transactions on Signal Processing*, Vol. 57, No. 7, pp. 2690-2700, March 2009.

[162] D. Messerschmitt, "Quantizing for Maximum Output Entropy (Corresp.)," *IEEE Transactions on Information Theory*, Vol. 17, No. 5, pp. 612-612, Septmeber 1971.