Department of Signal Processing and Acoustics

Spectrum Sensing for Cognitive Radios: Algorithms, Performance, and Limitations

Sachin Chaudhari

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Sachin Chaudhari

A doctoral dissertation completed for the degree of Doctor of Science (Technology) to be defended, with the permission of the Aalto University School of Electrical Engineering, at a public examination held at the lecture hall S3 of the school on the 23rd of November 2012 at 12 noon.

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Abstract

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Abstract

Inefficient use of radio spectrum is becoming a serious problem as more and more wireless systems are being developed to operate in crowded spectrum bands. Cognitive radio offers a novel solution to overcome the underutilization problem by allowing secondary usage of the spectrum resources along with high reliable communication. Spectrum sensing is a key enabler for cognitive radios. It identifies idle spectrum and provides awareness regarding the radio environment which are essential for the efficient secondary use of the spectrum and coexistence of different wireless systems.

The focus of this thesis is on the local and cooperative spectrum sensing algorithms. Local sensing algorithms are proposed for detecting orthogonal frequency division multiplexing (OFDM) based primary user (PU) transmissions using their autocorrelation property. The proposed autocorrelation detectors are simple and computationally efficient. Later, the algorithms are extended to the case of cooperative sensing where multiple secondary users (SUs) collaborate to detect a PU transmission. For cooperation, each SU sends a local decision statistic such as log-likelihood ratio (LLR) to the fusion center (FC) which makes a final decision. Cooperative sensing algorithms are also proposed using sequential and censoring methods. Sequential detection minimizes the average detection time while censoring scheme improves the energy efficiency.

The performances of the proposed algorithms are studied through rigorous theoretical analyses and extensive simulations. The distributions of the decision statistics at the SU and the test statistic at the FC are established conditioned on either hypothesis. Later, the effects of quantization and reporting channel errors are considered. Main aim in studying the effects of quantization and channel errors on the cooperative sensing is to provide a framework for the designers to choose the operating values of the number of quantization bits and the target bit error probability (BEP) for the reporting channel such that the performance loss caused by these non-idealities is negligible.

Later a performance limitation in the form of BEP wall is established for the cooperative sensing schemes in the presence of reporting channel errors. The BEP wall phenomenon is important as it provides the feasible values for the reporting channel BEP used for designing communication schemes between the SUs and the FC.

Keywords Autocorrelation based detectors, censoring, cooperative detection, imperfect reporting channels, quantization, sequential tests

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Preface

The research work leading to this thesis has been carried out under the able guidance of Academy Prof. Visa Koivunen at the Department of Signal Processing and Acoustics, Aalto University School of Electrical Engineering (formerly Helsinki University of Technology (TKK)) during the years 2007–2012. Our research group is part of SMARAD (Smart and Novel Radio Research Unit) which has been selected as a Center of Excellence (CoE) in research by the Academy of Finland.

I would like to acknowledge here one and all who have helped me to make this thesis possible. First of all, I would like to express my sincere gratitude to my supervisor Prof. Visa Koivunen for his guidance, support and patience during the entire course of this work. Visa, thanks for giving me lot of freedom in this research while also making sure that I am moving in the right direction with your gentle pushes at the right times!

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This research was also part of an European Union project SEnsor Network for Dynamic and cOgnitive Radio Access (SENDORA) during the

years 2008–2010. I would like to thank all the project members for many interesting technical discussions which greatly enriched my knowledge in the field of Cognitive Radios. Especially, I would like to thank Prof. Jussi Rynnänen, Dr. Marko Kosunen, Kari Kokkinen, Dr. Danyo Danev, and project coordinator Bertrand Mercier. The research was also funded by scholarships from Finnish Innovation Fund (SITRA), Jenny and Antti Wihurin Foundation, Nokia Foundation and Graduate School of Electrical Engineering. I sincerely appreciate the financial support they provided during the research.

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Espoo, October 8, 2012,

Sachin Chaudhari

Contents

List of Publications

This thesis consists of an overview and of the following original publications which are referred to in the text by their Roman numerals.

I S. Chaudhari, J. Lundén, and V. Koivunen, "Collaborative Autocorrelation-Based Spectrum Sensing of OFDM Signals in Cognitive Radios," in *Proc. of the 42nd Annual Conference on Information Sciences and Systems (CISS)*, Princeton, USA, Mar. 19–21, 2008, pp.191–196.

II S. Chaudhari, V. Koivunen, and H. Poor, "Distributed Autocorrelation-Based Sequential Detection of OFDM Signals in Cognitive Radios," in *Proc. of the 3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom)*, Singapore, May 15–17, 2008, pp.1–6.

III S. Chaudhari, V. Koivunen, and H. Poor, "Autocorrelation-Based Decentralized Sequential Detection of OFDM Signals in Cognitive Radios," *IEEE Transactions on Signal Processing*, vol. 57, pp. 2690–2700, Jul. 2009.

IV S. Chaudhari and V. Koivunen, "Effect of Quantization and Channel Errors on Collaborative Spectrum Sensing," in *Proc. of the 43rd Asilomar Conference on Signals, Systems, and Computers*, Pacific Grove, CA, USA, Nov. 1–4, 2009, pp. 528–533.

V S. Chaudhari, J. Lundén, and V. Koivunen, "BEP Walls for Collaborative Spectrum Sensing," in *Proc. of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Prague, Czech Republic, May 22–27, 2011, pp. 2984–2987.

VI S. Chaudhari, J. Lundén, and V. Koivunen, "Effects of Quantization on BEP Walls for Soft Decision Based Cooperative Sensing," in *Proc.*

of the 12th IEEE International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), San Francisco, USA, Jun. 26–29, 2011, pp. 106–110.

VII S. Chaudhari, J. Lundén, and V. Koivunen, "Performance Limitations for Cooperative Spectrum Sensing with Reporting Channel Errors," in *Proc. of the 22nd IEEE Symposium on Personal, Indoor, Mobile and Radio Communications (PIMRC)*, Toronto, Canada, Sep. 11–14, 2011.

VIII S. Chaudhari, J. Lundén, V. Koivunen, and H. Poor, "Cooperative Sensing with Imperfect Reporting Channels: Hard Decisions or Soft Decisions?," *IEEE Transactions on Signal Processing*, vol. 60, pp. 18–28, Jan. 2012.

List of Abbreviations

ASN	average sample number
AWGN	additive white Gaussian noise
BEP	bit error probability
BPSK	binary phase shift keying
BSC	binary symmetric channel
CAV	covariance absolute value
CDF	cumulative density function
CDMA	code division multiple access
CFAR	constant false alarm rate
CFN	covariance Frobenius norm
CGLRT	constrained generalized likelihood ratio test
CP	cyclic prefix
CS	cooperative sensing
CUSUM	cumulative sum
DFT	discrete Fourier transform
DSP	digital signal processing
DTV	digital television
DVB-T	digital video broadcasting — terrestrial
EGC	equal gain combining
FC	fusion center
FCC	Federal Communications Commission
FDMA	frequency division multiple access
FPGA	field programmable gate array
FSK	frequency shift keying
FSS	fixed sample size
GLR	generalized likelihood ratio
GLRT	generalized likelihood ratio test
GSM	global system for mobile communications

HD	hard decision
HSPA+	evolved high speed packet access
iid	independent and identically distributed
IQ	in-phase/quadrature
ISM	industrial, scientific and medical
LLR	log-likelihood ratio
LLRT	log-likelihood ratio test
LR	likelihood ratio
LRT	likelihood ratio test
LTE	long term evolution
MAC	medium access control
MIMO	multiple input multiple output
ML	maximum likelihood
MOE	maximum output entropy
MRC	maximal ratio combining
NP	Neyman-Pearson
OFDM	orthogonal frequency division multiplexing
pdf	probability density function
PHY	physical layer
pmf	probability mass function
PSK	phase shift keying
PU	primary user
RE	relative efficiency
RF	radio frequency
ROC	receiver operating characteristics
SD	soft decision
SDR	software defined radio
SNR	signal to noise ratio
SPRT	sequential probability ratio test
SU	secondary user
TDMA	time division multiple access
TV	television
TVWS	television whitespace
UMTS	universal mobile telecommunication system
WiMax	worldwide interoperability for microwave access
WLAN	wireless local area network
WMAN	wireless metropolitan area network

List of Symbols

$\hat{a}$	estimate of scalar a
a^*	conjugate of scalar a
$\|a\|$	modulus of scalar a
$\mathbf{a}^H$	conjugate transpose of vector $\mathbf{a}$
$\mathbf{A}^{-1}$	inverse of matrix $\mathbf{A}$
$E[\cdot]$	expectation operator
$f(\cdot)$	probability density function
$F(\cdot)$	cumulative density function
H_0	null hypothesis
H_1	alternative hypothesis
L	number of channel taps
L_n	log-likelihood ratio for the nth secondary user
L_n^{fc}	received quantized log-likelihood ratio at the fusion center from the nth secondary user
L_n^{su}	transmitted quantized log-likelihood ratio from the nth secondary user
M	number of observations at a secondary user
$\min$	minimum value
$\max$	maximum value
N	number of secondary users
N_0	noise spectral density
N_s	number of received OFDM symbols at a secondary user
$\mathcal{N}$	normal distribution
$\mathcal{N}_{ns}$	set of SUs in no-send region
$p(\cdot)$	probability mass function
$P(\cdot)$	probability function
P_0	prior probability for null hypothesis
P_1	prior probability for alternative hypothesis

$P_{f,n}^{su}$	probability of false alarm at the nth secondary user
$P_{m,n}^{su}$	probability of missed detection at the nth secondary user
$P_{f,n}^{fc}$	probability of false alarm corresponding to the nth secondary user at the fusion center
$P_{m,n}^{fc}$	probability of missed detection corresponding to the nth secondary user at the fusion center
$P_{f,cs}$	global probability of false alarm for cooperative sensing
$P_{m,cs}$	global probability of missed detection for cooperative sensing
$r(t,\tau)$	time dependent autocorrelation function at lag τ
$\mathcal{R}(x)$	real part of a complex value x
$s(t)$	transmitted signal
t	discrete time index
$\mathcal{T}$	test statistic
T_c	number of cyclic prefix samples in an OFDM symbol
T_d	number of data samples in an OFDM symbol
T_s	total number of samples in an OFDM symbol
u_n	hard decision from the nth secondary user to the fusion center
$w(t)$	additive white gaussian noise
$x(t)$	received signal
α_s	constraint on the probability of false alarm for single-user sensing
α_{cs}	constraint on the global probability of false alarm for the cooperative sensing
β_s	constraint on the probability of missed detection for single-user sensing
β_{cs}	constraint on the global probability of missed detection for the cooperative sensing
η	detector threshold
κ_n	communication constraint between the nth secondary user and the fusion center
τ	time delay
χ_M^2	central chi-square distribution with M degrees of freedom
$\chi_M^2(\gamma)$	non-central chi-square distribution with M degrees of freedom and non-centrality parameter γ

1. Introduction

1.1 Motivation

Wireless communication has been the fastest growing segment of the communications industry in the last decade. As a result, wireless systems have become ubiquitous with several applications (e.g., cellular telephony and wireless internet) and various devices (e.g., mobiles, laptops, and tablets). In addition, new applications like wireless sensor networks, automated factories, smart home appliances, remote telemedicine, and many more are emerging from research ideas to concrete systems [1].

With the incredible growth in the number of wireless systems and services, the availability of high quality wireless spectrum has become severely limited. This is evident from the frequency allocation charts for Finland [2] (see Fig. 1.1) and the United States [3]. This has lead to a common belief that the spectrum is a scarce resource and it is difficult to find spectrum for new applications. However, actual measurements carried out in various countries show that most of the radio frequency spectrum is inefficiently utilized with spectrum utilization mostly in the range of 5%-50% [4–7]. Therefore the real problem is not the spectrum scarcity but the inefficient spectrum usage. This inefficiency results from static spectrum allocations, rigid regulations, fixed radio functions, and limited network coordination.

Cognitive radio offers a novel solution to overcome the underutilization problem by allowing an opportunistic usage of the spectrum resources. This is evident from the definition of cognitive radio adopted by the Federal Communications Commission (FCC): *Cognitive Radio: a radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to*

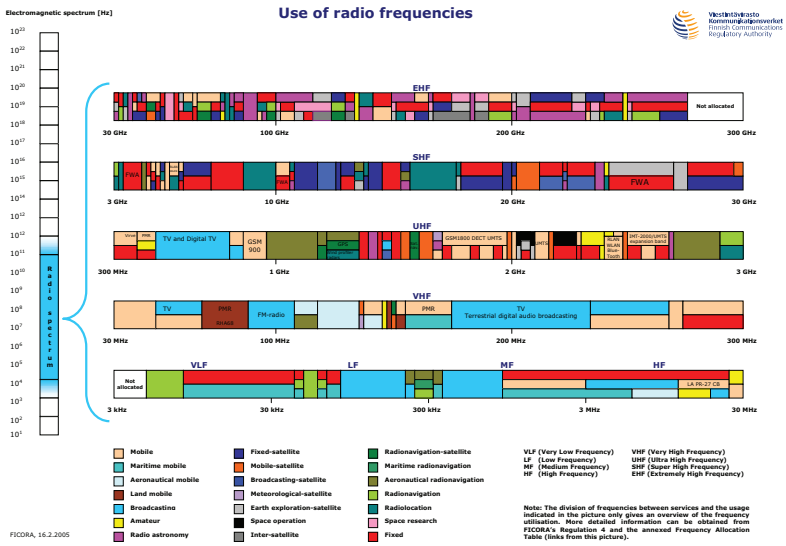

Figure 1.1. Finnish Communication Regulatory Authority's frequency allocation chart for Finland [2].

modify interference, facilitate interoperability, and access secondary markets [8].

In cognitive radio terminology, a *primary user (PU)* is defined as a legacy user or a licensed user who has higher rights on particular part of spectrum. Examples of licensed technology are global system for mobile communications (GSM) [9, 10], worldwide interoperability for microwave access (WiMax) [11, 12], and long term evolution (LTE) [12, 13] while examples of legacy technology are microphone and wireless local area network (WLAN) [12, 14]. On the other hand, unlicensed cognitive users with lower priority are defined as *secondary users (SUs)*. A SU can access spectral resources of a PU when the PU is not using them. However the SU has to vacate the frequency band as soon as the PU becomes active so that negligible (or no) interference is caused to the PU. Such opportunistic access of the PU resources by the SUs is called as **dynamic spectrum access**. A SU can opportunistically utilize different spectrum holes corresponding to different PUs in order to satisfy its bandwidth requirement without causing interference to the PUs as shown in Fig. 1.2.

Spectrum sensing is a key enabler for dynamic spectrum access in cognitive radios. It is the task of obtaining awareness regarding the radio spectrum as well as identifying idle spectrum. It enables the SUs to explore and exploit the unused PU spectrum. In addition it is crucial for managing the level of interference caused to the PUs of the spectrum.

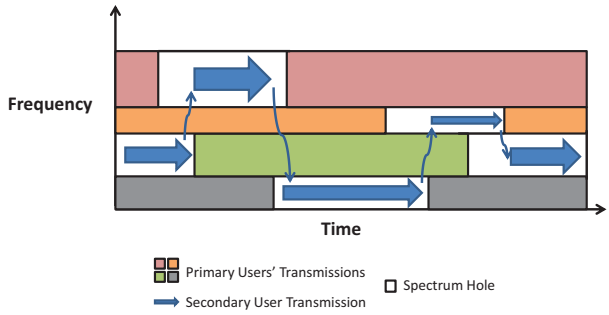

Figure 1.2. In cognitive radios, secondary users (SUs) opportunistically use the spectrum not used by the primary users.

Spectrum sensing can be done by an individual SU and is called as *single-user sensing* or *local detection*. Single-user sensing becomes difficult in challenging propagation environments like multipath fading, Doppler spread, and shadowing. In such a scenario a SU has to distinguish between a *white space*, where there is no primary signal, and a *deep fade*, where it is hard to detect the primary signal. *Cooperative sensing (CS)*, where different SUs collaborate to detect the presence of a PU, provides diversity gains to tackle the fading and shadowing effects. CS also helps to increase the SNR gain and network coverage, decrease the detection time, and simplify the detector design.

1.2 Scope of the thesis

Cognitive radio is a very broad and a highly multidisciplinary technology involving several fields of research such as smart antennas, hardware architectures, signal processing, communication theory, medium access control (MAC), learning mechanisms, dynamic spectrum allocation methods, cognitive network architecture, and protocol design. Moreover, cognition may take place in all layers of a protocol stack such as Open Systems Interconnection (OSI). However the main focus of this thesis is on the design and analysis of local and cooperative spectrum sensing algorithms for dynamic spectrum access from the physical layer (PHY) signal processing point of view. The problem of spectrum sensing is commonly formulated as a binary hypothesis testing problem and the desired sensing algorithms stem from the detection theory.

The **first goal** of this thesis is to *develop simple and computationally efficient local spectrum sensing algorithms* to detect Orthogonal Frequency

Division Multiplexing (OFDM) based PU transmissions. OFDM is a key technology for the present and future broadband wireless communication systems. It is used in various applications: IEEE 802.22 or digital television (DTV) broadcasting, IEEE 802.11a/g/n or wireless local area networks (WLANs), IEEE 802.16 or wireless metropolitan area networks (WMANs) , IEEE 802.20 or mobile broadband wireless access (MBWA) systems, LTE, for example. Therefore, it is fair to assume that many of the PUs will be OFDM based. Hence, the problem of detecting OFDM signals is very relevant. Local spectrum sensing schemes are proposed to detect OFDM based PU in Publications I and III.

The **second goal** of this thesis is to *develop fast, energy efficient, and practical collaborative sensing algorithms*. Cooperative sequential sensing schemes are proposed in Publications II and III. Cooperative sensing may involve multiple SUs searching multiple bands corresponding to different PUs. However, the discussion in this thesis is limited to the collaborative scenarios where a group of SUs are trying to detect the same PU in a given single frequency band. The developed methods stem from decentralized detection theory. Sensing policy, which resolves different issues related to CS such as user selection and sensing scheduling, is not considered in this thesis.

The **third goal** of this thesis is to *study the effects of non-idealities on the cooperative spectrum sensing algorithms*. The effects of some typical non-idealities such as quantization, censoring, and imperfect reporting channels on CS are studied in Publications I, IV-VIII. Quantization and censoring schemes help in saving the bandwidth and energy required for transmitting the decision statistics from the SUs to the fusion center (FC). However these savings come at the cost of performance degradation for CS. In addition, reporting channels from the SUs to the FC may introduce errors in the SU decision statistics and severely affect the CS performance in a practical scenario. Therefore it is important to take these issues into account while designing the CS systems so that the performance degradation caused is negligible. Note that the effects of non-idealities in the radio frequency (RF) front end such as carrier frequency offset, DC-offset, non-linearity, IQ imbalance, and phase noise are not considered in this thesis.

1.3 Contributions of the thesis

The contributions of this thesis are in two fields related to spectrum sensing: single-user spectrum sensing and cooperative spectrum sensing. The problem of detecting a PU activity is modeled as a binary hypothesis testing problem where the null and alternate hypotheses correspond to the absence and presence of PU transmission, respectively. The observations at the cooperating SUs are considered independent conditioned on the either of the two hypotheses. For cooperative spectrum sensing, a parallel network topology with a dedicated FC is considered where each SU sends decision statistic to the FC which makes the final decision. The performances of the proposed schemes are studied using analytical methods and extensive MATLAB simulations. For all the detailed derivations and simulation results see the Publications I-VIII.

The contributions of the thesis to the **SINGLE-USER SPECTRUM SENSING** for cognitive radios are listed as follows:

- **Autocorrelation based detectors** are proposed in Publications I and III which use the autocorrelation property of cyclic-prefix (CP) OFDM based PU signals to detect them. The proposed detectors are simple, computationally efficient, and require minimal knowledge regarding the OFDM based PU. It is shown that the log-likelihood ratio test (LLRT) statistic in the low SNR regime is the maximum likelihood (ML) estimate of the autocorrelation coefficient. The distribution of the test statistic has been derived under the two hypotheses. The performances of the proposed schemes are studied in additive white Gaussian noise (AWGN) and multipath channels. The gain in assuming the knowledge of synchronization and the CP length is also demonstrated.

The contributions of the thesis to the **COOPERATIVE SPECTRUM SENSING** for cognitive radios are listed as follows:

- **Censoring based CS** scheme is proposed in Publication I which uses autocorrelation based decision statistics to detect a CP-OFDM based PU system. In the censoring approach, only informative local decision statistics are sent to the FC. The motivation behind the censoring approach is to reduce the bandwidth and energy used for transmitting the decision statistics from the SUs to the FC. The distribution of the decision statistics at the SU and the test statistic at

the FC are established under both hypotheses. Significant reduction in the transmissions of decision statistics is obtained under the null hypothesis while the performance loss is minimal even under strict communication constraints.

- **Sequential detection** schemes are proposed in Publications II and III where SUs send autocorrelation based log-likelihood ratios (LLRs) to the FC which makes a decision sequentially. Expressions are derived for the *average sample number (ASN)*, which is the number of samples required to arrive at a reliable decision under either of the hypotheses. Later the performance of the proposed cooperative sequential scheme is compared to that of Neyman-Pearson (NP) fixed sample size (FSS) test in AWGN, multipath, and shadowing channels. Significant gains are shown in terms of the number of samples sufficient for achieving the desired performance criteria.

- **Effects of Quantization on CS** are analyzed in Publications IV. Main aim is to find the number of bits required for quantizing the decision statistics at the SUs such that the CS performance loss remains negligible. The loss in the CS performance caused by the quantization decreases with an increase in the number of bits for quantization. It is shown that as low as four bits are required to achieve performance similar to that of the unquantized versions by simply using a uniform quantizer and the Gray mapping.

- **Effects of Imperfect Reporting Channels on CS** are analyzed in Publications IV-VIII. It is shown that there is increase in the error probabilities of false alarm and missed detection when the reporting channel errors increase. The reporting channel errors are modeled using bit error probability (BEP). Performance limitations of the CS have been introduced in the form BEP wall in the presence of imperfect reporting channels. *The BEP wall is defined as the BEP value above which it is impossible to satisfy the imposed performance constraints on the detector error probabilities at the FC irrespective of the SNR on the listening channel or the sensing time at the SUs*. The performance is studied for CS schemes using one-bit hard decisions (HDs) and multi-bit soft decisions (SDs). It is shown that the BEP wall values are sufficiently low to be of practical importance and may cause severe performance limitation in certain CS schemes. Contrary to the popular belief that cooperation always im-

proves the CS performance, cooperation is shown to degrade the CS performance for some cases. Performance comparison of HD and SD based schemes have been provided to show the performance gain in using SDs for CS even in the presence of reporting channel errors.

1.4 Structure of the thesis and summary of the publications

This thesis consists of an introductory part and eight original publications. The **introductory part** is organized as follows. Chapter 2 reviews cognitive radio networks and their application to dynamic spectrum access. Chapter 3 gives a review of local sensing algorithms and issues related to them. In addition, an autocorrelation based detector (presented in Publications I-III) for detecting an OFDM based PU is discussed. The review of CS algorithms and related issues are presented in Chapter 4. In addition, CS algorithms like censored distributed detection (proposed in Publication I) and sequential detection (proposed in Publications II and III) are also discussed. The chapter also discusses the effects of non-idealities such as quantization and channel errors on the CS (presented in Publication IV) and the resulting performance limitations (presented in Publications V-VIII). Chapter 5 provides the concluding remarks.

In **Publication I**, a simple and computationally efficient autocorrelation based detector is proposed to detect an OFDM based PU in AWGN channel. Next, the proposed scheme is extended to the case of CS where the SUs send only the informative decision statistics to the FC. For censoring, the decision statistics used are autocorrelation values. Limits of the censoring region are found under constraints on the false alarm and transmission rates. The distributions of the local decision statistics at the SU and the test statistic at the FC are established under the two hypotheses.

In **Publication II**, a distributed autocorrelation based sequential detection scheme of OFDM signals is proposed. Each SU sends autocorrelation based LLR to the FC, which employs sequential detection. Expressions are derived for the ASN under either of the hypotheses. Next, comparison of the proposed sequential detection scheme is carried out with NP FSS test in the AWGN channel.

In **Publication III**, the work in Publications I and II is extended. It is shown that for CP based OFDM system, the ML estimate of the autocorrelation coefficient at the lags equal to the useful data length in an

OFDM symbol is the LLRT statistic in the low SNR regime. The proposed detector does not assume the knowledge of CP length in an OFDM symbol. The distributions of the local decision statistic are established under the two hypotheses. Next, the effects of exploiting information related to the CP length and synchronization on detection performance are studied. The performances of the proposed local detectors are studied in AWGN and multipath scenarios. Later, sequential detection is considered for CS where local detectors send autocorrelation coefficient based LLRs to the FC. Expressions are derived for the ASN under either of the hypotheses. The performance is then compared with the FSS test in AWGN and shadowing conditions.

In **Publication IV**, the effects of quantization and channel errors on the CS performance are studied. The autocorrelation coefficient based LLRs from the SUs to the FC are quantized to reduce the bandwidth consumption using a uniform quantizer. At the FC, the sum fusion rule is considered. The reporting channel errors are modeled using BEP and are considered to be independent and identically distributed (*iid*). The distribution of the decision statistics at the SU and the test statistic at the FC are established under either of the two hypotheses.

In **Publication V**, the existence of a performance limitation in the form of a BEP wall is demonstrated for HD based CS in the presence of imperfect reporting channels. Each SU sends a one-bit decision to the FC, which employs K-out-of-N fusion rule. Expressions for the BEP walls for the K-out-of-N rules (also called *counting rules*) are derived. Effects of parameters like false alarm probability, missed detection probability, K, and N on the BEP wall values are also studied.

In **Publication VI**, the existence of BEP walls for SD based CS is demonstrated in the presence of reporting channel errors. Cooperative detection is formulated as a composite hypotheses testing problem and PU signal distribution is assumed to be unknown. Each SU sends a quantized version of the ML estimate of the autocorrelation coefficient to the FC. Different quantization schemes such as uniform quantization and maximum output entropy quantization are implemented. The reporting channel is modeled as a binary symmetric channel (BSC) with a particular BEP. A sum fusion rule is implemented at the FC along with NP detection criteria.

In **Publication VII**, the work of Publication V is extended to the case where the reporting channels are not necessarily identical. Expression

for the BEP wall values in the general scenario is obtained for the K-out-of-N fusion rules. The BEP wall values in this case form a surface of BEP values which divides the BEP region into two regions: feasible and unfeasible. It is also shown that the robustness of different fusion rules depends on different performance constraints.

In **Publication VIII**, the BEP wall phenomenon is demonstrated for SD based CS. Unlike Publication VI, CS is formulated as a simple hypothesis problem and an optimal fusion rule is used at the FC which takes the reporting channel errors into account. The distribution of the decision statistics at the SU and the test statistic at the FC are established under either of the two hypotheses. In addition, comparison of HD and SD based CS schemes is carried out for AWGN and shadowed listening channels in the presence of erroneous reporting channels.

In all the publications, the author of this thesis did the theoretical analysis, simulations, and writing of the publications. The co-authors guided the research and helped in writing the publications. The censoring framework in Publication I and the sequential detection framework in Publications II and III were suggested by the co-authors.

2. Cognitive Radios for Dynamic Spectrum Access

Cognitive radio is an emerging concept which has a potential of being a disruptive technology and will enable the future wireless world [15, 16]. In [15], the author envisions cognitive radio to be a convergence of several functionalities in a smart radio thereby providing a base for useful and innovative applications such as dynamic spectrum access. However the cognitive radio technology is still in its infancy and has attracted a lot of attention from the researchers in the field of wireless communications. The concept of cognitive radio is highly multidisciplinary as inputs from several fields are needed on different issues. For example, smart antennas, hardware architectures including software-defined radio (SDR), signal processing, networking, communication and information theory, learning mechanisms, game-theory, policy definitions, and monitoring [15, 16]. Interested readers are referred to [15–19] for details on the history, background, and various multidisciplinary issues related to the cognitive radios.

The main focus of this thesis is on spectrum sensing in cognitive radios for dynamic spectrum access. This chapter starts with a general description of cognitive radio followed by its application for dynamic spectrum access. Later, brief overviews are presented on various issues related to the dynamic spectrum access including spectrum sensing, access policies, learning mechanisms, sensing policy, interference management, and standardization efforts.

2.1 Cognitive radio

2.1.1 Definitions

Cognitive radio is a broad concept in general and has different meanings in several contexts [8,17,20,21]. The term *cognitive radio* has been coined by Mitola as *an intelligent radio which is aware of its surrounding environment and capable of changing its behavior to optimize the user experience* [20,22]. Therefore a cognitive radio has three important characteristics: awareness, cognition, and adaptability. Slightly different cognitive radio characterizations are given in [21,23,24]. **Awareness** is the ability of the radio to measure, sense, and be aware of its environment and internal states. A radio may exhibit different levels of awareness such as spectrum awareness, location awareness, user awareness, and network awareness, etc. **Cognition** is the ability to process information, learn about the environment, and make decisions about its operating behavior to achieve predefined objectives. **Adaptability** is the capability of adjusting operating parameters for the transmission on the fly without any modifications on the hardware components. This capability enables the cognitive radio to adapt easily to the dynamic radio environment. There are several reconfigurable parameters: frequency, transmit power, waveforms, antenna configuration, communication technology, and protocol.

Dynamic spectrum access is cognitive radio's most important application, which promises to overcome the apparent spectrum scarcity problem caused by the rigid spectrum allocation and the underutilization of the spectral resources. In the context of dynamic spectrum access, a more pertinent definition of a cognitive radio is given by Haykin [21]: *Cognitive Radio is defined as an intelligent wireless communication system that is aware of its surrounding environment and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g. transmit power, carrier frequency, and modulation strategy) in real time with two primary objectives in mind: One: highly reliable communication whenever and wherever needed, Second: efficient utilization of the radio spectrum.*

2.1.2 Applications

Cognitive radio presents the possibility of numerous revolutionary applications apart from dynamic spectrum access. For example, cognitive radio may facilitate location services, seamless mobility, optimum performance, and coexistence of heterogeneous wireless systems. Cognitive radio may provide **location services** by helping the user locate services like restaurants, car rental, train, flights, etc., when he travels in a new country. Cognitive radio may facilitate **seamless mobility** by automatically detecting and inter operating with different networks like WLAN, wireless metropolitan area network (WMAN), Bluetooth, etc. Cognitive radio may be useful in obtaining **optimum performance** by optimizing spectrum usage, data rates, service cost, battery power minimization, etc., or a mix of such objective functions. **Coexistence of heterogeneous wireless systems** in the same frequency bands (e.g., IEEE 802.15.4 Zigbee and IEEE 802.11 WLAN) results in severe interference caused by different power levels, asynchronous time slots, and incompatible MAC and physical layer protocols [25]. This interference in turn severely degrades the performance of the coexisting wireless systems. Cognitive radio can provide solutions to reduce the interference among the coexisting heterogeneous wireless systems and improve their performance.

2.1.3 Enabling technologies

Many technologies and practical considerations, which are highly multidisciplinary, need to come together to result in the cognitive technologies [18]. There are a few enabling technologies that play an important role in cognitive radio systems: sensors, software technologies, and software defined radio.

Sensors are needed to create awareness about the environment. 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 unauthorized access and providing user centric experience in a multiuser scenario. GPS enables several useful applications for a cognitive radio by providing the location awareness.

Software technologies, which are enabling cognitive radio, include policy engine, machine learning, advanced signal processing, and net-

working protocols [15]. The spectrum usage is regulated by the regulatory body and regulation policies may vary depending on country, time, software, and hardware developers. Policy engine helps in adhering to different regulations by having a library of policies in the form of downloadable software. Machine learning focuses on automatically learning and making intelligent decisions based on the available information. Examples of machine learning approaches are artificial neural networks, reinforcement learning, and genetic algorithms. Advanced signal processing approaches are required in cognitive radios for communications (e.g., modulation/demodulation, forward error correction, channel estimation, equalization, filtering) and sensor signal processing (e.g., spectrum analysis, feature extraction, pattern recognition, wavelet synthesis). Networking protocols enable cooperation between different SUs which has the potential of increasing the cognitive radio capability. Moreover they may help SUs to coexist with the PUs and the other SUs. Examples of networking protocols are routing and medium access protocols.

A **software defined radio** or SDR, is a radio communication system where components that have been typically implemented in hardware (e.g. mixers, filters, amplifiers, modulators/demodulators, detectors, etc.) are instead implemented in software using digital signal processing (DSP). Therefore simply modifying or replacing software programs can completely change the functionality of the radio. This flexible radio functionality allows the use of different wireless communication techniques in a single portable device making SDR a key enabling technology for cognitive radios. Some examples of commercially available SDR are Universal Software Radio Peripheral (USRP), USRP2, FLEX-5000A [26].

2.2 Dynamic spectrum access

Currently dynamic spectrum access is the most important application of cognitive radios. It has attracted lots of interest among policy makers, regulators, network operators, and researchers [8, 18, 19, 21, 27–29]. Although cognition is a very broad term and has applications in all levels of a protocol stack, this thesis will focus only on the application of cognition to the PHY/MAC layers for dynamic spectrum access. Fig. 2.1 shows the considered scenario for dynamic spectrum access where multiple PUs and SUs are coexisting. The SU networks opportunistically access the PU bands such that the interference caused to the PUs is negligible. The

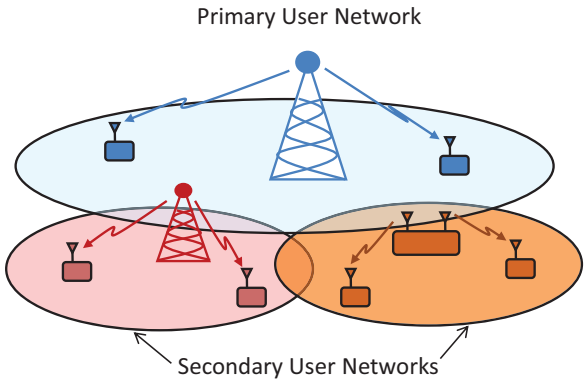

Figure 2.1. Coexistence of multiple primary and secondary user networks (homogeneous or heterogeneous).

SU networks operating may be homogeneous or heterogeneous. Examples of heterogeneous networks operating in the same frequency bands are WLAN (IEEE 802.11), Bluetooth, and Zigbee (IEEE 802.15.4).

Based on the **sharing models** or how the PUs share the spectrum with SUs, dynamic spectrum access can be broadly classified into three types [30]: dynamic exclusive use, spectrum commons, and hierarchical access. Similar categorization has been done in [31] with slightly different terminology. In the *dynamic exclusive use* model, the basic structure of the current spectrum policy is kept while introducing flexibility to improve spectrum utilization. There are two approaches under this model. First approach is spectrum property rights [32], where the license holder can trade spectrum and choose technology based on the market trend. Second approach is dynamic allocation [33], where spectrum allocation is varied at a faster scale as compared to current regulations by using the spectrum usage statistics of the PU in a particular location. In *spectrum commons model*, every user has equal rights for using the spectrum. This is also called as *open spectrum model* and has been successfully applied for wireless services operating in the unlicensed industrial scientific and medical (ISM) radio band (e.g., WLAN). In *hierarchical access* model, SUs can use the primary resources such that the interference to the PU is limited. There are three approaches under this model [19, 34, 35]: underlay, overlay, and interweave. While the SU utilizes gray spaces for the underlay and overlay approaches, the SU utilizes white spaces for the interweave approach. For the underlay approach, the SU transmits in the manner of ultra wideband (UWB) systems with sufficiently low power to limit the interference to the PU. In the overlay approach, SUs use the

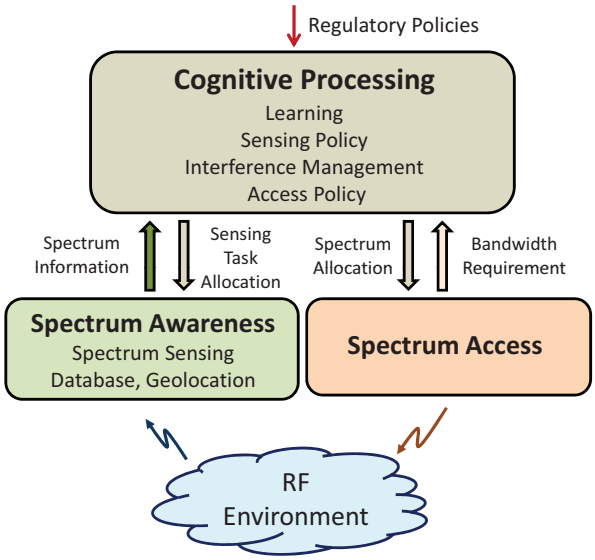

Figure 2.2. Dynamic spectrum access consists of three important functions: spectrum awareness, cognitive processing, and spectrum access. Spectrum awareness and spectrum access are the functions to explore and exploit the spectrum opportunities respectively. Cognitive processing is the intelligence and decision making function that includes several subtasks: learning, sensing policy, interference management, and access policy.

partial or full knowledge of the PU information like codebooks or transmitted data to boost the PU performance and mitigate the interference from the PUs. There is a mix of terminology in the literature regarding overlay and interweave paradigms. For example in [30], the interweave approach described above is called overlay while the overlay approach described above is not considered. In this thesis we follow the definitions of underlay, overlay, and interweave given in [19, 34, 35].

Dynamic spectrum access consists of three main functions: spectrum awareness, cognitive processing, and spectrum access. Fig. 2.2 shows these three functions and their interactions. *Spectrum awareness* creates awareness about the RF environment while *spectrum access* provides ways to exploit the available spectrum opportunities for efficient reuse. *Cognitive processing* is the intelligence and decision making function that includes several subtasks like learning about the radio environment, designing efficient sensing, and access policies along with managing interference for coexistence of the SU networks with the PU networks. Cognitive processing uses spectrum information, bandwidth requirement, and regulatory policies as inputs while it provides sensing task and spectrum allocations as outputs. Next we present a brief overview of these three functions.

2.2.1 Spectrum awareness

Spectrum awareness is the task of obtaining awareness about the spectrum usage and existence of PUs and SUs in a geographical area. A conventional approach to classify spectrum usage in space can be divided into three types [21]: black spaces, gray spaces, and white spaces. Black spaces are occupied by high power local interferers; gray spaces are occupied by low power interferers, while white spaces are free of any interferer excluding ambient noise. The white and gray spaces are the spectrum opportunities or *spectrum holes*, which can be used by the SUs. However this conventional approach of spectrum opportunities in [21] only exploits three dimensions of the spectrum: frequency, time, and space. There may be additional dimensions that can be utilized [36]: code, polarization, and angle of arrival. In addition to the detection of spectral opportunities, spectrum awareness can also provide various other useful information [37] such as radio environment map, channel gain map as well as locations and statistics of the PUs and SUs.

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. For example, use of geolocation, database, and beacons fall into this category [27, 36]. Passive methods need support from the PUs who are under no obligation to change their operation to aid the SU network. Therefore passive methods may be difficult to implement. An alternative solution might be to use a dedicated sensor network maintained for creating databases and PU information in a geographical location to aid an incoming SU [24]. Although the users might have sensing capabilities, such supporting sensor network may be necessary in the start-up phase of the cognitive service and in rural areas with low population. However the infrastructure requirement in this case may be complex and expensive. *In the rest of the thesis, we focus on spectrum sensing performed by cognitive radios because of its broader application areas and lower infrastructure requirement*.

Spectrum sensing schemes can be classified based on different criteria: detection target, architecture, number of primary users, number of secondary users, and number of bands to be sensed. Based on the **target for detec-**

tion, there are two approaches to spectrum sensing: detecting the transmitter and detecting the receiver. Most of the approaches, including the approaches proposed in this thesis, are based on detecting the transmitter. However the receiver is the actual victim of the secondary transmissions and detecting the transmitter only gives an approximate idea of the location of the receiver. Therefore detecting the receiver is an important task. Algorithms for detection of receiver have been considered in [27, 38] which exploit the local oscillator power emitted by the RF front end of the receivers. However, detecting the receiver may be a demanding task as the power of the oscillator leakage is low thereby restricting the reliable detection range below 20 m [27, 38].

Sensing can be performed via two different **architectures** [39, 40]: single and dual radio. In single radio, sensing is time multiplexed with the data transmission/reception while in dual radio, there is a dedicated RF front-end for both sensing and data transmission/reception. Single radio architecture has the advantages of low power consumption and hardware costs over dual radio architecture at the cost of sensing accuracy and efficiency. Based on the **number of bands** to be sensed, sensing can be classified as single-band and multi-band sensing [19]. There may be a case when there are **multiple primary users** in a given frequency band. For example, there are multiple users in a code division multiple access (CDMA) systems while WLAN and Bluetooth systems share the same bands. Detection of multiple users has been studied in [41] while performance analysis of spectrum sensing in the presence of multiple PUs has been done in [42]. Based on the **number of secondary users** for cooperation, sensing can be classified as single-user and multiuser sensing. Multiuser cooperative detection has several advantages over single-user detection (or *local detection*) like improved detector performance, increased coverage, and simplified local detector design. However these advantages come at the costs of increased complexity and overhead. Sensing can also be classified based on the **priority of the target**: detecting PU and detecting SU. Most of the techniques applicable for detecting the PUs are also applicable for detecting SUs. Due to the possibility of coordination between different SU networks, detecting SUs may be easier especially for the case of homogeneous SU networks [43]. Detecting PUs is much more important than detecting SUs as the secondary access is permitted only if the interference to the PUs is within a tolerable limit.

The main focus of this thesis is on the topics of local and cooperative

spectrum sensing for cognitive radios. In this thesis, we focus on active spectrum sensing techniques for detecting a single primary transmitter in a single-band. These techniques are applicable to both single and dual radio architectures. Without loss of generality, we have assumed detection of only PUs in this thesis.

2.2.2 Cognitive processing

Cognitive processing is the task of optimizing the sensing and access of the spectrum opportunities based on the sensing information, databases of spectrum occupancy, and regulatory policies. There are four subtasks of the cognitive processing: learning, sensing policy, interference management, and access policy. These four subtasks are inter-related to each other and will be discussed in the coming subsections. The cognitive processing function can be implemented in a centralized or distributed manner. In the centralized implementation, SUs process the observations and send sensing information to a centralized entity which performs the cognitive processing. In the distributed implementation of cognitive processing, SUs may or may not exchange information among each other but implement cognitive processing functionality on their own.

Learning

Learning is the subtask of estimating the current state and quality of the PU channels using experience rather than sensing alone which may be expensive. The occupancy and channel quality statistics are estimated in the frequency bands which may be favorable for the SUs requesting bandwidth. This helps in making efficient sensing policy, interference management, and access policy.

Assuming there are multiple frequency bands to be scanned, the SUs have to decide if they should exploit the identified spectrum opportunities or explore new frequency bands in hope of better opportunities at a later instant. Thus optimizing the sensing and access policies is similar to a bandit problem often encountered in stochastic optimization. Therefore, *reinforcement learning methods* which are often employed for the bandit problem can also be employed for designing sensing and access policies in cognitive radio networks [19]. In reinforcement learning, the SUs learn from experience and experiments. Thus its operation is in between the other two machine learning methods: supervised (teacher assisted) and unsupervised learning methods. Sensing and access policies based on

reinforcement learning methods have been proposed for cognitive radios in [44–46].

Sensing policy

Sensing policy defines which SUs sense which frequency bands and when. A sensing policy is needed as sensing the entire spectrum of interest simultaneously is demanding for the hardware and may be energy inefficient. Assuming the frequency bands to be sensed are decided or known, the sensing policy has two tasks: user selection and sensing scheduling. Although sensing scheduling can be implemented individually or collaboratively, user selection is specific to cooperative sensing.

Sensing scheduling decides which subbands will be sensed and when. Scheduling helps in improving the efficiency of spectrum exploration. It is worth sensing bands which are unused persistently so that the secondary throughput is increased while the sensing effort is reduced. As the sensing and access policies are closely connected to each other, cooperating SUs can jointly optimize the sensing and access efforts. The joint optimization of sensing and access policies is much easier in a centralized approach as compared to a decentralized approach. Individual sensing policies have been proposed in [47–50] using a decision-theoretic approach by formulating the design of optimal sensing policy as a partially observable Markov decision process (POMDP). Similarly cooperative sensing policies have been proposed in literature using different approaches: negotiation based policy [51], pseudo random policy [52], and reinforcement learning [44, 46].

User selection tells which SUs will participate in the cooperation. It is important to choose SUs experiencing independent fading and shadowing effects so that maximum diversity gain is achieved. In addition, inclusion of malicious users in the group should be avoided to ensure the reliability of the network. User selection can be implemented in two ways: centralized [53] and cluster based [54, 55]. Grouping different users for cooperation can also be modeled using game theory. Depending on the behaviors of different games, behaviors of the SUs can be modeled differently: coalitional game [56] and evolutionary games [57].

Interference management

Interference management is important in cognitive radio networks since secondary usage is allowed only if the SU interference does not degrade the PU quality of service below a tolerable limit [58]. In addition, there

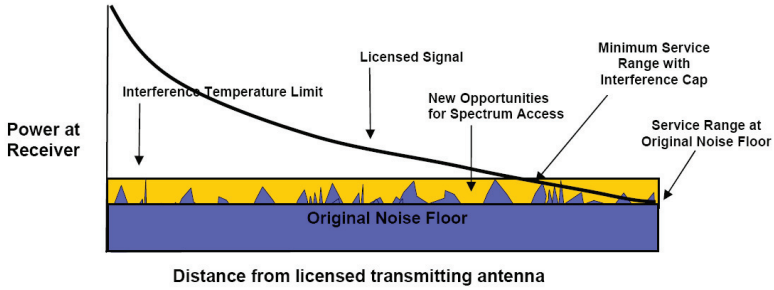

Figure 2.3. Received power of the licensed signal transmission as a function of the distance from the transmitter to illustrate the interference temperature concept [60].

may be interference between different SU networks due to the lack of coordination resulting in substantial reduction of SUs' throughputs. For the review of interference management and related issues in the context of cognitive radios, see [43, 58, 59].

Interference temperature model was introduced by the FCC for quantifying and managing the interference [60, 61]. Fig. 2.3 shows the received power of the licensed signal transmission as the distance from the transmitter. In this interference model, each primary receiver has an interference temperature limit that defines how much noise and interference it can tolerate to guarantee certain quality of service. This creates spectrum opportunities for the SUs. Using this model, cognitive radios can measure and model the interference environment and adjust their transmission characteristics such that the interference to PU is not above the regulatory limits. However, major drawback of the model is to measure the interference temperature at the primary receivers which is unfeasible in practice. The FCC has abandoned the concept of interference temperature as unworkable [62]. At the same time, the FCC has also encouraged the researchers to solve the problems related to the interference temperature and make it feasible.

Techniques managing the interference to the PUs can be broadly categorized into three groups [43]: interference avoidance, interference control, and interference mitigation. The *interference avoidance* approach is same as the interweave approach. The effects of errors in the detection of white spaces on the performances of both PU and SU network has been studied in [63]. To minimize the interference from the SU transmission to a PU becoming active, algorithms using hidden Markov model (HMM) to estimate the state of the channel in the next instant have been proposed in [47]. The *interference control* approach is same as the underlay ap-

proach. Different methods are suggested for limiting the power directed towards the PU: estimating the PU location [64], spectrum shaping [65], beamforming [66], and water-filling [59]. In *interference mitigation*, SUs use the partial or full knowledge of the PU information like codebooks or transmitted data while operating in gray spaces. The interference mitigation approach is same as the overlay approach. Different methods for interference mitigation have been proposed based on dirty paper coding in [67] and using multiuser decoding in [68].

Interference among the SU networks is also an important concern. Although most systems use interference avoidance mechanisms like listen-before-talk, they are designed to resolve the collisions between homogeneous networks. These mechanisms are less effective for heterogeneous networks where the employed standards, frame structure, communication protocols, and transmission powers are different in addition to the lack of coordination and synchronization [43].

Access policy

In the case of cooperating SUs, the problem is how to allocate the available channels among the SUs to optimize a given network objective function. Few examples of such network objective functions: maximize the sum capacity of the secondary network, maximize the minimum capacity for an individual SU or minimize the interference to the primary network with constraints on transmit power or/and fairness of resource allocations [30]. Note that the design of the access policy is also related with different medium access techniques such as time division multiple access (TDMA), frequency division multiple access (FDMA), and CDMA. Similarly the access policy is closely connected to the sensing policy and both these policies can be jointly optimized as done in [44–46].

There are several **approaches for designing policies to allocate or access the spectrum opportunities**. These access policies can be divided into two categories [69]: direct access based and dynamic spectrum allocation. The *dynamic spectrum allocation* policies exploit complex optimization algorithms to achieve a global purpose in an adaptive fashion. However they have issues of low scalability, negotiation delay and complexity. Examples of dynamic spectrum allocation policies are graph coloring scheme [70], game theory [71–73], stochastic algorithms [74], genetic algorithms [75], and swarm intelligence [76]. The *direct access based* policies do not allow any global network optimization. However they are simple and

have low computational cost and latency. The direct access based methods can be further classified as contention based and coordination based. In contention based policies, sender and receiver SUs exchange their sensing information. Then the pair compares available resources and negotiates the channel for communication. Examples involving contention based policy are cognitive MAC (COMAC) [77], heterogeneous distributed MAC (HD-MAC) [78]. In coordination based policies, each SU shares its channel usage information with its neighbors to increase sensing reliability and improve overall system performance. Example involving coordination based access policy is multichannel MAC for cognitive radio (MMAC-CR) [79].

2.2.3 Spectrum access

Once the spectrum opportunities are found, several SUs may want to access the spectrum opportunities to transmit their data. This may lead to collisions in the absence of coordination even when sufficient spectrum opportunities are available. In the case of limited spectrum opportunities, collisions between different SU transmissions and the resulting interference become unavoidable. Spectrum access or *spectrum sharing* is the task of accessing the unused PU spectrum by SUs such that the collisions and interference among different SUs are strictly controlled. Thus spectrum access helps in improving secondary network throughput. See [18,19,30,43,69] for overview on spectrum access or spectrum sharing. Note that spectrum access is different from access (or allocation) policy which is part of cognitive processing. *Spectrum access* defines *how* different SUs access the given spectrum opportunities. On the other hand, the *spectrum access policy* defines *which* SUs access *which* spectrum opportunities and *when*. Spectrum access policies have been explained earlier and this subsection focuses on spectrum access mechanisms.

Spectrum access can be classified based on the **cooperation model used by the SUs** [43]: cooperative and non-cooperative. *Cooperative access schemes* require coordination among the cooperating SUs. Examples of cooperative spectrum access schemes are coordination based multiple access schemes such as TDMA, FDMA, CDMA, and orthogonal frequency division multiple access (OFDMA). Since SUs may need to transmit over noncontiguous frequency bands, OFDMA is an attractive candidate for medium access in cognitive networks [30]. The reconfigurable subcarrier structure of OFDMA allows SUs to efficiently fill the spectral gaps left by the PUs without causing significant interference. However the

subcarrier spacing and symbol interval need to match with the spectral and temporal duration of spectrum opportunities. Moreover, there may be adjacent channel interference due to nonlinearity of the transmitter's power amplifier. In the absence of information from other users, SU can use *non-cooperative access* schemes. Although the non-cooperative access schemes are easy to implement, the absence of coordination among the SUs results in a performance loss compared to the cooperative access schemes. Examples of non-cooperative spectrum access schemes are contention based protocols like carrier sense multiple access with collision avoidance (CSMA/CA).

In case of **homogeneous secondary networks**, both cooperative and non-cooperative spectrum access techniques are easier to implement as the networks have same PHY/MAC protocols. However in case of **heterogeneous secondary networks**, different PHY/MAC strategies may limit the effectiveness of the non-cooperative listen-before-talk mechanisms in achieving fairness. For example, consider a coexistence scenario between CSMA/CA based devices and TDMA based devices. In this case, CSMA/CA devices will back off when there are TDMA transmissions while TDMA devices will not listen before transmitting. In case of cooperative access schemes, communication between the heterogeneous networks is required which limits the implementation of cooperative spectrum access schemes among heterogeneous networks. Even in case there are mechanisms such as a common control channel for sharing relevant coexistence information, a tight synchronization is required across all devices belonging to different networks. Moreover a negotiation process is involved between different competing networks.

Nowadays, radio systems often require larger bandwidths. In addition, the available spectrum opportunities at a given time instant may result from multiple PUs and may be scattered in the frequency domain. Therefore to be able to provide larger bandwidths in multiuser environment, especially in an opportunistic manner, multi-band operation could allow to perform **spectrum aggregation** or **spectrum pooling** of multiple spectrum segments from different spectrum owners (cellular, satellite, military, etc.) into a common pool [80]. Multi-band operation in a multi-primary environment significantly improves the spectrum usage in the considered bands [81], [24].

2.3 Standardization efforts

With the rising interest in cognitive radio technology, wireless standards developed recently or currently under development have started incorporating cognitive features [36, 43, 82–86]. IEEE 802.22 is the first worldwide effort to define a standardized air interface based on cognitive radio techniques for the opportunistic use of TV white spaces (TVWS) [82]. The standard is designed for the secondary usage of TVWS on a non-interfering basis so as to prevent any harmful interference to the incumbent operation (such as digital TV and analog TV broadcasting) and low power licensed devices (such as wireless microphones and medical telemetry devices). The primary application of this standard is fixed broadband access specially for hard-to-reach, low population density areas (typical of rural environments) and thus has a great potential for worldwide applicability. Cognitive functionalities included in the standard are PU detection, geolocation, coexistence with other WRANs, and frequency agility. The implementation of a database is mandatory for PU detection while sensing is optional.

Other standardization initiatives related to cognitive radios are IEEE 802.11 [14], dynamic spectrum access networks standards committee (DySPAN - SC) [84], IEEE 802.16 [11], and IEEE 802.19 [85]. IEEE 802.11af standard, which is currently under development, aims to define modifications to IEEE 802.11 PHY/MAC for TVWS operation [83]. IEEE 802.16h [86] 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. It was also formerly known as IEEE Standards Coordinating Committee 41 (SCC41) and IEEE P1900 standards committee. IEEE 802.19 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), 802.22 etc. IEEE 802.19 task group 1 focuses on wireless coexistence in the TVWS.

3. Single-User Spectrum Sensing

Availability of idle radio spectrum varies depending on time, frequency and location resulting in spectrum opportunities. SUs can use such idle spectrum in an opportunistic manner. Spectrum sensing helps SUs to achieve this objective by identifying underutilized spectrum reliably and rapidly. Spectrum sensing also helps in quickly determining if the PUs have become active so that those bands can be vacated immediately. This is important for ensuring that the interference caused to the PUs remains below a permitted level. Moreover, detection of other SUs may be necessary as well for co-existence with other secondary networks. Thus spectrum sensing is an integral part of the cognitive radios and has attracted a lot of attention from the research community. Several recent surveys on spectrum sensing and related issues along with long lists of up-to-date references can be found in [19, 36, 87–94].

We start this chapter with a brief review of different detection strategies, performance criteria, and state-of-the-art spectrum sensing techniques. The discussion in this chapter is limited to the *single-user sensing* (or *local detection*) scenario. The issues related to *cooperative sensing* (where the case of collaboration between multiple SUs is considered) are presented in Chapter 4. Similarly without any loss of generality, we limit our discussion only to the detection of PU for convenience. As we have proposed autocorrelation based detectors in Publications I and III, a special emphasis is given on the review of the state-of-the-art autocorrelation based detectors in Section 3.2.5. Later effects of different non-idealities on the single-user sensing are discussed. Finally, conclusions are drawn regarding the local spectrum sensing issues.

3.1 System model

A key task in spectrum sensing is to decide whether the spectrum is idle or not. In this thesis, the problem of detecting the presence or absence of the PU transmission is formulated as a binary hypothesis testing problem. The null hypothesis denoted by H_0 corresponds to the received signal being only noise. On the other hand, the alternative hypothesis denoted by H_1 indicates that the received signal contains the PU signal along with noise. In case the hypotheses have no unknown values the hypotheses are called simple. If there are unknown or unspecified values, then the hypotheses are called composite. As an example, a simple binary hypothesis test for detecting the PU transmission in an AWGN channel is given by

$$\begin{aligned} H_0 \quad &: \quad x(t) = w(t) \\ H_1 \quad &: \quad x(t) = s(t) + w(t), \end{aligned} \tag{3.1}$$

for $t = 1, \ldots, M$. Here t represents the discrete time index and M denotes the number of observations while $x(t)$, $s(t)$, and $w(t)$ indicate the received signal, PU signal, and AWGN, respectively. The corresponding observation vector is given by $\mathbf{x} = [x(1) \ldots x(M)]$. For binary hypothesis testing, the observation space is divided into two regions $\mathcal{X}_0$ and $\mathcal{X}_1$ such that if the $\mathbf{x}$ lies in $\mathcal{X}_0$, then H_0 is declared; otherwise H_1 is declared. In most practical cases, a scalar test statistic $\mathcal{T}$ is computed from the observation vector $\mathbf{x}$ and a threshold η divides the observation space (which is a line for a scalar quantity) into two regions. In such cases, detection is based on comparing the test statistic $\mathcal{T}$ to the threshold η. If the test statistic is greater than the threshold, then H_1 is declared true. Otherwise H_0 is declared true. In this thesis, we have focused on designing detectors involving a scalar test statistic and a threshold, unless stated otherwise. The design of the threshold depends on the decision making strategy and the distributions of the test statistics under different hypotheses. The choice of the test statistic and decision making strategy also depends on the desired performance parameters.

3.1.1 Test statistics

Under the assumption that the received observations are independent of each other conditioned on the hypotheses, the optimal test statistic for a **simple hypothesis test** under several detection criteria is the likelihood

ratio test (LRT). The LRT statistic is given by

$$\mathcal{T}_l = \frac{\prod_{t=1}^{M} p\big(x(t) \,|\, H_1\big)}{\prod_{t=1}^{M} p\big(x(t) \,|\, H_0\big)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_l. \tag{3.2}$$

If the distributions of the received signal under the two hypotheses depend on unknown parameters, then the test becomes **composite**. It can be modified to a simple test by integrating out the nuisance parameters given that the distribution of the random parameters are known. In this case the test takes the following form

$$\mathcal{T}_c = \frac{\prod_{t=1}^{M} \int p\big(x(t) \,|\, \theta_1; H_1\big) p(\theta_1) d\theta_1}{\prod_{t=1}^{M} \int p\big(x(t) \,|\, \theta_0; H_0\big) p(\theta_0) d\theta_0} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_c, \tag{3.3}$$

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

If some of the quantities in the distributions are **unknown yet deterministic**, then in some cases the test can be modified such that it does not depend on these parameters. Another approach is to estimate the unknown parameters using the ML estimator and substitute the obtained parameters in the LRT. The resulting test is called generalized likelihood ratio test (GLRT). Although the GLRT is a suboptimal detector, it gives satisfactory performance in most of the cases. The GLRT is given by

$$\mathcal{T}_g = \frac{\prod_{t=1}^{M} \max_{\theta_1} p\big(x(t) \,|\, \theta_1; H_1\big)}{\prod_{t=1}^{M} \max_{\theta_0} p\big(x(t) \,|\, \theta_0; H_0\big)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_g. \tag{3.4}$$

In some cases, it may be difficult (or computationally complex) to evaluate the above test statistics. In such scenarios, simpler test statistics like estimates of the energy, eigenvalues, correlation, etc., or their functions may be used.

When the statistics are only coarsely known **nonparametric** techniques can also be applied [95, 96]. Most nonparametric detectors are easier to implement than the parametric detectors because they rely on less information. The mostly used nonparametric detectors are sign and Wilcoxon detectors [95].

3.1.2 Performance criteria

Performance of spectrum sensing algorithms may differ in different scenarios. It is therefore important to compare and choose the best scheme

for a given scenario. At the same time, it is necessary to choose proper performance criteria for a fair comparison. In this section, we briefly present important performance parameters which can be used to evaluate the sensing algorithms:

- **False alarm probability**: It is defined as the probability that the detector declares the presence of PU, when the PU is actually absent. False alarm probability is also called *Type I error*. If there are too many false alarms, the spectrum opportunities may be overlooked resulting in an inefficient spectrum reuse. Therefore controlling the false alarm probability is crucial for efficient spectrum usage.

- **Missed detection probability**: It is defined as the probability that the detector declares the absence of PU, when the PU is actually present. Missed detection probability is also called *Type II error*. Too many missed detections may lead to collisions of the PU and SU transmissions causing interference to the PU. Therefore controlling the missed detection probability is crucial for keeping the interference to the PU under the permissible limits. It should be noted that establishing distributions of decision statistics helps in controlling the probabilities of missed detection and false alarm.

- **Sensing time**: If the receiver chain is time-duplexed for reception and sensing, it is desirable that the sensing durations are shorter and the data transmission durations are longer. If the sensing time is too long, the data transmission duration reduces thereby reducing the throughput of the SUs.

- **SNR**: The SNR of the received PU signal at the sensor depends on the PU transmitted power and the propagation environment. The two error probabilities (Type I and II) are linked to each other through sensing time, SNR, and detection threshold. The detection performance improves with an increase in the SNR.

- **Detection range**: It is the maximum distance between the sensor and the PU such that the detector should detect the PU reliably. Detection range depends on the detection performance of the detector, SNR at the receiver, sensing time and propagation environment. Spectrum sensing schemes should detect the PU signal reliably in low SNR regime as the PU receivers which are far away from the transmitter should not be interfered with. At the same time, the

sensor should not be too sensitive to detect the PU signals with extremely low SNR values and well outside its interference range.

- **Complexity and implementation issues**: It is desirable to have simple and implementable sensing algorithms which are also energy efficient. Therefore estimating the hardware cost and energy efficiency through computational complexity of the algorithm is also important.

- **Requirement on prior knowledge of PU parameters and noise distribution**: We may exploit the structural and statistical properties of the primary signals and noise in the process of designing spectrum sensing algorithms. The more we know about the PU and the noise distribution, the better the expected detector performance. For example, the PU signal may be deterministic or random. Similarly, we may have very specific information on statistical properties of noise (e.g., zero-mean complex white Gaussian noise with a known variance), or the knowledge of noise may be very vague (e.g., the noise distribution may be symmetric and unimodal). In addition to the statistical properties, knowledge of different PU parameters such as mobility, location, receiver sensitivity and type (transmitter or receiver) are beneficial.

- **Detecting different PU waveforms**: Ability to detect different PU waveforms is a desirable property as ideally one will want a single detector which can reliably detect all kinds of PU signals. Some detectors can detect many different PU signal types whereas some detectors are tuned for a specific waveform of a specific PU signal and cannot be used for other waveforms. For example, energy detector can be used to detect all kinds of PU waveforms.

- **Distinguish between different waveforms**: This is a desirable property as it helps the sensor to distinguish if the received signal is either a PU signal, a SU signal, noise, or an interfering signal.

- **Robustness against non-idealities**: The received signal may be distorted due to different non-idealities in addition to the channel effects. For example, loss of synchronization, hardware issues, and impractical assumptions. The resulting distortion of the received signal may degrade the detection performance further [92]. Non-idealities will be treated later in Section 3.3 in more detail.

The performance parameters of false alarm probability, missed detection, SNR, and sensing time are quantitative and are generally presented in the form two curves. First plot shows probability of detection as a function of SNR for given values of false alarm probability and sensing time. Second plot, which is also called as *receiver operating characteristics (ROC)*, shows the probability of detection as a function of false alarm probability for given values of SNR and sensing time. Other parameters are more qualitative as quantifying them may not be always possible.

Typically there are trade-offs between different performance parameters. For example, the secondary throughput can be increased by increasing the false alarm probability. However this will increase the missed detection probability for a fixed SNR value which in turn increases the interference to the PU. Therefore it is important to choose the performance parameters carefully to achieve the desired objective. For example, the problem of designing the sensing duration is studied in [97] with an objective to maximize the achievable throughput for the secondary network under the constraint that the interference to the PUs is within a reasonable limit. Similarly a joint optimization of detector thresholds and power allocation is carried out in [98] across multichannel links in order to maximize the aggregate opportunistic access in multicarrier cognitive radio networks.

3.1.3 Detection criteria

The choice of a detection criteria is based on the optimization of the desired objective function involving different performance parameters discussed in Section 3.1.2. There are several detection criteria [96, 99–101]: Bayesian, Neyman-Pearson, minimax, locally optimum, sequential detection, etc.

Bayesian formulation can be used to minimize the Bayes risk, which depends on the prior probabilities of two hypotheses, cost assignments, and conditional densities of the observations under the two hypotheses. However the required prior probabilities of the hypotheses and cost assignments may not be necessarily available to implement the optimal Bayesian decision rule. **Neyman-Pearson** (NP) formulation maximizes the probability of detection for a given constraint on the false alarm probability. Noise statistics are required for the NP implementation and may be estimated. Yet another criteria for detection is **minimax** which minimizes the maximum Bayes risk by using the Bayes decision rule corresponding to the least favorable prior probability assignment. Minimax concept re-

sults in *robust detection* where optimum detectors are designed for certain least favorable models like heavy-tailed noise models. Robust detection techniques are used when the observation statistics are not known exactly but only approximately. **Locally optimum detection** is the optimal detection scheme for weak signal detection as it maximizes the slope of the detection probability at a point where the signal strength tends to zero. **Sequential detection** minimizes the detection time for fixed false alarm and missed detection probabilities.

3.2 State-of-the-Art Sensing Algorithms

Spectrum sensing algorithms can be classified into three classes based on the amount of PU information used during the detector design process: energy detection, feature detection, and matched filter detection. Energy detection algorithms do not make any assumption on the PU signal statistics while matched filter detection algorithms make explicit assumptions on the known pilot waveform or the preamble to design the detectors. Feature detectors lie in middle of these two extremes and only make certain assumptions on the structural or statistical properties of the PU signal while designing the detectors. For example, almost all man-made signals exhibit distinct cyclostationary features which can be used to detect the signals. Again, the presence of CP induces a particular autocorrelation structure in an OFDM signal that can be used to design detectors for such signals. Circularity and non-circularity of complex-valued signals is also a distinguishing feature as the noise is typically circular. These kind of algorithms may also be useful to detect and distinguish different kinds of signals.

Next, most important classes of state-of-the-art sensing algorithms are presented. For a more complete list of sensing algorithms see [36, 89–91, 94].

3.2.1 Matched filter detection

A matched filter is obtained by correlating a known sequence with the received signal. The matched filter is the optimal linear filter which maximizes the output SNR in the presence of additive Gaussian noise. Therefore this method is the optimal method for the detection of PUs in AWGN when the transmitted signal is known. In this case the test statistic can

be written as

$$\mathcal{T}_{md} = \mathbf{s}^H \mathbf{C}_w^{-1} \mathbf{x} \tag{3.5}$$

where $\mathbf{x}$ is the observation vector, $\mathbf{s}$ is the known deterministic signal to be detected, and $\mathbf{C}_w$ is the noise covariance matrix. Thus the test statistic depends on the known signal vector and noise covariance matrix.

The main advantage of the matched filter detection approach is that the sensing time required to achieve given missed detection and false alarm probabilities is relatively short compared to the other methods. Also as the detector is a linear filter, it is easy to implement. On the other hand, the main disadvantage is that matched filters are specific to a particular PU signal and can be used to detect only one type of PU signal. Since cognitive radio will typically need sensing capability for variety of PU signals, a bank of matched filters are needed for detecting the PUs of interest. Certainly complexity is increased, hardware requirements are more demanding and it is hard to change the detector if new waveforms are introduced or the system evolves. In addition, perfect synchronization is required as coherent processing is done [5]. The presence of non-line-of-sight frequency selective channels and synchronization errors may distort the pilot structure in the received signal thereby seriously degrading the detection performance of the matched filters [92, 102]. In addition, if the preamble structure is not repeated frequently, the detection delay may be significant for the matched filters trying to detect the preamble [103, 104]. Also noise covariance must be perfectly known.

Matched filter pilot detection for cognitive radios has been proposed in [102–107]. Coherent detectors for advanced television systems committee (ATSC) - digital television (DTV) standard in North America signals employing the field sync segment have been proposed in [103, 104]. Pilot based detectors have been proposed for digital video broadcasting - terrestrial (DVB-T) standard in [102, 105, 106] to exploit the rich pilot structure in the DVB-T signal. In [107], an entropy based matched filter has been proposed, which compares the estimated entropy of the matched filter output to a threshold.

3.2.2 Energy detection

The classical energy detector, which is also called the *radiometer* , measures the received energy and compares it to a threshold. The basic energy

detector is given in [108] by

$$\mathcal{T}_{ed} = \frac{2}{N_0} \sum_{t=1}^{M} |x(t)|^2, \tag{3.6}$$

where N_0 is the noise spectral density. Factor 2 comes from the fact that under circularity assumption the complex noise power is equally divided between the real and imaginary parts.

For the case of detecting a deterministic signal in the presence of zero mean *iid* complex Gaussian noise, the energy detector test statistic obeys the following distribution [108]

$$\begin{aligned} H_0: &\quad \mathcal{T}_{ed} \sim \chi^2_{2M} \\ H_1: &\quad \mathcal{T}_{ed} \sim \chi^2_{2M}(2\gamma), \end{aligned} \tag{3.7}$$

where γ is the signal-energy-to-noise-spectral-density defined as $\gamma = E_S/N_0$. In this case, $E_S = \sum_{t=1}^{M} |s(t)|^2$ is the signal energy. Therefore the test statistic follows central chi-square distribution with $2M$ degrees of freedom under H_0 and non-central chi-square distribution with $2M$ degrees of freedom and non-centrality parameter 2γ under H_1. Equation (3.7) is applicable in all such cases provided that the probability of detection is considered a conditional probability of detection where the condition is a given amount of signal energy [108].

The main advantages of the energy detectors are that they are simple to implement and can be applied to detect any signal, known or unknown, deterministic or random. In case of *iid* Gaussian noise with known noise power the energy detector is the optimum detector for a random uncorrelated Gaussian signal and at least a GLRT for completely unknown random signals [101]. On the other hand, energy detectors cannot distinguish among different signals (PUs, SUs, interferences) and are not able to exploit the detailed information regarding the PU which is available generally. Also in case the noise statistics are not explicitly known it is difficult to maintain specified false alarm or missed detection probabilities. In fact, the presence of uncertainty in the noise statistics results in severe performance limitation in the form of the SNR wall phenomenon [109]: *In the presence of uncertainty, it is impossible to robustly distinguish the signal from noise at SNR values lower than the SNR wall even if the sensing time tends to infinity*.

A review of energy based detection literature has been provided in [110]. In addition, constant false alarm rate (CFAR) strategies for the channelized radiometer have been considered in [96]. CFAR detectors adaptively adjust their thresholds to maintain a constant false alarm property

if the additive noise is non-stationary. Recent performance analyses of energy detection in fading channels have been carried out in [111–115] as well. Experimental measurements of energy detection performance with noise uncertainty have been provided in [102, 116]. Energy detection of WiMAX systems for ultra-wideband/WiMAX coexistence has been considered in [117]. The detection of wireless microphone signals using the maximum of the frequency domain energy measurements has been proposed in [118]. Energy detectors have been proposed for colored Gaussian [119], independent non-Gaussian [99,120], and colored non-Gaussian noise [120] as well.

3.2.3 Spectrum estimation

Spectrum estimation methods are generally classified as parametric or non-parametric methods. The **parametric methods** assume a model for the signal and try to estimate the parameters of the model. The signal can be modeled by autoregressive (AR), moving average (MA) or Autoregressive moving average (ARMA) processes. Although the parametric methods may result in better performance than that of non-parametric methods, the accuracy of the parametric methods depend on the assumptions of the model [121]. Therefore the non-parametric approach may be more suitable for the spectrum sensing purpose as compared to the parametric approach to detect the unknown signals [89].

Classical **non-parametric spectral estimation schemes** like *Periodogram, Correlogram, Barlett method,* and *Welch method* can be used to detect the idle spectrum. These schemes and their variants have been presented in detail in [121] and make use of discrete Fourier transform (DFT). Accuracy of the estimation depends on frequency resolution, leakage, bias and variance of the estimated power.

A spectrum estimation technique called **multitaper spectrum estimation** has been proposed in [122] and this has been applied for the cognitive radio scenario in [21]. In multitaper spectrum estimation, the procedure involves linearly expanding the part of the time series corresponding to a fixed bandwidth in a family of sequences known as the *Slepian sequences*. These sequences have the property that their Fourier transforms have the maximal energy concentration in the bandwidth of interest under a finite sample-size constraint. This property can be utilized to reduce the variance of the spectral estimate without increasing its bias.

A **filter bank** based approached for spectrum sensing is proposed in

[123]. The input process is passed through a bank of filters and the output power of each filter is measured as an estimate of the spectral power over the associated subband. In [124] generalized filter-bank designs have been proposed to detect the spectral scan with particular shape. Also, a detector based on *Capon spectral estimator*, which is a filter bank approach using data dependent bandpass filters, is proposed [124].

A **wavelet** based approach for spectrum sensing has been proposed in [125, 126]. Wavelets can be considered as a special case of the filter banks with a single wavelet basis. Fine temporal analysis is done with contracted (high frequency) versions of the wavelets while the fine frequency analysis uses dilated (low frequency) versions [127]. Therefore unlike Fourier transforms, wavelets are typically good in describing singularities such as edges in the image or sharp band edges in OFDM and therefore suitable for spectrum sensing.

3.2.4 Cyclostationary detection

Cyclostationary processes are random processes for which statistical properties such as mean and autocorrelation change periodically as a function of time. Wireless communication signals typically exhibit cyclostationarity at multiple cyclic frequencies that may be related to the carrier frequency, symbol, chip, code or hop rates, as well as their harmonics, sums and differences. These periodicities can be exploited to design powerful sensing algorithms for cognitive radios. However, signals typically need to be oversampled (e.g. with respect to the symbol rate or the chip rate) to reveal the cyclostationary features. Cyclostationarity-based detectors have the potential to distinguish among the PUs, SUs and interference exhibiting cyclostationarity at different cyclic frequencies. Moreover, stationary random noise commonly does not possess cyclostationarity property. Cyclostationarity based detection has received considerable amount of attention in the literature. Recent bibliographies on cyclostationarity, including a large number of references on cyclostationarity-based detection, are provided in [128–130].

Most of the PU signal characteristics and parameters are specified in standards. In addition, regulatory bodies monitoring the spectrum allocation require such information to be disclosed. Therefore it is reasonable to assume the explicit knowledge of cyclic frequencies of the PUs. Cyclostationary properties of several widely used waveforms have been established in [131–134].

An optimum multicycle spectral correlation detector is proposed in [135] for a signal in an AWGN channel. However the knowledge of signal phase is required, otherwise the detector performance may suffer. A suboptimum detector is also proposed where the phase information is not needed. Still different information like modulation type, carrier frequency, symbol rate are needed. A suboptimum multicycle detector which only requires the knowledge of cyclic frequencies is introduced in [136]. On similar lines of [135, 136], a single cycle detector for detecting CDMA signals in universal mobile telecommunication system (UMTS) and DVB-T signal are proposed in [137] and [138], respectively.

In [139], a single cycle GLRT for the presence of cyclostationarity has been proposed. The tests are based on testing whether the expected value of the estimated cyclic autocorrelation value at a given cyclic frequency is zero or not. Moreover, a generalization of the above test for the presence of the kth order cyclostationarity has been done. In [134], the GLRT has been formulated for the presence of non-conjugated second order cyclostationary as well. Note in case the cyclic frequency is not known, the test can be carried out at various values of cyclic frequency. However this is computationally very expensive.

In [130, 140], GLRT multicycle detectors have been proposed. This is generalization of the results in [139]. In addition, two simplified multicycle test statistics are proposed and their performance analyzed. Similar multicycle detectors have been proposed to detect the OFDM based DVB-T [141] and spread spectrum signals [142]. In [143], a multicycle detector based on Fourier representation of the autocorrelation function has been proposed. In [144], a locally optimum multicycle detector in non-Gaussian noise has been derived. A spatial sign cyclic correlation based detector has been proposed for robust spectrum sensing in [145]. Robust sign detector trades off optimality with robustness to various non-idealities [92].

3.2.5 Autocorrelation detection

CP based OFDM is a key technology for several broadband wireless systems including wireless local and metropolitan area networks (WLANs and WMANs), DVB systems and LTE. Therefore it is highly probable that most of the PUs will be OFDM based systems. Hence detecting an OFDM based system in a cognitive radio scenario is crucial.

Fig. 3.1 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 in an OFDM

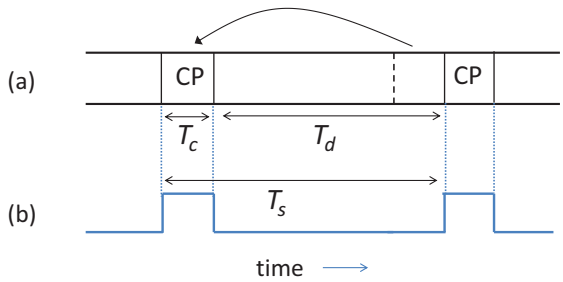

Figure 3.1. (a)An example of CP based OFDM symbol. (b) Corresponding autocorrelation function $r(t,\tau)$ at lag $\tau = T_d$.

symbol so that $T_s = T_c + T_d$. For OFDM signal, the last T_c samples of the data block are copied in front of the data block. This results in the autocorrelation function $r(t,\tau) = E[x(t)x^*(t+\tau)]$ at lags $\tau = \pm T_d$ to be periodic as shown in Fig. 3.1. The periodic autocorrelation function can be expressed using the Fourier series [141] as

$$r(t,\tau) = R^0(\tau) + \sum_{k=-T_s/2, k\neq 0}^{k=T_s/2-1} R^k(\tau) e^{j2\pi kt/T_s} \tag{3.8}$$

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

$$R^k(\tau) = \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} x^*(t)x(t+\tau)e^{-j2\pi kt/T_s}. \tag{3.9}$$

Thus OFDM signal can be considered as consisting of two components: stationary (the first term in (3.8)) and cyclostationary (the second term in (3.8)). Cyclostationary detectors presented in Section 3.2.4 detect the OFDM signal by exploiting the fact that $R^k(\tau)$ is non-zero for $k \neq 0$ and $\tau = \pm T_d$ [130, 134, 141]. In this section, we focus on spectrum sensing schemes which mainly exploit the fact that the stationary part of the autocorrelation function ($R^0(\tau)$) at the lags $\tau = \pm T_d$ is non-zero for the OFDM signal. This significantly simplifies the detector design at the cost of slight performance loss. For simplification, we will denote $R^0(\tau)$ as $R(\tau)$ in the rest of this chapter. If we denote the received observations as $[x(0), \ldots, x(M+\tau-1)]$, then the ML estimate of the autocorrelation at the lag τ is given by

$$\hat{R}(\tau) = \frac{1}{M} \sum_{t=0}^{M-1} x(t)x^*(t+\tau). \tag{3.10}$$

Here the conditional distributions of the received samples $x(t)$ under the two hypotheses are considered Gaussian as was shown in Publications I and III.

Several detectors based on the correlation property have been proposed to detect the OFDM signal in Publications I, III, [105, 106, 146–151]. Most of these detectors are NP detectors as the prior probabilities of $P(H_0)$ and $P(H_1)$ are usually unavailable or may vary as a function of time and are therefore hard to estimate. Table 3.1 summarizes the information assumed by different autocorrelation based detectors for sensing OFDM based PUs. *Synchronization* in the table refers to the knowledge of the start of OFDM symbols and thereby position of the CP in the received OFDM signal. Note that the *assumed information* may or may not be easily available. For example, some of the parameters like T_c and T_d may be easily available from the standards while information on signal variance, noise variance, and synchronization may not be necessarily available and have to be estimated. The errors in estimation can cause further performance loss in the detectors assuming this information. Again, these schemes can be classified based on the *threshold calculation*. If the decision statistics are derived conditioned on the null hypothesis, threshold for the NP detector can be easily found analytically. Otherwise, the threshold has to be evaluated empirically, which is a major disadvantage. The empirical calculation is done by passing sufficient number of white Gaussian noise samples of a corresponding noise variance through the signal detector, calculating the test statistics and finding the threshold for the given probability of false alarm.

Autocorrelation detectors in Publications I and III

The LRT statistic in this case is the real part of $\hat{R}(T_d)$ and is given in Publication I by

$$\mathcal{A}_1 = \mathcal{R}\{\hat{R}(T_d)\}. \tag{3.11}$$

In Publication III, the autocorrelation coefficient is used instead of the autocorrelation value so that the test statistic is normalized with respect to the received signal variance. Therefore the threshold calculation depends only on the number of observations and need not be calculated every time the received signal variance changes. Under the assumption that the conditional distribution of $x(t)$ is Gaussian under either of the hypotheses, the ML estimate of the autocorrelation is shown to be the log-likelihood ratio test (LLRT) statistic in the low SNR regime and is given by

$$\mathcal{A}_2 = \frac{\frac{1}{M}\sum\limits_{t=0}^{M-1} \mathcal{R}\{x(t)x^*(t+T_d)\}}{\frac{1}{2M}\sum_{t=0}^{M-1} |x(t)|^2}. \tag{3.12}$$

Detectors	Information required					*Thres. Calc.*
	T_c	T_d	σ_s^2	σ_n^2	*Sync.*	(A or E)
Autocorrelation detector ($\mathcal{A}_1$) [I]	-	x	-	-	-	A
Autocorrelation coefficient detector ($\mathcal{A}_2$) [III]	-	x	-	-	-	A
Autocorrelation coefficient detector ($\mathcal{A}_3$) [III]	x	x	-	-	x	A
CP detection ($\mathcal{A}_4$) [148]	x	x	x	x	-	A
Robust detector ($\mathcal{A}_5$) [149]	x	x	x	x	-	A
CP based tests ($\mathcal{A}_6$) [105, 106]	x	x	-	x	-	E
CAV and CFN ($\mathcal{A}_7$) [146]	-	-	-	-	-	A
Ratio test ($\mathcal{A}_8$) [147]	-	x	-	x	-	A
Optimal NP detector [150]	x	x	x	x	x	E
GLRT ($\mathcal{A}_9$) [150]	x	x	-	-	-	E
Synchronized Multipath and CP based GLRT [151]	x	x	-	x	x	E
Unsynchronized Multipath and CP based GLRT [151]	x	x	-	x	-	E

Table 3.1. Information assumed by different autocorrelation detectors for sensing OFDM based PUs. *Thres. Calc.* means *threshold calculation* which can be done analytically (A) or empirically (E). *Sync.* means *synchronization* to the symbol timing is required.

In $\mathcal{A}_1$ and $\mathcal{A}_2$, we have assumed a very conservative view that we do not have any knowledge of the CP duration in samples, the range of values CP length can take and the synchronization information (position of the CP in an OFDM block). The effects of exploiting information related to CP on detection performance are shown in Publication III by using the following test statistic

$$\mathcal{A}_3 = \frac{\frac{1}{M_1}\sum_{n=0}^{N_s-1}\sum_{t\in CP}\mathcal{R}\{x(t+nT_s)x^*(t+nT_s+T_d)\}}{\frac{1}{2M}\sum_{t=0}^{M-1}|x(t)|^2}. \tag{3.13}$$

where $N_s = M/T_s$ is the number of received OFDM symbols and $M_1 = N_sT_c$. The distributions of the test statistics given by (3.11), (3.12) and (3.13) under both hypotheses have been derived analytically in Publications I and III. See Publications I and III for detailed derivations and simulation results. The schemes $\mathcal{A}_1$ and $\mathcal{A}_2$ proposed in Publications I and III require knowledge of T_d. This is a reasonable assumption on the PU waveforms as this information is specified in the standards. Even if the exact value is not known, we can detect for different values of T_d from the possible few options. The proposed autocorrelation based detectors have been used as the local detector in the rest of our Publications II, IV-VIII. The test statistic $\mathcal{A}_1$ is used in Publication II whereas the test statistic $\mathcal{A}_2$ has been used in Publications IV-VIII. Moreover, the implementation of the proposed detectors $\mathcal{A}_1$ and $\mathcal{A}_2$ in a FPGA environment has been well studied along with the effects of hardware non-idealities and simple solutions to overcome these effects [92, 152, 153].

The performances of the proposed autocorrelation-based detectors in the Publications I and III have also been studied in different multipath channels in addition to the AWGN channel. Note that it is sufficient that the coherence time of the multipath channel is longer than the duration of an OFDM symbol so that the data and the corresponding CP are affected by the same channel. This will ensure the CP correlation is not significantly degraded. The performance of correlation estimator in different channel conditions (AWGN, Multipath: Rayleigh (frequency flat and frequency selective), frequency flat Rician, Shadowing) has been compared with different detectors in [91] and [92].

Other autocorrelation detectors

In [148], a NP test is proposed under the assumption of knowing T_c, T_d, signal variance, and noise variance. The LRT statistic used is

$$\mathcal{A}_4 = |\hat{R}(T_d) + c|^2, \tag{3.14}$$

where $c = \frac{\mu\sigma_n^2}{(1+2\mu^2)\text{SNR}+2}$ with SNR $= \sigma_s^2/\sigma_n^2$ and $\mu = \frac{T_c}{T_c+T_d}$. Here σ_s^2 and σ_n^2 are signal and noise variances, respectively. The distribution of the normalized test statistic $\frac{|\hat{R}(T_d)+c|^2}{\sigma_{\hat{R}}^2}$ is non-central chi-squared with two degrees of freedom. The authors also proposed $c = 0$ to overcome the issue of dependence of the threshold on T_c, T_d, and signal variance. However the threshold still depends on the knowledge of noise variance.

In [149], the test statistic proposed in the low SNR regime can be approximated for $M \gg T_d$ as

$$\mathcal{A}_5 = |\hat{R}(T_d)|^2 - \frac{1}{M}|\hat{R}(0)|^2. \tag{3.15}$$

This way the noise variance no longer affects the test statistic. Therefore the detector is claimed to be robust to the noise uncertainty. In addition, the detection criterion focuses on minimizing false alarm probability for a given missed detection probability. In this case, the distributions of the test statistic under both hypotheses are non-central chi-squared with different non-centrality parameters.

In [105], a CP based sliding correlation test statistic is proposed for one OFDM symbol. It has been extended to multiple OFDM symbols and any number of received samples in [106] by using the following modified test statistic

$$\mathcal{A}_6 = \max_{\Theta} \left| \sum_{n=0}^{N_s-1} \sum_{t=\Theta+nT_s}^{\Theta+T_c+nT_s} x(t)x^*(t+T_d) \right|, \tag{3.16}$$

where $\Theta \in \{0, \ldots, T_s - 1\}$. If we take the real part of the sum instead of the absolute value, we get the second test statistic proposed in [106].

In [146], two test statistics have been proposed based on the sample covariance matrix. It is based on the fact that the off diagonal elements of such matrices are zero under the H_0 hypothesis assuming white noise. The general test statistic is given by

$$\mathcal{A}_7 = \frac{\sum_{n=1}^{L_s} \sum_{m=1}^{L_s} |\hat{R}(n-m)|^k}{\sum_{n=1}^{L_s} |\hat{R}(0)|^k}. \tag{3.17}$$

where L_s is the number of lags. For ($k = 1$), we get the first method called covariance absolute value (CAV) while ($k = 2$) gives the second method called covariance Frobenius norm (CFN) detection. The optimality of the proposed schemes is not discussed and the schemes may become computationally complex if the number of lags is large.

A ratio test is proposed in [147] to detect a CP-OFDM system in the

presence of frequency flat channel. The test statistic in this case is

$$\mathcal{A}_8 = \frac{|\mathcal{R}\{\hat{R}(T_d)\}|}{|\mathcal{R}\{\hat{R}(T_d-1)\}|}. \tag{3.18}$$

The conditional distributions of the numerator under the two hypotheses are Gaussian with different mean and variances. On the other hand, the denominator has the same Gaussian distribution under both the hypotheses. The test statistic $\mathcal{A}_8$ has a standard Cauchy distribution under H_0. Although the moments are not defined for the Cauchy distribution, the cumulative distribution function (CDF) is defined making it possible to determine the threshold analytically. In case the channel is frequency selective, the detection statistic should be modified by replacing $\hat{R}(T_d-1)$ with $\hat{R}(T_d-L)$, where L is the number of channel taps. The proposed detector is shown to outperform the energy detector.

In [150], an optimal NP test has been proposed under the assumption that the signal variance, noise variance, synchronization (start of an OFDM symbol), CP length T_c, and data length T_d are known. Moreover a GLRT statistic is proposed based on the second order statistics when signal variance, noise variance, and synchronization are unknown. The proposed detector employs the following test statistic

$$\mathcal{A}_9 = \max_{\tau} \frac{\sum\limits_{t=0}^{N_s-1} |\zeta_t|^2}{\sum\limits_{t\in C_\tau} \left|\zeta_t - \frac{1}{T_c}\sum\limits_{t\in C_\tau} \mathcal{R}\{\zeta_t\}\right|^2 + \sum\limits_{t\notin C_\tau} |\zeta_t|^2}, \tag{3.19}$$

where $\zeta_t = \frac{1}{N_s}\sum_{n=0}^{N_s-1} x(t+nT_s)x^*(t+T_d+nT_s)$ for $t = 0,\ldots,T_s-1$. Here C_τ represents the CP part of the OFDM symbol assuming a timing offset of τ samples. The proposed test is a CFAR test as the empirical threshold computation for a fixed false alarm probability in this case is independent of the noise variance.

In [151], it is shown that the autocorrelation coefficient based detection algorithm presented in Publication III is a special case of the constrained generalized likelihood ratio test (CGLRT) for the no-multipath case. In addition, a multipath-based CGLRT is proposed which takes into account the correlation induced by the multipath channel. These two correlation features can also be combined to get a better performance. A modification is suggested which can work in unsynchronized case with slightly degraded performance.

The **choice of an autocorrelation based detector for sensing the OFDM signal** depends on the detector performance, information available, complexity and robustness. It is expected that performance can be

improved by using more knowledge about the PU waveform at the cost of complexity or robustness. The detectors assuming synchronization like autocorrelation coefficient detector ($\mathcal{A}_3$ in Publication III), optimal NP detector [150] and synchronized multipath and CP based GLRT [151] are expected to perform better than the rest of the schemes. However the assumption of synchronization is not practical and may lead to significant degradation in the detection performance. Therefore these schemes may only serve to provide upper bounds on the performance of a detector in their considered scenarios. Similarly schemes assuming the knowledge of signal or/and noise variances like the detectors of [105, 106, 147–149, 151] may be susceptible to errors in the estimates of signal and noise variances when these informations are unknown. The schemes in Publications I ($\mathcal{A}_1$), Publication III ($\mathcal{A}_2$) and GLRT ($\mathcal{A}_9$) [150] are more practical and robust as the parameters assumed in these schemes like T_c and T_d are easily available from the standards. Although the detection schemes CAV and CFN in [146] assume the least information and are among the most robust schemes, they have high computational cost. Other detection schemes with high computational cost are the detectors like the optimal NP test [150] and the detectors in [151]. The empirical nature of the threshold calculation also adds to the computationally complexity in the schemes which do not analytically derive the detector thresholds. On the other hand, schemes with analytical threshold calculations like detectors in Publication I, Publication III and ratio test [147] have low computational complexity. Moreover, unlike under the analytical approach, desired false alarm rate or missed detection probability are not guaranteed with empirical methods.

3.2.6 Sequential detection

Sequential detection requires on average fewer samples to achieve the same performance level as the fixed sample size (FSS) test. Sequential detection is useful in cases where data acquisition is costly and when both reliability and small decision delay are important considerations [154]. The sequential detection test after receiving k data samples is given by [154]

$$\begin{aligned} \mathcal{T}_k \leq \eta_a, &\qquad \text{Decide } H_0 \\ \mathcal{T}_k \geq \eta_b, &\qquad \text{Decide } H_1 \\ \textit{Otherwise}, &\qquad \text{Take Next Data Sample.} \end{aligned} \tag{3.20}$$

where $\mathcal{T}_k$ is the test statistic after k data samples while η_a and η_b are the upper and lower thresholds. Literature on sequential detection can be found in [96, 154–157].

Most of the proposed sequential detectors are based on the *sequential probability ratio test (SPRT)* proposed by Wald in [158]. In terms of the LLRs, the SPRT [158] after receiving k data samples is

$$\begin{aligned} \sum_{m=1}^{k} L_m \leq \log B, &\qquad \text{Decide } H_0 \\ \sum_{m=1}^{k} L_m \geq \log A, &\qquad \text{Decide } H_1 \\ \textit{Otherwise}, &\qquad \text{Take Next Data Samples.} \end{aligned} \tag{3.21}$$

where L_m is the LLR corresponding to the mth observation, $A = \frac{1-\beta_s}{\alpha_s}$ and $B = \frac{\beta_s}{1-\alpha_s}$. Here α_s and β_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 β_s. Among all the tests with equal and or smaller error probabilities, the SPRT is optimal for testing simple hypotheses test as it minimizes the ASN under H_0 and H_1 [159]. However, note that the distribution of the observations needs to be known to evaluate the LLRs at the local detectors.

Although the probability that the test will terminate with a finite number of samples is one, there is no upper bound on the number of samples required for SPRT and the sample size can be occasionally extremely large [155]. Also if there is a mismatch between the actual and assumed values of the parameter, then the SPRT may be less efficient than the FSS test. There have been numerous efforts to design sequential detection tests for the case of composite hypotheses, such as truncated SPRT [155, 160], 2-SPRT [161], invariant SPRTs [162], sequential generalized likelihood ratio (GLR) tests [163], robust and nonparametric sequential detectors tests. For more information, see [155, 156] and references therein.

Applications of the sequential detection framework for local detection in cognitive radios have been studied in [145, 164, 165]. In [145, 165], cyclostationary based sequential detection methods are proposed, while energy based sequential methods are proposed in [164]. Sequential detection schemes are proposed for binary [145, 164, 165] and multiple [165] hypotheses testing problems. The proposed sequential detector in [165] uses a single cycle detector with both phase and magnitude information. Note that a fixed sample size scheme does not suffer any performance

loss due to the loss of phase information. In [145], a single user truncated sequential detection approach based on spatial sign cyclic correlation estimator has been proposed. In [164] sequential detectors with varying thresholds (triangular and reverse parabolic thresholds) are presented to ensure that the test terminates in certain number of samples.

QUICKEST DETECTION

Like ordinary sequential detection, quickest detection also involves choice of a stopping rule. However the basic hypotheses of interest in quickest detection is not binary, but there is one hypothesis for each possible observation time. In particular, the tth hypothesis is that the distribution of the observations changes at time t for $t = 1, 2, \ldots, k$. The quickest detection problem is to detect the change in distribution as soon as possible after it occurs with some constraint on the rate of false alarm. There are two basic formulations: one in which the change point t is assumed to be a random variable with known prior distribution and second in which t is assumed to be unknown but nonrandom. For the introduction and details on quickest detection, see [157].

Quickest detection has been applied to spectrum sensing for cognitive radios in [166], [167]. In [166], the authors have used cumulative sum (CUSUM) test for detecting the change in spectrum for the case when signal and noise variances are known. Also tests are presented for the case where these parameters are unknown. Mathematical analysis for minimum detection delay for a given false alarm rate is done. However, the schemes described in this paper have high implementation complexity. In [167], quickest detection of off periods in multiple on-off processes has been proposed. The main idea here is to abandon the current process when its busy state is unlikely to change in the near future and seek opportunities in a new process. In this case, a Bayesian formulation of quickest change detection in multiple on-off processes with geometrically distributed busy and idle times is obtained within a decision-theoretic framework. A low-complexity threshold policy for channel switching and change detection is proposed. Superior performance over the single-channel approach is seen.

3.2.7 Compressive sensing

Compressive sensing or *sparse sampling* is a technique for finding sparse solutions to a under-determined linear system; see [168] and the ref-

erences therein for details. The underutilization in most of the spectrum bands results in sparseness in the frequency domain. Such sparsity has motivated the use of compressive sensing in finding available spectrum opportunities for dynamic spectrum access. Using wideband spectrum sensing techniques, CR nodes can scan the whole spectrum at once and avoid the delay and complexity of channel-by-channel scanning [169]. Compressed sensing techniques for identifying the unused spectral resources have been proposed in [126], [170]. In [126], the autocorrelation of the received signal sampled at Nyquist rate is compressively sampled. Next the compressive sampling reconstruction is done followed by obtaining an estimate of the spectrum by using a wavelet edge detector. In [170], compressive sampling is directly done on the wide-band analog signal using an analog-to-information converter instead of doing compressive sampling on the autocorrelation of the discrete-time signal obtained at Nyquist rate as done in [126].

3.2.8 Multiantenna detector

Multiple input multiple output (MIMO) technology uses multiple antennas at the transmitter and receiver to improve communication performance (array gain, diversity gain, interference suppression gain, spatial multiplexing). In addition, multiantenna systems may also provide direction of arrival information of the signal. Because of these advantages, MIMO has attracted a lot of attention in the field of wireless communication. For example, it is an important part of wireless communication standards such as WLAN (IEEE 802.11n), 3rd Generation Partnership Project (3GPP) LTE, WiMAX and evolved high speed packet access (HSPA+).

These multiple antennas can also be used for the spectrum sensing tasks. MIMO can trade-off between beamforming gain, parallel sensing gain and diversity gain for detecting the PU. Beamforming helps improve the received SNR while parallel sensing reduces the sensing time and diversity gain helps overcome the effects of multipath fading channel.

In Chapter 4, we will present the case of cooperative sensing (CS) where several SUs cooperate to detect the PU. The multiantenna systems can also be thought of as cooperative systems with colocated antennas. The degree of spatial diversity determines the kinds of gain that can be obtained in using CS. If the antennas see uncorrelated fading, diversity gain will be available; otherwise, mainly SNR (or array) gain is obtained. In some propagation environments like shadowing, diversity gains obtained

by multiantenna systems will be lower than that by CS as the channels may be more correlated for the case of multiple antennas. In addition, an obvious disadvantage of multiantenna systems is the significant cost increase as multiple RF front ends are needed. On the other hand, MIMO has an advantage that the sensing information from different antennas can be fused instantly while in the CS scenario the FC has to wait for the sensing data from the SUs. Also there are no issues related to errors over the reporting channel.

Several multiantenna sensing algorithms have been proposed in [93, 171–176]. In [171], a multiresolution multiantenna spectrum sensing technique has been proposed where a coarse sensing stage is followed by a fine sensing stage. This helps in avoiding the need to sense the entire bandwidth with maximum resolution. In [172], multiantenna energy detection schemes based on the maximum ratio and selection combining are presented. It has been shown in [173] that a multiple antenna based OFDM detection scheme using the square law combining energy detector has better performance than the single antenna scheme. In [174–176], GLRT schemes are proposed for the multiantenna detector case. These methods do not require prior knowledge of one or more parameters like channel gains, noise variance and primary signal variance.

3.2.9 Multistage detection

Two stage sensing schemes have been proposed in [177,178]. In the first of the two stages of energy detection suggested in [177], the total spectrum is divided into several contiguous coarse sensing blocks of equal bandwidth and spectrum sensing is performed on these blocks. In the next stage, fine sensing is done on the blocks with idle channels. It is shown that the two stage sensing with a small coarse sensing bandwidth outperforms the traditional one stage sensing scheme when the fraction of idle channels is low. A slightly different approach was adopted in [178] where two stage sensing was considered with energy detection for the first stage and cyclostationary based detection in the second stage. It is shown that the proposed two-stage sensing provides improved performance over energy detection specially in the low SNR regime while the mean detection time is much lower than that in the cyclostationary scheme for most of the SNR range.

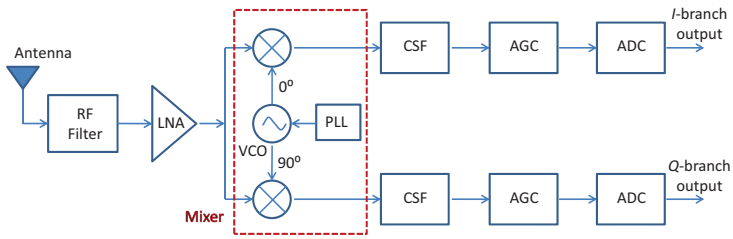

Figure 3.2. Typical RF front end of a direct conversion receiver. The components of the analog front end: wideband antenna, RF filter, low noise amplifier (LNA), voltage controlled oscillator (VCO), phase locked loop (PLL), channel select filter (CSF), automatic gain control (AGC), and analog-to-digital converter (ADC).

3.3 Non-idealities

Performance of the sensing algorithm may degrade in the presence of practical non-idealities like *channel impairments, loss of synchronization, hardware non-idealities,* and *errors in the underlying assumptions*. Examples of different channel conditions are AWGN, shadowing, and multipath fading. Also there may be errors in the assumptions made for the PU signal, channel, and noise.

Hardware issues of the RF front end may depend on the type of receiver implemented: super heterodyne or direct conversion. Modern direct conversion has several advantages over super heterodyne: cost benefit, possibility of using microprocessors, high selectivity, and no issue of image frequency. This is a more cost effective solution for enabling high-performance multistandard/multiband radio designs. *In this thesis we will focus on issues related to direct conversion receiver as it is typical in modern radios and is commonly used also in cognitive radio sensor nodes* [5, 92]. The typical RF front end of a direct conversion receiver is presented in Fig. 3.2. However a direct conversion receiver also has non-idealities: DC offset, non-linearity, narrowband interference, IQ imbalance, phase noise, and synchronization errors [92, 179, 180].

Next we describe few of the non-idealities relevant to local spectrum sensing:

- **Channel Impairments**: The performance of a local detector degrades in the presence of propagation effects such as shadowing and multipath fading [91]. For example, frequency selective fading distorts the pilot structure thereby severely degrading the performance of the DVB-T pilot detector [92]. Again, these channel con-

ditions may result in the hidden node problem, where a secondary transceiver is outside the listening range of a primary transmitter but close enough to the primary receiver to create interference.

- **Nonlinearity**: Nonlinearity may originate in the low noise amplifier (LNA), mixer, filters, automatic gain control (AGC), and analog-to-digital converter (ADC). The presence of nonlinearity generates harmonics and intermodulation products resulting in out-of-band signal detection in all the detection algorithms [92]. The probability of false detection in the band of interest is dependent on the linearity of the receiver front-end and on the SNR at the digital-to-analog converter (DAC) output. While energy detection is always affected by any out-of-band signal, the effect will be less pronounced for the feature detectors if the out-of-band signal has different features than the in-band signal.

- **DC offset**: DC offset is caused by a second order non-linearity and ADC threshold offset, which may or may not vary as a function of time [92]. DC offset may affect the sensing algorithms in two ways. First, it may be detected as a primary signal and thus cause false alarms. Second, it can cause interference which decreases the detection performance by effectively decreasing the SNR. Although DC offset affects most of the sensing algorithms, it can be removed by estimating its value from the input signal and compensating for it [92, 152, 153].

- **Narrowband Interference**: Spurious interference is caused by clock feed-through and feed-through of interference from implementation of DSP blocks in the receiver chain [92]. It may also be caused by an intentional interferer or jammer. If narrowband interference is strong, it can saturate the detector and the detector will only detect the interferer [92].

- **Synchronization errors**: Synchronization errors like carrier and sampling frequency offsets result from the transmitter and receiver operating at different frequencies. The performance of the detectors using the phase information may be severely affected because of carrier frequency offset. For example, the performances of DVB-T pilot detector [106], pilot aided cyclostationary detector [180], and the autocorrelation detectors in Publications I and III degrade in

the presence of carrier frequency offset [92]. On the other hand, performances of the considered energy and cyclostationarity detectors are unchanged as phase information is not used. In [179], it is shown that the energy detector is not sensitive to sampling clock offset while the considered cyclostationarity detector suffers from a high performance degradation.

- **IQ imbalance**: IQ imbalance results from the physical differences in the in-phase (I) and quadrature (Q) branches of the receiver. There is negligible effect of IQ imbalance on the performances of the energy and cyclostationary detectors [179] and pilot based cyclostationary detector [180].

- **Phase noise**: Phase noise is the random perturbation in the phase of the carrier signal generated by the oscillators. In [180], the phase noise is shown to degrade the performance of a pilot aided cyclostationary OFDM detector.

- **Noise model uncertainty**: There may be uncertainty or errors in the modeling of the additive noise which may cause performance degradation. For example, there may be **uncertainty in the noise variance**. Although it is typically assumed that the noise variance is exactly known, noise power may vary due to temperature and out of band interference. Moreover, the noise variance cannot be perfectly known and has to be estimated at the receiver based on a finite number of observed samples in a signal free band. Therefore there will be some uncertainty in the estimate. Normally the noise uncertainty is in the range of 1 dB in the absence of interference [181]. In the presence of interference, the value can be significantly higher. The variance of the noise variance estimate may tend to zero if the number of samples is extremely large which is not practical. In [109], a performance limitation resulting from the noise uncertainty is shown in the form of a *SNR Wall*, which is a lower bound on the SNR at which detection is possible. There may also be **uncertainty in the assumed distribution of the noise**. For example, the noise is modeled Gaussian in most of the detection literature. However, man-made noise in many outdoor and indoor frequency bands is impulsive in nature. For example, noise generated by microwave ovens, electric motors, switches, etc., fall into this category [182]. The distribution of a typical impulsive noise has

a heavier tail than the Gaussian distribution. The presence of multiple such impulsive noise sources generates interference and may degrade the performance of spectrum sensing schemes which assume noise to be Gaussian. Robust nonparametric detection methods have been suggested for cyclostationary based detectors in non-Gaussian noise in [145, 183].

3.4 Discussion

In this chapter, several important aspects of single-user spectrum sensing schemes have been reviewed: *detection strategies, performance parameters, and non-idealities*. The *state-of-the-art sensing algorithms* are also reviewed and it is seen that several tools from diverse fields like spectrum estimation, compressive sensing, multiantenna systems, quickest detection, etc., have been applied to design the sensing schemes for cognitive radios.

Special emphasis has been given in this chapter on the **review of autocorrelation based OFDM sensing schemes** as we have proposed autocorrelation based detectors in Publications I and III. In Publication I, an autocorrelation based detector is proposed for local spectrum sensing while in Publication III an autocorrelation coefficient based detector is proposed. The only difference between the two schemes is that the test statistic in III is normalized by the received signal variance, thereby eliminating the need for recalculating the threshold whenever there is a change in noise variance. The statistical properties of the decision statistics are established. The proposed autocorrelation based detectors are simple, efficient and assume the least amount of PU information. The implementation of proposed detectors in a FPGA environment has been well studied along with the effects of hardware non-idealities and simple solutions to overcome these effects [92, 152, 153]. In addition, the proposed detectors are among the earliest detectors proposed for sensing CP based OFDM systems based on their autocorrelation. Most of the later works on autocorrelation detector have assumed our work as the base work and improved the performance of the detector at the cost of increased complexity and more prior knowledge regarding the PU activity and used waveforms.

Several **state-of-the-art sensing algorithms** have been presented in this chapter. Table 3.2 shows qualitative performance comparison of representative spectrum sensing schemes belonging to different categories.

Detectors	Detection performance	Complexity	Robustness	Distinguish diff. signals	Detect diff. PUs
Robust detector	*	***	*****	*****	*****
Energy detector	**	*****	**	*	*****
Autocorrelation detector	***	****	***	***	***
Cyclostationary detector	****	**	****	*****	*****
Matched filter detector	*****	*	*	*****	*****

Table 3.2. Qualitative performance comparison of representative spectrum sensing schemes belonging to different categories. '*****' corresponds to excellent performance and '*' corresponds to extremely bad performance.

There is no feasible quantitative scaling of the performance that could be used for all the spectrum sensing techniques considered and therefore a qualitative performance comparison is used. The detection performance is assumed to be for given values of false alarm probability, sensing time and SNR. For the results shown in the table, it is assumed that the probability of detection can be improved with increase in the knowledge of the PU signal and noise at the cost of complexity.

It is clear from the **performance comparison** table and discussion on pros and cons of the detectors that *no one detector has the best performance for all scenarios*. The energy detector is the simplest of all the detectors. 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 synchronization errors and frequency selective fading channels. Note that even though a matched filter cannot detect any other signal, the receiver parameters can be tweaked to detect different PU signals at the cost of increased complexity and under the assumption that the preambles/pilot signals are known. With regulatory bodies like FCC and

Ofcom removing the obligation for the use of sensing for TV white spaces (TVWS) in DTV frequencies [184, 185], use of the DVB-T pilot detector may be limited. 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. The robust detector trades off detection performance with robustness to non-idealities and therefore the implementation of robust detectors will be limited to the cases where the non-idealities seriously affect the sensing performance.

Since no one detector is optimal for all scenarios, *it is desirable to have a bank of sensing algorithms* which will satisfy the requirement in the majority of cases. Note that it should be sufficient to have only a few complementary sensing algorithms in the bank of algorithms so that we can use a multistage detector to trade off between the different performance parameters. For example, a simple bank of sensing algorithms may have two algorithms: one sensing algorithm which is simple and fast (like an energy detector or an autocorrelation detector) for coarse sensing and another sensing algorithm which is robust and capable of detecting and distinguishing different signal transmissions (like a cyclostationary detector).

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 propagation effects and non-idealities. 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. Cooperative detection will be the topic of the next chapter.

4. Cooperative Spectrum Sensing

The performance of a local detector degrades in the presence of propagation effects such as shadowing and fading caused by multipath. These channel conditions may also result in the problem of *hidden node*, where a secondary transceiver is outside the listening range of a primary transmitter but close enough to the primary receiver to create interference. These issues can be overcome using *cooperative sensing (CS)*, where neighbouring yet geographically distributed SUs cooperate in sensing a common PU transmission by exchanging sensing information among them before making a final decision. Most of the CS schemes stem from the field of distributed detection [96, 154, 186, 187]. Fig. 4.1 shows an example of CS, where N SUs sense listening channels for the PU signal activity and send the sensing information on reporting channels to the fusion center (FC), which makes the final decision. It is very unlikely that all the channels between the PU and the SUs will be in a deep fade simultaneously. Thus cooperative detection helps in mitigating the channel effects through multipath diversity [5, 188]. Other benefits of cooperative detection include improved detector performance, increased coverage, simplified local detector design, and increased robustness to non-idealities. Therefore, CS has generated lot of interest in the cognitive radio literature. Recent surveys on cooperative spectrum sensing and related issues along with long lists of up-to-date references can be found in [18, 19, 36, 37, 90, 189, 190].

There are several components of CS: knowledge of PU waveform and activity, selection of SUs for cooperation, listening channels, local detectors, cooperation models, reporting channels, detection criterion, and fusion rule at the FC. Most of these topics have already been briefly discussed in the previous chapters. The focus in this chapter will be on cooperation models, fusion rules, and effects of non-idealities on CS performance. This chapter starts with a brief discussion on cooperation models. Next, differ-

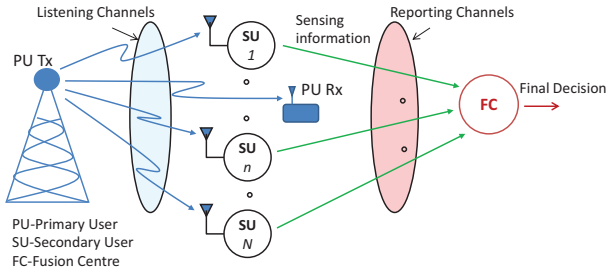

Figure 4.1. Cooperative Sensing (CS): Secondary users (SUs) sense a common PU on the listening channels and send the sensing information to a fusion center (FC) over reporting channels. The fusion center processes this information and makes the final decision whether the PU is active or not.

ent fusion rules are presented. Later, the effects of non-idealities on CS are discussed. As this thesis has contributions in the fields of sequential detection, CS with censoring, CS with quantized decision statistics and effects of reporting channel errors on CS, special emphasis is given on these topics.

4.1 Cooperation models

Cooperation models describe how sensors process the data, how they exchange information among themselves, and who combines the data/decision statistics and makes the final decision. Based on **how local sensors process the data**, cooperative detection can be modeled in two ways: centralized and decentralized (or distributed). In a *centralized* system, each sensor sends all of its observations to a central decision maker or a FC who makes the final decision regarding which of the hypotheses is true using classical detection theory. In a *decentralized* system, each sensor sends a summary of its observations to the FC. The loss of information in summarizing the observations results in minor or no performance degradation for the decentralized system as compared to the case of centralized system. However, the bandwidth requirement for the decentralized system is much smaller than that required for the centralized system [186]. In addition, the energy efficiency is much better for the distributed systems as compared to the centralized system since data transmission consumes energy. These are the reasons why decentralized detection is very important in practical scenarios and has attracted lot of attention in the research community. Introduction to distributed detection theory and various issues related to distributed detection can be found in [96,154,186,187,191].

Cognitive radios have some intelligence and processing capabilities. In addition, there are the constraints on the bandwidth of the reporting (or control) channel and energy consumption of the battery-operated terminal. Therefore, distributed detection is considered more suitable than centralized detection for cognitive radio applications. Hence *we focus on distributed detection systems in the rest of this thesis unless stated otherwise*.

Cooperation models can also be classified based on **how information is exchanged among different SUs**. Some of the widely used topologies for cooperation are: parallel, serial, and tree. In a *parallel* configuration, sensors do not communicate with each other and there may or may not be a FC [187]. In the case of distributed detection without fusion, the detectors observe a common phenomenon and make local decisions. Although the detectors do not communicate with each other, the costs of decision making are coupled as a system wide optimization is performed [96]. This results in coupled thresholds (each threshold is a function of other thresholds) and thereby couple the operations. In this thesis we are interested in the case where the decisions are fused. More information and thus more gain can be expected by fusing the decisions as compared to the case without fusion. In case of parallel fusion networks, there may or may not be a dedicated FC. An example of a parallel fusion network with a dedicated FC is shown in Fig. 4.1. In case there is no dedicated FC, one of the sensors can act as the FC or the role of FC may rotate, e.g., clusterheads in an ad hoc network. The dedicated FC approach is well suited for a wireless network with a base station and has been advocated by the IEEE 802.22 draft standard [192]. On the other hand, the approach without a dedicated FC is suited for *ad-hoc networks*, which do not require a pre-existing infrastructure and where each node participates in routing by forwarding the data for other nodes. However, this approach is suited only for small area networks.

In a *serial* configuration, a sensor sends its decision statistics to another sensor which combines its own observation and decision statistics of the previous sensor to generate a new decision statistic. The second sensor then forwards these decision statistics to the next sensor. The last sensor makes the final decision. In general, serial networks suffer from issues like unreliability, excessive delays and ordering of the sensors. In addition, the error probability of the serial networks is bounded away from zero even as the number of sensors tends to infinity [187].

In a *tree* network, the FC serves as the root of the tree while the sensors

form the leaves of the tree. The information flows only in one direction from one sensor (child) to an other sensor (parent) in the direction towards the FC. In the end, the information from all the sensors reaches FC, which makes the final decision. The details on deriving the fusion rules for the tree topology and other general topologies can be found in [96].

The topologies described above do not consider any feedback from the FC or communication among the sensors. *More general networks* with such additional communication capabilities have been presented in [96, 187] and can improve the system performance. In [193], a parleying approach is presented, where each sensor transmits its tentative decision to all other sensors and the sensor makes another tentative decision based on the original observations and the recent set of tentative decisions. This process continues till a consensus is reached. General networks with feedback have been presented in [96]. In addition, different interesting topics like the case of asynchronous decisions, rules with direct observations, correlated decisions are also covered [96]. An overview and discussion of several important issues, such as randomization and computational complexity is given in [186].

4.2 Fusion rules

Fusion rules describe how the data or the local decision statistics from the SUs will be combined to generate the test statistic at the FC. In a centralized system, the SUs send their observations to the FC which makes the final decision. Therefore, the detection problem for centralized detection is similar to that of the local detection and classical hypothesis testing discussed in Chapter 3 can be used to arrive at the final decision. In this section, we will focus on fusion rules for distributed systems, where SUs send processed data to the FC. As the decision is made on the basis of less information in the distributed systems, there may be some performance loss as compared to the centralized systems. Based on the performance comparison of the fusion rules in a distributed system to that of the optimal fusion rule in a centralized system, the fusion rules for the distributed systems can be classified as lossless fusion and lossy fusion.

4.2.1 Lossless fusion

If each of the users sends a sufficient statistic (such as likelihood ratio (LR) or log-likelihood ratio (LLR)) of its observations to the FC, then it is possible to combine the decision statistics such that there is no performance loss in such distributed system as compared to the case of centralized system. Each of the N cooperating SUs evaluates a LLR L_n and sends it to the FC. The LLR L_n at the nth SU is given by

$$L_n = \log \frac{\prod_{t=1}^{M} p\big(x_n(t) \mid H_1\big)}{\prod_{t=1}^{M} p\big(x_n(t) \mid H_0\big)}, \tag{4.1}$$

where $x_n(t)$ are the observations at the nth SU. Under the assumption of independence of the observations at the SUs conditioned on either of the hypotheses, the optimal fusion rule using these LLRs from the SUs is given by

$$\mathcal{T}_{llr} = \sum_{n=1}^{N} L_n, \tag{4.2}$$

while the corresponding LLRT is given by

$$\mathcal{T}_{llr} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_{llr}, \tag{4.3}$$

where η_{llr} is the threshold at the FC and depends on the detection strategy to be employed, i.e., Bayesian, NP, Min-max, etc. For example, in the NP detector, the threshold depends on the false alarm probability $P_{f,cs}$ and the distribution of the test statistic at the FC under the null hypothesis. This approach has been used in Publications I, II, III by using autocorrelation based LLRs. Note that the distributions of the data under both hypotheses are required. However, these quantities may not always be available. In such a case it may be possible to obtain a sufficient statistic which is independent of the signal distribution. For example, the autocorrelation estimate is used as a sufficient statistic in Publication I. Note that the knowledge of the test statistic's distribution under the null hypothesis is still required. It is also assumed that the sufficient statistics are transmitted as exact values to the FC which may consume excessive bandwidth. In addition, an erroneous or malicious local detector may offer a wrong likelihood ratio which dominates the global likelihood ratio [194].

4.2.2 Lossy fusion

Soft Combining

Sometimes it may become impractical to implement a lossless fusion rule at the FC due to the difficulty in evaluating the sufficient statistic or the threshold. For example, the optimal LLR test statistic becomes quadratic for the case of local detectors employing energy detection and finding the optimal threshold for the test statistic is not mathematically tractable [195]. An easier approach in this case is to use maximum ratio combining (MRC) or equal gain combining (EGC) by using a linear fusion rule given by

$$\mathcal{T}_{lin} = \sum_{n=1}^{N} w_n E_n \tag{4.4}$$

where $E_n = \frac{1}{M}\sum_{t=1}^{M} |x(t)|^2$ and w_n is the weighting coefficient such that $0 \leq w_n \leq 1$ and $\sum_{n=1}^{N} w_n = 1$ [88]. If the source signal power received by each user is known, the optimal combining coefficients can be found for the MRC [97, 195]. For the low SNR case, the optimal weights [88, 97] are given by $w_n = \sigma_{s,n}^2 / \sum_{i=1}^{N} \sigma_{s,i}^2$, where $\sigma_{s,n}^2$ is the received signal power (excluding the noise) at the nth 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 $w_n = 1/N, \ \forall n$. Other ways of combining include selection combining and switched combining. In selection combining, the SU with maximum value among the decision statistics is chosen. Therefore, $w_n = 1$ for the SU with maximum value of the decision statistic and $w_n = 0$ for all others. In switched combining, the receiver switches to another signal when the currently selected signal drops below a predefined threshold. Assuming *iid* channel conditions and same experimental parameters for performance comparison, performance in general improves with more information in the following order: switched combining, selection combining, EGC, and MRC.

The decision statistics like sufficient statistics, energy or SNR levels convey local decision along with a confidence level with which a decision has been made and therefore the fusion of such decision statistics is also termed as *soft combining*. The topic of energy (or SNR) based soft combining has been addressed in the distributed detection literature [112] and the cognitive radio literature [113, 115, 188, 196–203]. In [196], CS algorithms to detect vacant TV channels are proposed and their performance

is compared with the AND fusion rule. In [201], a comparison of different CS algorithms like LRT, MRC, and EGC is carried out. The MRC and EGC schemes have also been considered in [199]. In [203], soft combination schemes are proposed under NP and minimax criteria. However the derived combination schemes require highly accurate information of noise power levels and PU signal energies which are extremely difficult to obtain in the low SNR regime. It is also shown that the optimal combining scheme is better than MRC when the noise power levels are not identical at different SUs.

Collaborative energy detection schemes for different channel conditions have been considered: Rayleigh, Nakagami, and Rician fading channels [112], Rayleigh and Nakagami fading [199], Rayleigh fading and log-normal shadowing [113, 115, 197, 201], Suzuki fading with correlated and uncorrelated shadowing [198] and Rayleigh fading with a block obstacle shadowing model [188].

Hard Decision Combining

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 final decision. Examples of one-bit HD combining are Boolean fusion rules such as OR, AND, and MAJORITY. Advantages of HD combining are that they are easy to implement and reduce the bandwidth requirement on the reporting channel between the sensors and the FC. However these advantages come at the cost of performance loss resulting from the quantization. HD combining has been well studied in the detection literature [96, 186, 187]. If u_n is the decision sent by the nth SU, then the optimal fusion rule for both the Bayesian formulation and NP formulation is a likelihood ratio given in [96] by

$$\mathcal{T}_{cv} = \sum_{n=1}^{N} \left[u_n \log \frac{1 - P_{m,i}}{P_{f,i}} + (1 - u_n) \log \frac{P_{m,i}}{1 - P_{f,i}} \right]. \tag{4.5}$$

This fusion rule is also termed the *Chair-Varshney fusion rule* and is a weighted sum of incoming local decisions, where the weights depend on the local probabilities of false alarm $P_{f,i}$ and missed detection $P_{m,i}$. The optimal decision rules at the FC and at the local detectors are LRTs in both the Bayesian and the NP formulation [96]. However, finding the local and global thresholds is not trivial and may involve complex optimization techniques like Lagrangian or person-by-person optimization (PBPO) methods. Moreover, knowledge of the local false alarm and missed detec-

tion probabilities may not be available and have to be estimated. These local probabilities can be estimated empirically [204], which is a major disadvantage.

The optimal fusion rule reduces to a K-out-of-N fusion rule (also called *counting rule*) for the case of identical sensors with *iid* observations. Counting rules are a general class of Boolean fusion rules which include the widely used OR, AND and MAJORITY fusion rules. They have the added advantage of ease of implementation and low computational complexity. The optimum value of K is derived in [96] which minimizes the Bayesian risk. However, it is shown in [205] that the probability of error does not tend to zero as N tends to infinity if the probability distributions under the hypotheses do not satisfy certain conditions. For certain examples, it is also shown that the performances of the OR and AND fusion rules are worse than that of a single sensor.

HD based CS for cognitive radios has been considered in several works [188, 196, 199–201, 206–208]. Energy based local detectors are used in [196, 199–201, 206, 207] while cyclostationary based local detectors are considered in [208]. The optimum number of cooperating users for energy detection based cooperation has been investigated for AND and OR fusion rules in [206] and for K-out-of-N fusion rules in [207]. It was observed that including SUs experiencing bad channels for cooperation may degrade the performance [206]. In [207], the optimal K that minimizes the total error probability for *iid* sensors with identical local decision rules for the general K-out-of-N fusion rule was found to be $\lceil N/2 \rceil$ for typical error probabilities. In [188,196,199–201], soft combining schemes are compared with one or more hard decision schemes. Hard decision schemes considered in these papers belong to the class of counting rule. It is a common conclusion that there is more performance loss with hard combining than in the case of soft combining. However the performance difference between soft and hard combining can be relatively small as was shown for energy based local detectors for large number of SUs in [188].

4.3 Sequential detection

Sequential detection, which was discussed in Section 3.2.6, has also found application in cooperative detection. There are many flavors of cooperative sequential detection: centralized [100, 155, 157], distributed [96, 155, 209–212], and quickest [157, 213, 214]. In the **centralized version**, se-

quential detection is applied at the FC based on the observations from the sensors. In the **distributed** version, sequential detection can be applied at the individual sensors or/and at the FC. Distributed sequential testing at the FC has been considered in [209,211] where the FC makes a sequential decision based on the summarized observations from the sensors. Distributed sequential testing at sensors has been considered in [212] where there is no FC and the sensors are coupled with a common objective function. In [215] a decentralized SPRT (D-SPRT) scheme is proposed in which both the local sensors and the FC employ SPRTs. In **quickest detection**, the aim is to detect the change in the state of the system as soon as possible. The topic of cooperative quickest detection will be treated later in this section.

Application of sequential detection framework in cognitive radios has been studied in Publications II, III, [176, 216, 217]. While Publications II, III and [176, 217] employ distributed sequential tests at the FC, [216] employs a centralized sequential test. In Publications II and III, autocorrelation based LLR evaluated for a data block is sent to the FC while [176, 217] use energy based LLR as a decision statistic. This way the decision statistic can be approximated using Gaussian distribution without consideration of the statistical distribution of the primary signals under both the hypotheses. However, knowledge of the received SNR at each SU is needed. Simple hypotheses are considered in Publication II, III, [176,216,217] and composite hypotheses in [216]. In [217], the cooperative sequential scheme with censored and ordered transmission is used so that the subsequent LLRs would have values with a lesser magnitude than the earlier LLRs. This is extension of work in [218] for cognitive radio context and unlike [218], only K LLRs with the highest magnitudes out of the N LLRs are processed.

4.3.1 Autocorrelation based sequential detection of OFDM systems

In Publications II and III, SPRT is proposed such that each SU sends an autocorrelation based LLR to the FC which makes the decision sequentially. The difference in the two publications is that autocorrelation value $\mathcal{A}_1$ given by (3.11) is used in Publication II while autocorrelation coefficient $\mathcal{A}_2$ given by (3.12) is used in Publication III. Note that since the two detectors are the same, except for the normalization, they will have similar performances. In both the papers, distributions of the deci-

sion statistics (LLRs from the SUs) conditioned on either hypothesis are established. Under the assumption of *iid* observations, the ASN of the proposed sequential detector is derived in Publication III and is given by

$$K_{sprt} = \max\{E[K|H_0], E[K|H_1]\} \tag{4.6}$$

where $E[K|H_0]$ and $E[K|H_1]$ are the ASNs under the null and alternative hypotheses, respectively. The performance of the sequential detection schemes is studied and compared with the FSS test in AWGN channel in both publications and in shadowing channels in Publication III. The benefit of sequential detection over FSS test is expressed in terms of *relative efficiency (RE)* given by

$$RE = \frac{K_{fss}}{K_{sprt}}, \tag{4.7}$$

where K_{fss} is the minimum sample size for FSS test to achieve the same false alarm probability and missed detection probability. It is shown that there are significant savings in the number of SU decision statistics required while using sequential detection as compared to the FSS test for the same reliability level. For example, $RE = 2.042$, i.e., only half of the number of samples are required for SPRT as compared to FSS when the given values of false alarm probability and missed detection probability are both 0.01. For detailed derivations and simulation results, please see Publications II and III.

4.3.2 Quickest detection

The cooperative quickest detection problem has been considered by several authors [157,213,214,219]. The proposed schemes are based on using CUSUM or its variant as the test statistic. In [213], a change detection scheme is proposed where each sensor quantizes the observed signal and sends it to the FC which makes the decision whether or not a change has been detected. One shot schemes for decentralized quickest change detection are proposed in [214], where a sensor communicates with the FC only once and the FC then has to make a decision. The CUSUM stopping rules for all sensors are asymptotically (as the mean time between false alarms tends to infinity) sufficient statistics for the problem of quickest detection. Therefore asymptotically, there is no loss of performance as compared to the case of centralized quickest detection.

Cooperative quickest sensing in cognitive radios has been considered in [220–224]. In [220, 221] distributed quickest detection is considered without a FC in the presence of network delay. A two-thread CUSUM

algorithm is proposed for a simple two-node network in [220] while a multi-thread CUSUM test is proposed for a general multi-node network in [221]. In [222], a Dual CUSUM test is proposed such that CUSUM tests are performed both at the sensors and at the FC. Each sensor transmits only if the CUSUM is above some threshold. Variants of the Dual-CUSUM scheme are proposed in [223] and [224]. The local sensors use GLR CUSUM algorithms in [223] while autocorrelation based LLRs are used to detect OFDM transmission in [224].

4.4 Performance evaluation criteria

In this section, performance evaluation criteria is presented which is important to make a fair comparison of different cooperative sensing schemes. In this thesis, the performance evaluation criteria is considered to be consisting of performance parameters and non-idealities, which are described in the following two subsections:

4.4.1 Performance parameters

Cooperation may result in gain and overhead as compared to the 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. Most of the performance parameters for a CS algorithm are the same as for the local sensing algorithms explained in Subsection 3.1.2: false alarm probability, missed detection probability, SNR regime, sensing time, computational complexity, energy consumption, and robustness against non-idealities. In addition, there are a few parameters which are specific to cooperative detection scenario and those are

- **Cooperation delay**: Cooperation delay includes the time taken for reporting the decision statistics from the SUs to the FC and processing the decision statistics at the FC. For example, cooperation delay may be caused by collisions and resulting retransmissions while using random medium access scheme. As cooperation delay is in addition to the local sensing time, it increases the overall sensing time and therefore this parameter should be as small as possible. The effect of cooperation delay has been included in [225] and references therein.

- **Reporting overhead**: A reporting or control channel is required 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. Thus reporting overhead decides the amount of cooperation between SUs. Issues related to the reporting overhead have been considered in [225] and Publications IV-VIII.

- **Cooperation footprint**: It is the area where SUs cooperate with each other. Since cooperative gain is obtained from spatial diversity, cooperation footprint is an important parameter. The distances between the SUs should be sufficiently large such that the observations are not correlated. However if the cooperation footprint is too big, some of the SUs may be far away from the PU affecting the CS performance. In addition, a bigger cooperation footprint may result in inefficiencies in the spectrum reuse which is a local concept. It is also important to consider the SU distribution (which depends on the number of SUs and the cooperation footprint) in addition to the distance between the SUs while designing sensor network dimensioning and user selection schemes. Network dimensioning for cooperative sensing has been considered in [226] and references within.

- **Number of SUs**: Performance gain in CS depends on the number of SUs. For AWGN listening channels, the gain is mostly SNR gain that increases with the number of cooperating SUs. However the diversity gain for multipath channels is obtained with diminishing returns as the number of SUs is increased [227]. In case of correlated channels, the obtained diversity gain can be very small [227]. It is desirable to have as few SUs as possible since the reporting overhead increases with an increase in the number of SUs.

It is evident that the degree of cooperation depends on different and possibly conflicting performance parameters. Performance parameters like detection probability, false alarm probability, sensing time, and robustness may improve with an increase in the number of SUs. However cooperation delay, reporting overhead, and energy consumption may increase with an increase in the number of SUs, which is undesirable. Therefore degree of cooperation is a trade-off between different performance parameters to achieve the desired objective.

4.4.2 Non-idealities

In the previous sections, most of the assumptions made for cooperative sensing are valid only in ideal conditions. In a practical scenario, there may be several non-idealities caused by the propagation environment, hardware issues, malicious users, bandwidth, and power constraints. Following are a few examples of the non-idealities for cooperative sensing:

- **Correlated observations**: Most of the optimal fusion rules are derived under the assumption of conditional independence of observations for the two hypotheses. Correlated observations might arise due to shadowing or line-of-sight channel conditions. Shadowing can result in observations being correlated even for relatively large distances. Collaborative distributed spectrum sensing with correlated listening channels has been considered in [187, 188, 196, 228] and with correlated reporting channels in [229]. While the optimal solution is intractable in general for such a scenario [187], using suboptimal fusion rules may result in a performance loss [188]. Asymptotic performance analysis for the correlated nodes case shows that the missed detection probability does not converge to zero [196]. A linear quadratic deflection-optimizing detector has been proposed in [228] for fusing the binary decisions from the local energy detectors at the FC. The proposed detector performs better than the K-out-of-N fusion rules in correlated log-normal shadowing. In [229], it is shown that the performance degradation caused by correlated shadowing at the reporting channels is similar to that at the listening channels.

- **Bandwidth constraints on reporting channels**: Optimal detection performance for cooperative sensing can be achieved if each user transmits exact value of the sufficient statistics (like LLR) and the FC combines them using an optimal fusion rule. However this results in excessive bandwidth consumption. The reporting channel bandwidth is limited and it poses constraints on the amount of data transmitted for cooperative sensing thus determining the level of cooperation. Techniques like quantization and censoring help in reducing the excessive bandwidth consumption at the cost of slight performance loss. As the thesis has contributions in the fields of censoring (Publication I) and quantization (Publications IV-VIII) for cooperative sensing, they are discussed in more detail later.

- **Energy constraints**: The functions of sensing and data reporting add to the energy consumption of the cooperating SUs. This is a serious issue in battery-operated mobile terminals. The resulting energy or power constraints may affect the cooperative sensing performance by limiting the level of cooperation between the SUs. As more energy is spent in data transmission as compared to data processing, techniques like quantization and censoring help in achieving better energy efficiency. Another approach to minimize the energy consumption is to optimize the cooperative sensing performance with energy constraints [230] or minimize energy consumption with detection performance constraints [231].

- **Imperfect reporting channels**: Erroneous reporting channels corrupt the decision statistics sent by the SUs to the FC. This may increase the error probabilities at the FC [232] and thereby affect the CS performance as shown in Publication IV. Moreover, performance limitations of CS in the presence of reporting channel errors have been shown in [233] and Publications V-VIII. This necessitates the use of error coding to cope with reporting channel errors. At the same time, the overhead caused by error control codes should be minimized. In fact, error coding can be avoided in low-cost and low-power sensor networks if the channel errors do not significantly affect the CS performance [234]. The issue of reporting channel errors will be discussed later in detail.

- **Synchronization issues**: Most of the cooperative schemes assume that all the cooperating SUs are synchronized to a common clock and that the decision statistics from the SUs are available to the FC at predetermined instants. However, it is very practical to have timing and frequency synchronization issues between the SUs and the FC. In addition, the decision statistics from the SUs may arrive at different instants at the FC owing to networking and transmission delays. The loss of synchronization may eventually affect cooperative sensing performance. The effects of networking delays on distributed detection and spectrum sensing have been studied in [96, 232] and [235] respectively.

- **Security**: Sensing a frequency band consumes energy and time. Hence users have an incentive to sense for a shorter duration than stipulated. Again, the resource allocation of the vacant frequency

bands is based on the quality of decisions the SUs send. Therefore there is also an incentive for *malicious users* to fake the detection results. The presence of untrusted SUs has been shown to degrade cooperative sensing performance [188]. The issue of untrusted SUs can be tackled by using schemes which use anomaly detection on the decision statistics sent by the SUs to distinguish and remove the malicious users from the group. For example, a weighted SPRT with reputation-based mechanism is proposed in [236] and a consensus based scheme is presented in [237] to overcome the effect of untrusted SUs.

4.5 Censoring

A censoring based approach is introduced in [238] where only informative observations are sent to the FC. The decision statistics are deemed *informative* if they are sufficiently high or low, i.e., favor one of the hypotheses clearly. This approach provides significant benefits in terms of reduction in bandwidth requirement and energy requirements while the performance loss is negligible as compared to the conventional case of cooperative detection without censoring.

Distributed detection using censored statistics has been considered in several works [218, 238–243]. It is shown in [238] that the optimal no-send region is a single interval using different criteria like Bayesian, NP and distance between hypotheses (where the measure used belongs to Ali-Silvey family). This simplifies the problem of finding the no-send region as we need to find just two thresholds for each detector instead of an arbitrary N-dimensional set. This is further simplified under certain conditions [238, 239] where the lower threshold tends to zero and we only need to find the upper threshold. A robust and locally optimal formulations of the censoring problem is considered in [239], for the cases where the signal and noise distributions are not completely known. In [243], the knowledge of fading channels is integrated in developing optimal and suboptimal fusion rules for the case of cooperative sensing with censoring. Performance analysis is carried for different channels like Rayleigh, Rician and Nakagami fading channels. In [218], a censoring and ordered transmission based approach gives considerable reduction in transmissions as compared to the optimal censored but unordered scheme with minimal performance loss.

The censoring based approach has been applied to cooperative spectrum sensing in [54, 217, 231, 244] and Publication I. While [54, 231] send energy based HDs to the FC, [244] uses cyclostationary based SD, [217] uses energy based SD and Publication I uses autocorrelation based SD. The common conclusion is that there are significant savings in bit transmissions at the cost of negligible performance loss. In [54], the performance of the proposed censoring scheme for the OR fusion rule is studied for the cases where the reporting channel may or may not be erroneous. In the presence of channel errors, the sensing performance decreases as compared to that in a perfect channel. In [231], the authors consider a combined sleeping and censoring scheme to minimize the energy consumed in distributed sensing subject to constraints on the detection performance. A censoring and ordered transmission based approach is considered in [217] for cognitive radio context. In [244], the asymptotic distribution of the cyclostationary based test statistic under the null hypothesis is derived by numerically inverting the characteristic function using a Fourier series method. This is done as the truncation of the test statistics due to censoring makes an analytic solution intractable for finite observations. In Publication I, a censoring approach similar to [244] is proposed for autocorrelation based local test statistic for detecting OFDM systems, instead of cyclostationary property as was done in [244]. This will be briefly presented next.

4.5.1 Autocorrelation based censoring scheme for detecting OFDM systems

The local test statistic in this case is the maximum likelihood estimate of the autocorrelation at the lag T_d, i.e., $\mathcal{A}_1$ given by (3.11). For simplicity, this value is denoted for the nth SU by $\hat{\rho}_n$. The censoring region for the collaborating users is determined using the constraint on the data rate. The lower threshold is $-\infty$ while the upper threshold η_n is given by

$$P(\hat{\rho}_n > \eta_n | H_0) \leq \kappa_n \quad \forall n = 1, \ldots, N, \tag{4.8}$$

where $\kappa_n \leq 1$ is the send rate of the user n. Let $\mathcal{N}_{ns} = \{n : \hat{\rho}_n \leq \eta_n\}$ be the set of SUs in the no-send region. Now the test statistic at the FC is given by

$$\mathcal{T}_c = \sum_{n \notin \mathcal{N}_{ns}} \hat{\rho}_n + \sum_{n \in \mathcal{N}_{ns}} E_{\mathcal{N}_{ns}}[\hat{\rho}_n] \tag{4.9}$$

where $E_{\mathcal{N}_{ns}}[\hat{\rho}_n]$ is the average value of the test statistic in the no-send region for the nth SU under the null hypothesis. The detection criterion

used is NP. The distributions of the local decision statistic and test statistic at the FC under the null hypothesis are established in Publication I. Once the distribution of the test statistic under the null hypothesis is established, the threshold at the FC can be evaluated so that the desired constraint on the false alarm probability can be achieved. It is shown that there is negligible performance loss in using censoring even for very tight communication constraints resulting in significant reduction in energy and control bandwidth consumption. Detailed derivations, theoretical and simulation results can be found in Publication I.

4.6 Quantization

Decision statistics like sufficient statistics, energy levels or their quantized versions serve as *soft decisions* (SDs). Use of SDs improves cooperative detection performance in comparison to the one-bit HD case [196,202,245]. However in this section, we will focus mostly on the *multi-bit* or *quantized* version of SDs and their effect on cooperative detection. An argument that is often made against the use of SD based CS is that the bandwidth requirement scales linearly with the number of bits used for quantization. This is not necessarily true. The presence of a frame header and additional information like interference levels, channel states and occupancy information, or probabilities for the channel occupancy [238,246], may result in a significant overhead even in the HD case. Therefore the relative increase in the transmitted data needed for the SDs may be small.

The problem of designing optimum quantization algorithms for signal detection and fusing the quantized data has received lot of attention in the distributed detection literature [96, 186, 247–250]. In [186, 249], likelihood ratio quantizers (LRQs) have been shown to be the optimal quantizers for signal detection. In [247], a locally optimum quantizer is proposed while a minimum average error (MAE) quantizer is presented in [251]. In [250], multibit distributed detection of weak random signals in additive, possibly non-Gaussian, noise is considered for the case where the signal observations are correlated at sensors. In [194], optimum local decision partitioning for distributed detection is considered. Here the global optimization criterion for the desired objective function involves multibit local decision statistics, local decision thresholds, FC decision statistic and FC threshold. It is shown that quantizing the decision statistic is equivalent to subpartitioning the false alarm and missed detection prob-

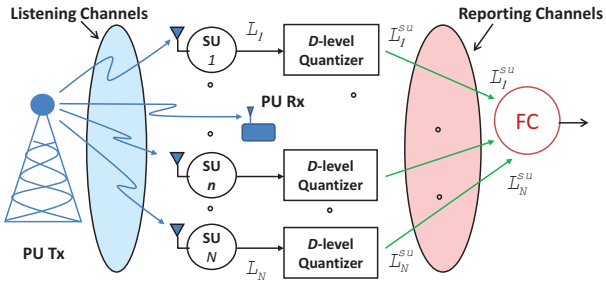

Figure 4.2. Secondary users (SUs) send quantized sensing information to the fusion center (FC) through error free reporting channels.

abilities. Also it is shown that with optimal subpartitioning of the local decision space, detection performance increases monotonically with the number of partitions at the cost of complexity.

The problem of SD based CS has been addressed in the cognitive radio literature [199, 200, 202, 252, 253], Publications IV, VI, VIII. While publications IV, VI, and VIII use quantized versions of autocorrelation values or the LLRs as SDs, papers [199, 200, 202, 252, 253] use quantized versions of SNR or energy values as SDs. Most of these papers compare their proposed detection schemes with one or more fusion rules belonging to the counting rule family (OR, AND, and MAJORITY) and the common conclusion is that the use of SDs gives significant performance gain as compared to HD based CS and negligible loss as compared to the use of unquantized SDs.

Different schemes have been considered to quantize the decision statistics in different papers: *uniform quantization* in [252], Publication IV, and VI, *maximum output entropy (MOE) quantization* in Publications VI and VIII, *Lloyd-Max quantization* in [253]. The schemes in [253] and Publication IV require the distributions of the received signal under both hypotheses to be known while the schemes in [252] and publication VI depend only on the probability of false alarm so that the distribution of the received signal under H_1 is not required.

4.6.1 Autocorrelation based soft decisions for detecting OFDM systems

In Publications IV, VI, and VIII, the effects of quantization are analyzed on the performance of CS with and without reporting channel errors while using autocorrelation based SDs. In this section, the effect of quantization on CS in the absence of reporting channel errors will be presented and

the case with channel errors will be dealt with later when discussing the effects of reporting channel errors on the CS performance.

Fig. 4.2 shows the considered cooperative sensing scenario using quantized LLRs. The nth SU quantizes the decision statistic using a $D-$level (or equivalently a $d-$bit) quantizer where $D = 2^d$. For example, autocorrelation based LLR L_n is quantized to get the quantized version L_n^{su}. The quantized decision statistic is mapped to a bit sequence and sent to the FC over an error free reporting channel using binary phase shift keying (BPSK). At the FC, the bit sequence is again mapped back to the levels. A sum test statistic is assumed at the FC. Under the assumptions that the observations at the SUs are *iid*, the optimal test statistic at the FC is to sum the received quantized LLRs.

While Publications IV and VIII use quantized versions of autocorrelation based LLRs, Publication VI uses quantized versions of autocorrelation coefficient instead of LLRs. Publication IV uses uniform quantization, Publication VIII considers MOE quantization while Publications VI compares the uniform and MOE quantization schemes. The schemes of Publication IV and VIII require the distributions of the received signal at the SU under both hypotheses are required while the schemes in Publication VI depend only on the probability of false alarm so that the distribution of the received signal under H_1 is not required. *Gray* and *binary* mappings are assumed to map the quantization levels to the bit sequences at the SU and vice-versa at the FC in Publication IV. Gray mapping is shown to give better performance than binary mapping, specially at small values of D. Therefore only Gray mapping is considered in Publications VI and VIII. AWGN listening channels are considered in Publications IV, VI and VIII, while shadowing effects are also considered for the listening channels in Publication VIII.

In Publications IV, VI, and VIII, the distributions of the quantized decision statistics from the SUs are derived. Under the assumption that the observations at the SUs are independent conditioned on either of the hypotheses, the decision statistics from the SUs are independent of each other. Therefore, the probability mass function (pmf) of the test statistic can be derived by convolution of the pmfs of the corresponding individual random variables. Since the test statistic at the FC is a discrete random variable, randomization has to be used to implement the NP criterion. Also note that the considered sum test statistic at the FC is optimal under the assumptions that the observations at the SUs are *iid* and that

there are no reporting channel errors.

In Publications IV, VI, and VIII, the theoretical and simulation results show that using $d \geq 3$ bits, there is negligible loss as compared to the unquantized LLRs in the absence of reporting channel errors. Also MOE quantization performs better than uniform quantization scheme at the cost of complexity.

4.7 Imperfect Reporting Channels

Issues related to erroneous reporting channels in distributed detection have been studied in [232, 234, 254–257]. In [232], the effects of transmission delay and channel errors on the performance of a HD based distributed sensor network have been studied. Channel errors are modeled as a BSC. The optimal fusion rule and the local tests have been shown to be LRTs for a NP formulation [232] and Bayesian formulation [255]. In [254], the performances of different fusion rules such as the LR, Chair-Varshney fusion rule, MRC and EGC with binary decisions for Rayleigh faded reporting channels have been compared assuming a finite number of sensors and the use of phase shift keying (PSK) for reporting the decisions. Different modulation schemes (frequency shift keying (FSK) and on/off keying (OOK)) and different fusion rules (the counting rule and Square Law Combining (SLC)) are considered in [234] as well. The asymptotic error exponents are calculated using large deviation theory for slow Rayleigh fading channels and AWGN channels in [234]. Channel aware distributed detection is considered in [254, 256, 257] for improved performance and better energy efficiency. In [257], a new LR-based fusion rule is proposed which requires only the knowledge of channel statistics whereas channel state information is required in [254]. In [256], joint source-quantization and channel-encoding algorithm is proposed which exhibits inherent adaptivity in resource (bit) allocation in response to varying channel conditions. That is, the less reliable the reporting channels are, the fewer quantization level in the optimal quantizer output, hence more redundant bits are used to combat any possible channel impairment.

The effects of reporting channel errors in cognitive radios have been studied for SNR (or energy) based local detectors in [233, 245, 258–261] and for autocorrelation based local detectors in Publications IV-VIII. Cooperative communication schemes for sensing are considered to overcome

the channel effects in [233, 259–261] while non-cooperative communication schemes are suggested in [245, 258]. An amplify-and-forward relay strategy has been proposed for two user networks in [259] and for multiuser networks in [260]. In [261], a transmit diversity based cooperative sensing scheme is proposed to address the performance degradation caused by the reporting channel errors. In [233], a performance limitation of OR fusion rule is shown in the presence of reporting channel errors. To overcome the effects of reporting channel errors, a robust cooperative spectrum sensing scheme is proposed where multiple nodes come together to form a virtual antenna array and space time coding is employed. In addition, a cognitive space frequency coding is also proposed for reporting decisions from SUs to the FC. In [258], a two step detector is proposed in which the local decisions are first estimated using a maximum a posteriori (MAP) detector at the FC from their corrupted versions and then fused to arrive at a final decision. The performance loss of this computationally simple algorithm is minimal in AWGN as compared to the optimal detector. However, performance comparison with non-cooperative schemes shows that the non-cooperative scheme may be more effective in some cases. In [245], the FC determines a set of users that maximizes the detection probability for a given false alarm probability by solving an optimization problem using the interference-to-noise ratio (INR) and SNR reports from the SUs.

In Publications IV-VIII, the effects of reporting channel errors on the performance of CS with HDs and SDs are considered. Publications V and VII mainly deal with the performance limitations for HD based CS while Publications IV, VI and VIII mainly deal with CS with quantized versions of SDs. In addition, a performance comparison of hard and soft combining schemes is carried out in publication VIII. In the next three subsections, we briefly discuss the work in Publications IV-VIII as they are the major contributions of this thesis. For detailed derivations and simulation results, see the corresponding publications.

4.7.1 Effects on hard decision combining

Fig. 4.3 shows the considered scenario of HD based CS where the nth SU sends one-bit HD u_n^{su} to the FC over an erroneous reporting channel. The received one-bit decision is denoted by u_n^{fc}. The reporting channels are assumed to be *iid* binary symmetric channel (BSC) with a certain bit error probability (BEP) P_b while listening channels are AWGN. For HD based

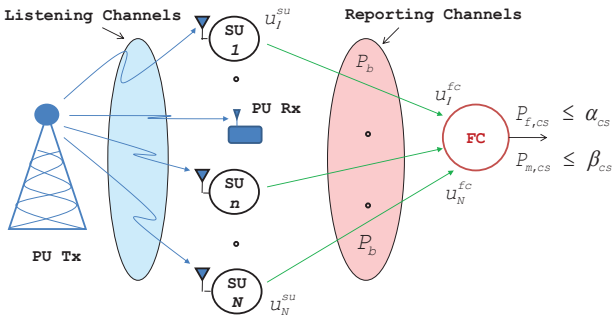

Figure 4.3. Secondary users (SUs) send one-bit hard decision (HD) to the fusion center (FC) over an erroneous reporting channel.

CS at the FC, counting rules or K-out-of-N fusion rules are employed at the FC for HD based CS as the K-out-of-N fusion rule is a more general class of fusion rules and includes the widely used OR, AND and MAJORITY Boolean fusion rules. For CS, the important performance parameters of false alarm probability and missed detection probability are denoted by $P_{f,cs}$ and $P_{m,cs}$, respectively. Moreover the constraints on the probabilities of false alarm and missed detection for CS are denoted by α_{cs} and β_{cs}, respectively.

The reporting channel errors are modeled using the BEP as it is a convenient and a widely applicable method to model the end-to-end performance of the system including the transmitter, the channel and the receiver. Therefore, the effects of channels, modulation, coding and interleaving schemes can be incorporated through a corresponding BEP value. An assumption is made here that the erroneous sensing data received at the FC is used in CS irrespective of the error detecting or/and correcting codes used. However we do not consider the case where the transmitted packet is dropped if packet errors are detected. The problem with dropping the packets and resending the messages from the SUs to the FC may cause significant delay in decision making at the FC.

In **Publications V**, a performance limitation in terms of BEP wall was demonstrated for HD based CS under the constraints on false alarm and missed detection probabilities: *If the effective BEP of the reporting channel is above the BEP wall value, then the constraints on the detector performance cannot be met at the FC irrespective of the received signal quality on the listening channel or the sensing time at the SUs*. The concept of BEP wall can be explained using Fig. 4.4 which plots SNR loss vs. BEP curves for different K-out-of-N fusion rules for $N = 5$. Here SNR Loss is the min-

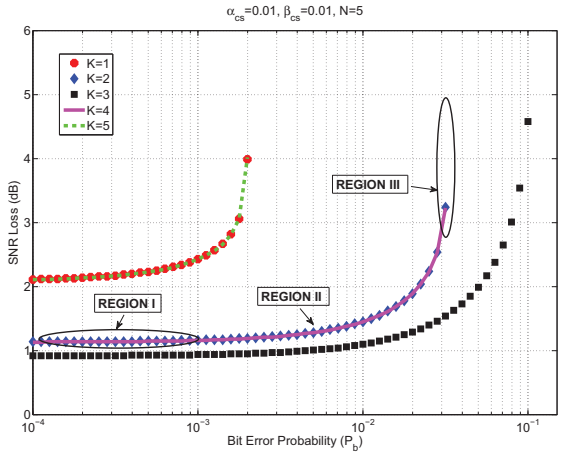

Figure 4.4. SNR Loss in dB vs. P_b for the K-out-of-N fusion rules for $\alpha_{cs} = 0.01$, $\beta_{cs} = 0.01$ and $N = 5$. The SNR Loss is the required increase in the local SNR for maintaining the same error levels at the FC as in error-free reporting channel case. The BEP wall phenomenon is clearly observed.

imum additional SNR required at the SUs to meet the same performance constraints for the considered CS scheme with the erroneous reporting channels as compared to the ideal case (optimal fusion rule, exact LLRs and error-free reporting channels). There are three distinct regions for each of the curves. In region i, channel BEP has negligible affect on the CS performance and all the SNR loss is due to quantization. In region ii, an increase in the BEP leads to an increase in the SNR Loss, however the constraints can still be met. In region iii, a slight increase in BEP leads to an exponential increase in the SNR loss and the SNR loss tends to infinity as BEP approaches the limiting value. Since the phenomenon looks like a wall at a certain BEP, we have termed it as BEP wall.

Expressions for the BEP wall values have been derived for the K-out-of-N fusion rule in Publication V assuming *iid* reporting channel conditions and are given by

$$P_{b,wall} = \min(\mathcal{B}^{-1}(K-1, N, 1-\alpha_{cs}), 1 - \mathcal{B}^{-1}(K-1, N, \beta_{cs})), \tag{4.10}$$

where $\mathcal{B}^{-1}(k, n, p)$ is the inverse of Binomial CDF with parameters k, n and p. It is shown through theoretical and simulation results that the BEP wall values are significantly low (on order of 10^{-2}) making error correction coding necessary in such cases. It is shown in Fig. 4.5 that the widely used OR and AND fusion rules are very sensitive to the reporting channel errors while the MAJORITY fusion rule is very robust against the reporting channel errors.

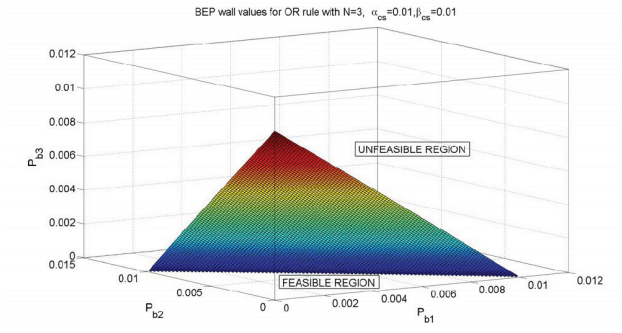

Figure 4.5. Under the assumption that the reporting channel errors need not be identical, the BEP wall values for the OR fusion rule, $N = 3$, $\alpha_{cs} = 0.01$ and $\beta_{cs} = 0.01$ are calculated in Publication VII. The BEP wall values for the OR fusion rule are given by the surface $1 - (1 - P_{b1})(1 - P_{b2})(1 - P_{b3}) = \alpha_{cs}$ as the constraint corresponding to the false alarm constraint is dominant.

The work in Publications V is extended in **Publication VII** to the case in which the reporting channel errors can be non-identical. The feasible BEP values for the counting rule have been shown to satisfy the following inequalities in Publication VII:

$$1 - \sum_{l=0}^{2^N-1} \mathcal{I}_{\left\{\sum_{n=1}^{N} u_n^l \geq K\right\}} \prod_{n=1}^{N} \left\{(1 - P_{b,n})u_n^l + P_{b,n}(1 - u_n^l)\right\} \leq \beta_{cs}, \quad (4.11)$$

$$\sum_{l=0}^{2^N-1} \mathcal{I}_{\left\{\sum_{n=1}^{N} u_n^l \geq K\right\}} \prod_{n=1}^{N} \left\{P_{b,n}u_n^l + (1 - P_{b,n})(1 - u_n^l)\right\} \leq \alpha_{cs}, \quad (4.12)$$

where $P_{b,n}$ is the BEP of the reporting channel from the nth SU to the FC. Moreover, $\mathcal{I}_{(\cdot)}$ is a indicator function and $\mathbf{u}^l$ is the binary vector corresponding to the decimal value l. Thus in this case, there are several BEP wall values. The BEP wall values are the BEP values on the boundary of the feasible region corresponding to the dominant of the two constraints (4.11) and (4.12) as increasing the BEP value for any of the N reporting channels will lead to a violation of the constraints. Thus the BEP wall values form a surface of BEP values satisfying both the constraints in (4.11) and (4.12) with at least one constraint satisfied with equality. This surface divides the BEP region into two parts: feasible and unfeasible. In the unfeasible region, it is not possible to satisfy the cooperative detection performance constraints even if the SNR on the listening channel or the sensing time is increased. For example, Fig. 4.5 shows the surface of the BEP wall values for the OR fusion rule for $N = 3$, $\alpha_{cs} = 0.01$ and $\beta_{cs} = 0.01$ along with the feasible and non-feasible BEP regions.

In **Publication VIII**, the detection probability for the K-out-of-N fu-

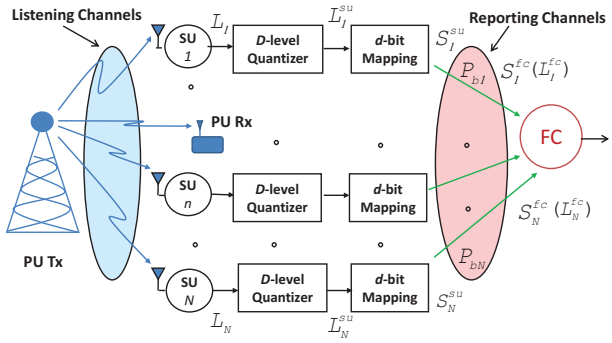

Figure 4.6. Secondary users (SUs) send multi-bit soft decision to the fusion center (FC) over erroneous reporting channels.

sion rule is derived for the general case in which the sensors may experience different average SNRs on the listening channels. Simulation results for shadowed listening channels show that the OR fusion rule has the smallest performance loss while the AND fusion rule has the highest performance loss as compared to the ideal case (exact LLRs, optimal fusion rules and no reporting channel errors). However the locations of the BEP walls remain unchanged.

4.7.2 Effects on soft decision combining

Fig. 4.6 shows the considered scenario of SD based CS. The quantized version of the LLR L_n^{su} at the nth SU is mapped to a bit sequence S_n^{su} and sent to the FC over an erroneous reporting channel using BPSK. The FC receives corrupted bit sequence S_n^{fc}, which may be different from the sent version. At the FC, the bit sequence is again mapped back to the levels L_n^{fc}. Let $P_{b,n}$ denote the BEP for the reporting channel from the nth SU to the FC.

In **Publication IV**, the distribution of the received decision statistic L_n^{fc} is shown to also depend on the statistics of the channel errors such that the pmf of L_n^{fc} is given by

$$P(L_n^{fc} = l_{i,n}|H_j) = \sum_{i=1}^{D} P_{b,n}^{d_{i,k}}(1-P_{b,n})^{d-d_{i,k}} P(L_n^{su} = l_{i,n}|H_j). \tag{4.13}$$

where $d_{i,k}$ is the Hamming distance between the d-bit sequences corresponding to $l_{i,n}$ and $l_{k,n}$. The sum of the received quantized LLRs is used as the test statistic at the FC. The pmf of this test statistic can be evaluated by convoluting the pmfs of L_n^{fc} for all SUs. Through theoretical and simulation results for *iid* channel errors ($P_{b,n} \triangleq P_b$) it is shown in Publication IV that the reporting channel errors significantly affect the

performance of CS. Due to the channel errors, the probabilities of false alarm and missed detection increase. The effect is significant for low D and high P_b while the effect is negligible for high $D \geq 8$ and low $P_b \leq 0.01$.

In **Publication VI**, a SD based CS scheme using an estimator-detector structure is proposed for composite hypotheses testing for detecting OFDM based PU. The SDs are the quantized versions of the maximum likelihood estimate of the autocorrelation coefficient instead of LLRs as in Publication IV. For quantization, two schemes *uniform quantization* and *MOE quantization* are considered. However, the proposed SD based CS schemes suffer significant performance loss in the presence of channel errors and exhibit BEP wall phenomenon. The BEP wall values are low enough to be a cause of concern for CS. Simple modifications to these quantization schemes are suggested to improve their robustness to the channel errors.

In **Publication VIII**, the distributions of the optimal fusion rule under the null and alternate hypotheses are derived in the presence of channel errors and a specific quantization scheme. The performance of the optimal fusion rule is analyzed through theory and simulations. Through simulation results, the existence of a BEP wall for the SD based CS is established. However the BEP wall values are too high (on the order of 10^{-1}) to be of practical importance for the considered fusion rule and the quantization algorithm. Later, a performance comparison of the HD and SD based CS in the presence of reporting channel errors is conducted. It is shown that there is a considerable performance gain in using SDs for cooperative detection as compared to HDs for various listening channel conditions even in the presence of reporting channel errors.

While quantifying performance limitation caused by the channel errors in terms of the BEP wall, it is assumed that only the channel statistics such as the BEP value are known (i.e., we only know how channel behaves on average and the instantaneous channel coefficients are unknown). Under this assumption, the model can be used for fast or slow fading channels by using BEP value corresponding to the channel. In cases where partial or full information regarding the reporting channels may be available, the performance limitation has to be redefined in terms of the known channel parameters such as the channel order, channel tap coefficients, coherence time, coherence bandwidth, etc. Although it is possible to obtain the channel information through channel estimation and feedback from the FC, it adds to the complexity, communication overhead and delay for the CS.

4.8 Discussion

In this chapter several important issues related to CS schemes have been discussed: *cooperation models, fusion rules, performance evaluation framework, and effects of non-idealities such as censoring, quantization, and reporting channel errors*. Different **cooperation models** for distributed detection have been presented: parallel, serial, and tree. Each one of the network topologies has its own advantages and disadvantages.

Next, several **fusion rules** are discussed: LRT, MRC, EGC, switch combining, selection combining, 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: detection performance, false alarm control, sensing efficiency, available information, complexity, energy consumption, and robustness to non-idealities. The LRT gives the best performance among all the fusion rules. However, the LRT assumes the distributions of the observations to be known under both hypotheses. Moreover the performance of the LRT is optimal under the assumption of independent observations conditioned on the hypotheses. Therefore their performance may suffer in a scenario where the assumptions are inaccurate or invalid. In addition complexity in some cases may be excessive. In such cases linear combination schemes such as the MRC and EGC can be used at the cost of slight performance loss. 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. The local probabilities may not be always available and have to be estimated empirically, which is a major disadvantage. Hard combining schemes like OR, MAJORITY, and AND belonging to the class of K-out-of-N fusion rules have been widely implemented because of their simplicity. However there are disadvantages of loss of performance and robustness.

Sequential detection is a reliable and quick way to arrive at a cooperative decision. Sequential detection is suitable for the cases where the decision statistics from the SUs are arriving at the FC asynchronously or/and data acquisition is costly. For example this is possible while using TDMA for transmission of decision statistics. On the other hand, sequential fusion may not be suitable for the case where the cost of taking a observation is low and the decision statistics are available at the FC synchronously. This is possible while using access schemes such as FDMA

and CDMA. For a simple hypothesis, the SPRT minimizes the ASN among all the tests with equal or smaller error probabilities. However information to evaluate the LRs are required such as the conditional distributions of the observations under H_0 and H_1. If there is any deviation in the assumed parameters from the actual parameters, the ASN may increase for the SPRT and it may be even greater than that for the FSS test. In Publications II and III, SPRT has been applied for detecting OFDM using autocorrelation based LLRs from the SUs. These publications are among the first works in the literature to use and analyze sequential detection schemes at the FC in the cognitive radio context. Most of the later works on sequential detection in the cognitive radio context have referenced our work and shown improvement in the performance at the cost of increased complexity.

Next, a **performance evaluation framework** has been presented for CS. There are several performance parameters like probability of detection, probability of false alarm, sensing time (local sensing time + cooperation delay), SNR, cooperation footprint, number of SUs, robustness against non-idealities and computational complexity. As some of these parameters may be conflicting in nature, cooperation may result in gain and overhead as compared to the 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. Thus the degree of cooperation is a tradeoff between different performance parameters to maximize cooperation gain and minimize cooperation overhead. Most of the performance analyses in the literature on CS is done for one or two parameters at a time while keeping others fixed. Although it gives a good idea on how the CS performance behaves with the given parameter, it does not give provide insights when there are more variables acting together in the CS. There is a need to form objective function as a function of various parameters having priority based weights so that the combined effect of different parameters can be observed on the CS performance.

The **effects of non-idealities** like censoring, quantization, and reporting channel errors have been considered as well in this thesis. Non-idealities such as censoring and quantization are required for the feasibility of practical cooperative schemes while reporting channel errors can not be avoided in a practical scenario. Therefore studying the effects of such non-idealities is important.

A **censoring** based approach helps in limiting the bandwidth and energy consumption without significantly degrading the cooperative sensing performance. In Publication I, a censoring approach is used to detect an OFDM based primary such that only informative decision statistics are sent to the FC. Huge savings in the number of transmitted decision statistics from the SUs to the FC has been seen under the null hypothesis at the cost of negligible performance degradation.

The effects of **quantization** and **imperfect reporting channels** on CS have been studied in Publications IV-VIII. The work in these publications presents the framework to obtain the design parameters of *number of bits for quantization* and *operational BEP value* such that the CS performance loss due to the quantization and channel errors is minimal. It has been seen that a performance similar to the case of using unquantized decision statistics can be obtained by using as low as four bits for a simple uniform quantization scheme. Although multi-bit quantization improves the detection performance for CS, there is an exponential increase in complexity with the number of bits for quantization for schemes such as MOE or LR quantization. As only few number of bits are required in practice, this is not a big concern.

An important performance limitation for CS in the form of a **BEP wall** resulting from reporting channel errors has been demonstrated in Publications V-VIII. Performance limitation for the CS has not received sufficient attention in the cognitive radio literature. Establishing the limitations of a fusion rule is an important topic as it helps in designing practical detectors and communication protocols between the detectors and the FC. Therefore demonstration and analysis of the BEP walls has been an important contribution.The BEP wall phenomenon has been analyzed for hard decision combining (Publications V, VII, VIII) and soft decision combining (Publications VI, VIII). It has been found that the OR and AND fusion rules are very sensitive to the BEP Wall phenomenon while MAJORITY fusion rule and soft decision combining are robust to the reporting channel errors. Moreover, the performance of the OR and AND fusion rules degrade with increase in the number of cooperating users. Most of the papers in literature consider OR and AND fusion rules because of their simplicity without realizing their serious limitations. *In my view, BEP walls for the* OR *and* AND *fusion rules are analogous to the SNR walls for energy detectors*. Similarly, the choice of quantization scheme has been shown to significantly affect the BEP wall values for soft combining and

needs to be paid sufficient attention during the design of practical cooperative sensing schemes.

Comparison of hard and soft combining schemes for cooperative spectrum sensing has been carried out in Publication VIII for different listening channel conditions. It has been shown that there is a considerable gain in cooperative detection performance and robustness while using soft decisions instead of hard decisions. There is a common misconception that bandwidth requirement increases linearly with increasing number of quantization bits for soft decisions. However the presence of significant overhead of header information means that the increase in traffic resulting from using 3-4 bit long soft decisions is negligible. Therefore more emphasis should be given to cooperative spectrum sensing using soft combining as compared to hard combining, whenever possible.

5. Conclusion

Limited usable radio frequencies and current rigid frequency allocation policies have resulted in the apparent scarcity of the radio spectrum even though the overall spectrum occupancy is still very low. Cognitive radios offer the promise of enabling the future wireless world by increasing spectrum efficiency through dynamic spectrum access. In dynamic spectrum access, the secondary users access the underutilized primary user spectrum opportunities such that the interference to the primary users is under allowed limits. Spectrum sensing is a key enabler for cognitive radios. Sensing provides awareness regarding the radio environment so that the spectrum opportunities can be efficiently reused while limiting the interference to the primary user. *The focus of this thesis has been on the local and cooperative spectrum sensing algorithms along with the effects of non-idealities on their performance.*

Single-user spectrum sensing schemes have been proposed in this thesis to detect OFDM based primary user transmissions. OFDM is a key technology for the present and future wireless systems and therefore detecting OFDM transmissions is a very relevant task for cognitive radios. The detector exploits the autocorrelation property of the OFDM symbol resulting from the presence of the cyclic prefix. Later, the proposed sensing schemes are extended to the case of cooperative sensing where multiple secondary users collaborate for the task of spectrum sensing. The proposed local detectors are simple and efficient. Minimal assumptions regarding the primary user and noise statistics are made by these autocorrelation detectors. These assumptions are either available from standards or valid in a practical scenario. Moreover the proposed detectors have been implemented in a FPGA evaluation environment and the effects of different non-idealities on their performances have been well studied. The proposed detectors are among the earliest autocorrelation based

detectors for OFDM detection and are highly cited in the later works on autocorrelation detectors.

Cooperative sensing has several advantages over local detection such as diversity gain, increased coverage and simpler detector design. Sequential detection minimizes the detection time for the given constraints on the probabilities of false alarm and missed detection. Decentralized sequential sensing scheme has been proposed in this thesis where the secondary users send sufficient statistics like log-likelihood ratios to the fusion center which sequentially makes the final decision. Performance comparison with a fixed sample size test shows significant reduction in the number of samples required to arrive at the final decision with the same error probabilities. The proposed sequential detection scheme has received a lot of attention in the literature and has been highly cited. Censoring based cooperative sensing has also been considered in which each secondary user sends autocorrelation based decision statistic to the fusion center only if it is sufficiently informative. The censoring approach has shown to provide significant reductions in the transmissions of decision statistics, especially when the primary user is inactive, at the cost of slight performance loss. This also improves energy efficiency as the transmission of decision statistics consumes considerable energy. Later the effects of quantization and imperfect reporting channels have been considered. Our main aim in studying the effects of quantization and channel errors on the cooperative sensing is to provide a framework for the designers to choose the operating values of the number of quantization bits and the target bit error probability for the reporting channel such that the performance loss caused by these non-idealities is negligible. Moreover, a performance limitation in the form of bit error probability (BEP) wall has been established for the cooperative sensing schemes in the presence of reporting channel errors. The BEP wall phenomenon is important as it provides the feasible values for the reporting channel BEP used for designing communication schemes between the secondary users and the fusion center. It has been shown that soft decision combining gives better performance than hard decision combining in the presence of quantization and reporting channel errors. In addition, the hard decision OR and AND fusion rules have been found to be very susceptible to the BEP wall phenomenon and any increase in the number of cooperating users make them more vulnerable to the limitations caused by the reporting channel errors. It has been also shown that the choice of a quantization scheme

for soft decision combining significantly affects the BEP wall values.

Although a lot of research has been done on spectrum sensing, there are still **several challenges**. In the *second opinion and order* report, the FCC has eliminated the spectrum sensing requirement for TV band devices that use geolocation and database access. However it has been emphasized in the report that the sensing technology offers significant promise for improving spectrum access and efficiency both in the TV bands and in providing dynamic access to other spectrum bands. Therefore the opportunity to submit applications for certification of sensing-only devices has been kept open and a rigorous process has been suggested for approval of such devices. Although sensing is not mandatory in IEEE 802.22, most wireless standards being developed for operation in the TV white spaces do include features to support sensing, which can provide additional tools for optimization of the system performance and protection of incumbents. The database may give satisfactory performance in TV white spaces but may not be sufficient for dynamically accessing the white spaces corresponding to more dynamic primary users. Moreover, the sensing approach may be more suitable to increase the spectrum efficiency by accessing gray spaces in addition to the white spaces. Sensing can also facilitate the coexistence of heterogeneous networks in the same frequency bands, which is an important research challenge. Therefore *sensing is still important in the current context of dynamic spectrum access in TV white spaces and it is also going to be a key enabler in the next evolutionary step of cognitive radios for dynamic spectrum access*. Thus there is still plenty of room and motivation to design innovative and efficient spectrum sensing schemes, especially for the cooperative scenario.

Cognitive radio is a highly multidisciplinary field and is still in its infancy. Apart from sensing, other important areas for cognitive radios are sensing and access policy design, coexistence among multiple primary and secondary networks, cooperative communications, network security, cognitive network architecture and protocol design, cognitive radio architecture, software abstractions, business considerations and regulatory policies. Although some cognitive features are being used in various wireless standards and systems, there is still lot of research to be done in the important areas mentioned above for making cognitive radio networks a reality. Moreover, collaboration among researchers across these diverse fields is crucial for realizing the full potential of cognitive radios for dynamic spectrum access.

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Errata

Publication I

Equation (7) is written incorrectly. The correct equation is

$$E[|r|^2|H_1] = \frac{(\sigma_s^2 + \sigma_n^2)^2 + 2\mu_1^2}{M} + \mu_1^2.$$

Publication IV

Fig. 1 is not printed properly. The proper figure is given below

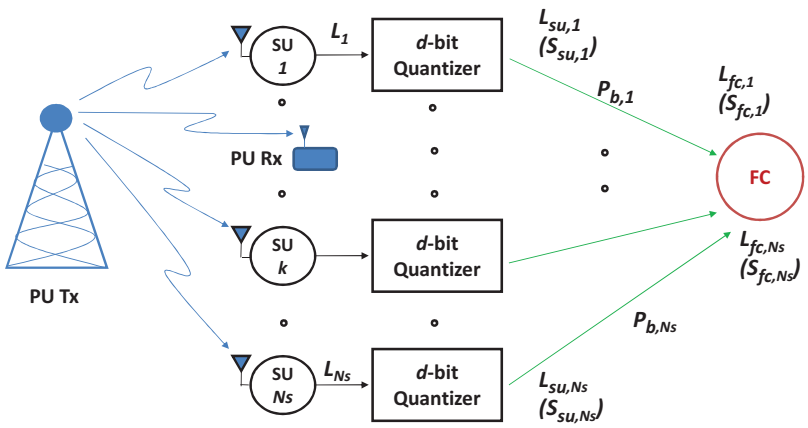

Figure 5.1. Secondary users (SUs) cooperate to detect CP-OFDM based primary user (PU) transmission. The nth SU evaluates LLR (L_n), and transmits d bit symbol $S_{su,n}$ corresponding to the quantized LLR $L_{su,n}$. Due to the channel errors, the FC receives symbol $S_{fc,n}$ corresponding to the quantized value $L_{fc,n}$. The FC then combines the received LLRs from the cooperating secondary users to make a final decision.

Publication V

In this paper and Publications VII and VIII, it is assumed that $K = \lceil \frac{N}{2} \rceil$ for the MAJORITY fusion rule. This definition of the MAJORITY rule is appropriate only while using *odd* values of N as was done in these publications. However this definition of the MAJORITY fusion rule is incorrect for *even* values of N and the correct general definition is $K = \lceil \frac{N+1}{2} \rceil$.

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