Low complexity spectrum sensing for cognitive radio enabled aeronautical communication systems

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Low Complexity Spectrum Sensing for Cognitive Radio Enabled Aeronautical Communication Systems

Libin K Mathew

School of Computer Science and Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

2020

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I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Prof. A S Madhukumar

Authorship Attribution Statement

This thesis contains material from six paper(s) published/submitted in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 3 is published as

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The contributions of the co-authors of the paper are as follows:

- Prof Vinod provided the initial project direction and edited the manuscript drafts.
- I prepared the manuscript drafts.
- I co-designed the study with Prof Vinod and performed all the experiments.

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"But you, be strong and do not let your hands be weak, for your work shall be rewarded!"

—2 Chronicles 15:7

To my dear family

Abstract

Air traffic has seen tremendous growth over the last decade and is expected to grow continuously. The state of the art of current aeronautical communication system is not capable of handling future developments due to the scarcity of the spectrum resources and demands enhanced air traffic management schemes. The L-band Digital Aeronautical Communication System (LDACS) is gaining traction as a scheme of choice and aims to exploit the capabilities of modern digital communication techniques and computing architectures. To improve the quality of air traffic management, the spectrum required to be used efficiently. Cognitive Radio (CR) based approaches have also been proposed for LDACS to improve spectrum efficiency and communication capacity. The CR-based system enables opportunistic and on-demand access to L-band channel(s) while meeting the reliability and safety requirements. This allows an aircraft to identify vacant spectral bands in the air-to-ground spectrum using spectrum sensing techniques and choose the proper channel to initiate an LDACS air-to-ground transmission, similar to the case with ground-based CRs. However, spectrum sensing for LDACS presents unique challenges compared to terrestrial systems; aircraft in the range of the system is always in motion resulting in a continually varying network structure, while the channel conditions between the communicating entities can change very rapidly, requiring much more complex processing compared to terrestrial CR systems. At the same time, the limited energy budget of the aircraft demands low complexity techniques to improve energy efficiency. Computationally efficient, fast, and reliable detection techniques that perform well in low signal-to-noise ratio and noise uncertainty scenarios are required in LDACS. New spectrum sensing algorithms and their low complexity implementations are proposed in this thesis to address the aforementioned challenges.

The first work presents an energy-difference detection-based spectrum sensing scheme for CR-enabled LDACS system. The detection method utilizes the unique shape of the spectrum after removing the legacy system signals from the known spectral gaps. Irregularities of the power spectrum density across continuous narrow bands are detected by comparing the absolute energy difference of the neighbouring LDACS and

legacy channels with a predefined decision threshold. Simulation studies show that the proposed energy-difference detection based sensing scheme offers improved detection performance than the conventional Energy Detection (ED) scheme at the low SNR scenarios and identical performance at relatively high SNRs. Though the technique improves the detection accuracy, it suffers from higher computational complexity, also the scheme is applicable only for the sensing of the LDACS spectrum. An adaptive energy detection scheme is proposed as the second work to reduce the computational complexity further, and to provide a generic sensing scheme. In this technique, the historical energy observations from previous sensing epochs are adaptively used to improve the detection accuracy. An enhanced real-time noise variance estimation technique is developed with the aid of cyclic prefix in the LDACS signals. The noise variance can be estimated effectively in real-time irrespective of the primary signal being on or off. The proposed technique does not incur dedicated hardware blocks for noise variance estimation, leading to an efficient hardware implementation of the scheme without significant resource overheads. The proposed technique is integrated into a cognitive radio platform on a field-programmable gate array (FPGA) device to quantify resource overheads. Results of simulation studies show that the scheme provides better detection accuracy compared to the existing ED techniques.

To reduce the SNR wall to a lower value compared to the first and second works using the prior knowledge of the preamble signals, a multiplier-less correlator based sensing scheme is proposed. The proposed correlator can also serve as the receiver synchronizer for the LDACS air-to-ground links. The architecture is designed in such a way that it can cater to the preamble structure of LDACS air-to-ground transmissions. The computational precision of the system is enhanced to improve the performance in very low SNR conditions. The proposed architecture offers improved detection performance over traditional energy detection even at low SNR with lower energy consumption than a multiplier-based correlator, while also assisting in receiver synchronization. A simplified cyclostationary detection (CD) scheme is proposed as the fourth work to get the best trade-off between accuracy, complexity, and sensing duration. In this scheme, a sliding correlation-based CD is proposed. The test statistic is a likelihood ratio test (LRT) in which the cyclostationary feature is normalized with the real-time noise variance. The proposed scheme is implemented in Verilog and mapped on a Xilinx FPGA device to quantify the overall resource consumption. Results show that the scheme offers comparable detection performance with

the multiplier-less correlator with only one-third of resource overheads and power consumption and better performance than the conventional CD schemes.

Wideband spectrum sensing is essential to find the different possible spectral holes in the frequency spectrum of interest. Conventional Nyquist wideband sensing is not a power-efficient solution as it requires massive computing capability due to the higher sampling and quantization and for subsequent processing. In this context, a power-efficient wideband spectrum sensing is proposed to alleviate this issue by providing the best accuracy-complexity trade-off. The current research proposes and implements a wideband sensing architecture based on a one-bit quantization at the CR receiver. A Finite Impulse Response (FIR) filter bank is used to split the wideband to several narrow bands; then, the detection algorithm is applied to each narrow-bands individually. In the proposed scheme, the sampling and quantization unit is reduced to a high-speed comparator, and the multiplication in each filter tap is replaced by a sign changer, which is implemented using a 2's complement circuit and a 2:1 multiplexer. The scheme considerably reduces the computational complexity of the conventional filter bank based sensing by using a sign changer instead of a multiplier.

Contents

Acknowledgements	ix
Abstract	xiii
List of Figures	xxi
List of Tables	xxv
Symbols and Acronyms	xxvii
Symbols and Acronyms	xxix
1 Introduction	1
1.1 Cognitive Radio for Aeronautical Communications	2
1.2 Spectrum Sensing	4
1.3 Motivation	6
1.4 Major Contributions	7
1.5 Outline of the Thesis	8
2 Spectrum sensing for aeronautical communication: A literature review	11
2.1 Evolution of aeronautical communication systems	11
2.1.1 Future communication infrastructure activities	12
2.2 LDACS System Specifications	15
2.2.1 LDACS deployment	15
2.2.2 Physical frame characteristics of LDACS	16
2.2.2.1 FL frame structure	16
2.2.2.2 RL frame structure	16
2.2.2.3 Spectral Mask of air station Tx LDACS signal	18
2.2.2.4 LDACS frequency allocation	19
2.2.3 Airborne radio system for LDACS	19
2.3 Cognitive Radio(CR) for Dynamic Spectrum Access	20
2.3.1 Definitions of cognitive radio	20
2.3.2 Operating modes of cognitive radio	20
2.3.3 Functionalities of cognitive radio	21
2.3.3.1 Spectrum sensing	21

2.3.3.2	Spectrum Management and Decision making	21
2.3.3.3	Spectrum sharing	22
2.3.3.4	Spectrum mobility	22
2.4	Spectrum Sensing Techniques	23
2.4.1	Narrowband sensing	24
2.4.1.1	Energy detection	25
	Test statistic	26
	Theoretical performance	26
	Design Parameters	27
	The number of signal samples	28
2.4.1.2	Alternative forms of ED	29
	Double threshold ED	29
	Adaptive threshold-based ED	30
	Improvements in ED schemes	30
2.4.1.3	Cyclostationary feature detection(CFD)	31
	Performance analysis	32
	Improvements in CFD	32
2.4.1.4	Matched filter detection	33
2.4.1.5	Eigenvalue detection	34
2.4.1.6	Learning-based sensing techniques	34
2.4.2	Wideband Spectrum Sensing	35
2.4.2.1	Nyquist rate based wideband sensing	36
	Wavelet transform based detection	36
	FilterBank based sensing	36
	Per-channel approach	37
	Modulated filter banks	37
	Fast filterbanks (FFB)	37
	Coefficient decimation based filter banks	38
	Frequency response masking based filter banks	38
	FFT power spectral density detection	38
2.4.2.2	Sub-Nyquist rate based detection	39
	Non-blind compressive sensing	39
	Blind compressive sensing	39
2.4.3	Cooperative spectrum sensing in cognitive radios	40
2.4.3.1	Data fusion	40
2.4.3.2	Decision fusion	40
2.4.4	Implementation of spectrum sensing schemes	40
2.5	Summary	42
3	Improved Energy Detection Schemes: Energy-difference Detection and Adaptive Energy Detection	43
3.1	Introduction	43
3.2	Energy-difference Detection based Spectrum Sensing Scheme	44

3.2.1	Motivation for proposing energy-difference algorithm	44
3.2.2	Proposed energy-difference detection based spectrum sensing Scheme	47
3.2.3	Analysis of the Test statistic of Energy-difference Detection Algorithm	47
	Threshold setting	48
3.2.4	Simulation results of energy-difference detection scheme	49
	3.2.4.1 Simulation setup	49
	3.2.4.2 Analysis of detection performance	51
3.3	Adaptive Energy Detection Scheme with Real-time Noise Variance Estimation	52
3.3.1	Proposed Spectrum Sensing Scheme	53
	3.3.1.1 The channel state model	55
	3.3.1.2 Weighted Energy Averaging Scheme (WEAS)	56
	Probability of false alarm	57
	Probability of detection	58
	The decision threshold	59
	3.3.1.3 Weight Optimization	59
	3.3.1.4 Energy-Difference Algorithm	60
3.3.2	Noise Variance Estimation	61
3.3.3	Simulation Set-up and FPGA Implementation	63
	3.3.3.1 Simulation Set-up	63
	LDACS signal generation	63
	Filter architecture	63
	3.3.3.2 FPGA Implementation	64
3.3.4	Results and Discussions	66
3.4	Summary	72
4	An Efficient Spectrum Sensing Scheme Using Low-Power Correlators	75
4.1	Introduction	75
4.2	Multiplierless Correlator for Spectrum Sensing	76
	4.2.1 Architecture of Multiplierless Correlator	77
	4.2.2 Proposed Correlator in the LDACS Processing Chain	79
	4.2.3 Integration into LDACS Radio Platform	80
4.3	Results	82
	4.3.1 Implementation Results	82
	4.3.2 Spectrum Sensing Effectiveness	84
4.4	Summary	88
5	Design and Implementation of a simplified cyclostationary feature detection scheme	91
5.1	Introduction	91
5.2	System Model	93
5.3	Proposed Spectrum Sensing Scheme	94
	5.3.1 Test statistic definition	94

5.3.2	Analysis	96
5.3.2.1	Analysis of the statistical properties of Λ_x^α	96
	Mean and variance of $\Lambda_x^\alpha / \mathcal{H}_0$:	96
	Mean and variance of $\Lambda_x^\alpha / \mathcal{H}_1$:	97
5.3.2.2	Probability of false alarm (P_{fa})	99
5.3.2.3	Probability of detection	99
	Probability of detection-AWGN channel ($P_{d,AWGN}$):	99
	Probability of detection-Rician fading channel ($P_{d,Ric}$):	100
5.3.2.4	Deflection coefficient ($\mathcal{D}_\mathcal{C}$)	100
5.3.3	Analysis of the estimation of $\hat{\sigma}_w^2$	101
5.4	FPGA Implementation	102
5.5	Results	104
5.5.1	Results of Simulation Studies	105
5.5.2	Hardware implementation Results	108
5.6	Summary	109
6	Power-efficient Wideband Spectrum Sensing Scheme	111
6.1	Introduction	111
6.2	Signal Model of the Wideband Spectrum	114
6.3	Conventional Method: Filter Bank based Wideband Spectrum Sensing	114
6.4	Proposed Sensing Scheme	116
6.4.1	Power-efficient architecture of the wideband sensing scheme	116
6.4.2	Detection Algorithm	117
6.4.3	FPGA Implementation	118
6.5	Results and Discussion	120
6.5.1	Simulation Results	120
6.5.2	Implementation Results	123
6.6	Summary	124
7	Conclusions and Future Research	127
7.1	Accuracy-complexity trade-off of the proposed schemes	128
7.2	Summary of Contributions	129
7.2.1	Energy detection based schemes	130
7.2.2	Low-power correlator detection	130
7.2.3	Low-complexity cyclostationary feature detection	131
7.2.4	Power-efficient Wideband Spectrum Sensing Scheme	132
7.3	Future research directions	132
A	Derivation of Noise variance estimation	135
	Bibliography	139
	Publications	139

List of Figures

1.1 Cognitive Radio enabled architecture for future Air-to-Ground Communication system.	3
2.1 Aeronautical communication evolution in Europe and the United States: From the early 2000s to the next 30 years.	13
2.2 FCI: Different Components.	14
2.3 LDACS deployment: An inlay approach.	15
2.4 Forward link communication: Frame Structure.	17
2.5 Reverse link communication : Frame duration.	17
2.6 LDACS frame structure: Reverse link.	18
2.7 Air station spectral mask of LDACS signals.	18
2.8 LDACS frequency deployment.	19
2.9 Airborne radio architecture of LDACS system.	20
2.10 Different spectrum sensing techniques: an overview.	23
2.11 Schematic representation of the performance matrices of spectrum sensing: the probability of detection, the probability of missed detection, and the probability of false alarms.	25
2.12 Experimental setup of conventional ED.	26
2.13 Minimum number of samples required for the desired performance i.e., $P_d = 0.9$ and $P_{fa} = 0.1$	28
2.14 Schematic representation of the double threshold ED scheme.	29
2.15 Block diagram of matched filter detection	33
2.16 Block diagram of Eigenvalue detection	34
2.17 Block diagram of wavelet transform detection.	36
2.18 Schematic representation of filterbank based spectrum sensing.	37
2.19 Block diagram representation of the FFT based sensing.	38
3.1 LDACS spectrum Scenario: (a) With DME interference (b) After DME removal.	46
3.2 Wideband spectrum sensing using energy-difference detection.	46
3.3 Detection performance comparison of proposed energy difference algorithm and conventional energy detection technique [91] (SNR Vs probability of detection).	50
3.4 Detection performance comparison of proposed energy difference algorithm and conventional energy detection technique [91] using ROC curves (Probability of false alarm Vs Probability of detection).	50

3.5 Utilizing historical information for improved spectrum sensing.	53
3.6 Flowchart of the energy difference incorporated weighted energy averaging scheme.	54
3.7 The probability distribution for the test statistic. (a) Conventional ED (b) WEAS.	55
3.8 The channel state change model using two state Markov chain.	56
3.9 Frame structure of OFDM based LDACS signals.	61
3.10 RMSE of estimated noise power versus SNR.	62
3.11 Higher level architecture of the proposed system: Integration of spectrum sensing logic into the receive path of the LDACS radio platform.	64
3.12 Hardware architecture of the proposed sensing scheme.	65
3.13 Detection performance of sequential ED: Probability of detection during Static channel ($\mathcal{H}_1 \rightarrow \mathcal{H}_1$) and during state change conditions ($\mathcal{H}_0 \rightarrow \mathcal{H}_1$) (at SNR=-16 dB).	66
3.14 Average detection performance comparison of the Conventional ED [91], IED [91], sequential ED [86] and the energy difference incorporated WEAS (proposed scheme) in static PU and frequent PU state cases.	67
3.15 Detection performance comparison of the proposed technique (Matlab and hardware results) and Matched filtering based sensing.	68
3.16 Effect of weight in WEAS for different signal to noise ratios (SNR's).	68
3.17 Performance comparison of the proposed scheme Vs conventional ED [91] scheme with and without noise uncertainty (NU).	69
3.18 Overview of the energy-difference detection and adaptive energy detection schemes.	72
4.1 Architecture of the multiplierless correlator.	77
4.2 Variation of detection accuracy with quantisation levels of multiplierless correlator for LDACS-1 frame.	78
4.3 Integrating the multiplierless correlator into the LDACS processing chain.	79
4.4 Integrating multiplierless correlator into the radio platform on Zynq.	81
4.5 Frequency plots of generated LDACS RL frames under different SNR conditions.	85
4.6 Correlator output at SNR of 0dB and -10dB.	86
4.7 Comparison of detection accuracy of the proposed scheme using different detection techniques: Conventional ED [91], Low complexity CFD [126], Single cycle CFD [17], and autocorrelation scheme [163].	87
4.8 Overview of the multiplier-less correlator based sensing scheme.	88
5.1 The autocorrelation induced by the cyclic prefix in OFDM signals.	94
5.2 The physical meaning of the deflection coefficient.	101
5.3 Hardware architecture of the proposed LRT based cyclostationary spectrum sensing logic for implementing on an FPGA platform.	102
5.4 ROC curves of the proposed scheme for both AWGN and Rician fading channels P_{fa} Vs. P_d	106

5.5	Detection performance of the proposed scheme for varying SNR (SNR Vs. P_d); both AWGN and Rician fading channels.	106
5.6	Performance comparison of different spectrum sensing schemes includes the proposed scheme, multiplierless correlator (Mless correlator) (presented in Chapter 4), SCD scheme [126], ED-based schemes [13].	107
5.7	Analysis of the effect of noise uncertainty (NU) for different spectrum sensing schemes.	108
5.8	Deflection coefficient versus SNR.	108
5.9	The overview and contributions of Chapter 5.	110
6.1	(a). Filterbank assisted wideband spectrum sensing scheme. (b). Transposed direct form FIR filter structure.	115
6.2	Proposed filterbank assisted one-bit quantizer wideband spectrum sensing scheme.	115
6.3	Multiplier-less FIR filter design for single bit input signal.	116
6.4	Illustration of the effect of one-bit quantization on the power spectral density.	117
6.5	Architecture of the cognitive radio enabled LDACS radio platform on the Xilinx Zynq FPGA.	119
6.6	Probability of detection versus SNR: Effect of filter coefficients bit-width.	121
6.7	Probability of detection/probability of false alarm (in red color) versus SNR under different uncertainty factors (α) in dB.	122
6.8	Probability of detection curves for the proposed one-bit quantization scheme versus the ED [91], multiplier-less correlator [Chapter 4], and one-bit autocorrelation [195] based scheme.	122
6.9	The overview and contributions of Chapter 6.	124
7.1	The accuracy-complexity comparison of the proposed narrowband sensing schemes	128
7.2	Overview of the proposed schemes of this thesis.	129

List of Tables

2.1	Technology recommendations for different flight domains.	13
2.2	OFDM design parameters of LDACS.	16
2.3	Narrowband sensing techniques: Advantages and disadvantages	35
3.1	Simulation parameters of the energy-difference detection scheme.	51
3.2	Computational complexity comparison of the energy difference detection and the conventional ED schemes	51
3.3	Simulation Parameters for LDACS Signal Generation	63
3.4	Resource utilisation of the Zynq radio platform after integrating the spectrum sensing logic.	71
3.5	Resource utilization comparison of the proposed scheme, conventional matched filtering, and energy detection.	72
4.1	Detailed resource consumption of the multiplierless correlator on a Zynq XC7Z045 device as a standalone module.	83
4.2	Resource comparison of proposed correlator on the Zynq XC7Z045 and the multiplier-based correlator on the Zynq XC7Z100 device.	83
4.3	Resource utilisation of the Zynq radio platform after integrating the proposed correlator.	84
5.1	Resource consumption of proposed design on Zynq XC7020, compared to the multiplierless correlator-based spectrum sensing (Mless sensing), multiplier based correlators, and Eigenvalue detection schemes	109
6.1	Resource consumption of proposed design on Zynq XC7Z045, compared to the multiplierless correlator-based spectrum sensing (Mless sensing).	123
7.1	Summary of the detection accuracy and power consumption of the proposed narrowband sensing schemes.	128

Symbols and Acronyms

Symbols

$\mathcal{H}_0$	Hypothesis 0
$\mathcal{H}_1$	Hypothesis 1
$s(n)$	Transmitted Signal
$w(n)$	Additive Noise
$h(n)$	Channel Response
$x(n)$	Received Signal
P_d	Probability of Detection
P_{fa}	Probability of False Alarm
λ	Threshold
$\mathcal{T}_i$	Test Statistic
N	Number of signal samples
σ_w^2	Noise Variance
σ_s^2	Signal Variance
$\mathcal{N}(\mu, \sigma^2)$	Normal Distribution with mean μ and variance σ^2
$\mathcal{Q}$	Marcum Q function
γ	Signal to Noise Ratio(SNR)
α	Cyclic Frequency
$\mathcal{R}_x^\alpha$	Cyclic Spectral Density of Received signal $x(n)$
Λ_x^α	Likelihood Ratio Test for Hypothesis Testing
ρ	Normalized Autocorrelation Coefficient
N_D	Useful Data Length of one OFDM Symbol
N_{CP}	Cyclic Prefix Length
E_i	Energy of i^{th} Sensing Slot
E_d	Energy Difference between i and $i - 1^{th}$ Sensing Slots.

Symbols and Acronyms

Acronyms

ADC	Analog to Digital Converter
AF	Amplify-and-Forward
AS	Airborne Stations
ATM	Air Traffic Management
AWGN	Additive White Gaussian Noise
CD	cyclostationary detection
CP	Cyclic Prefix
CR	Cognitive Radio
CSB	Centralized Spectrum Broker
CSD	Cyclic Spectral Density
DC	Dedicated Control
DCT	Discrete Cosine Transform
DFT	Discrete Fourier Transform
DFTFB	Discrete Fourier Transform Filter Bank
DMA	Dedicated Memory Access
DME	Distance Measuring Equipment
DSA	Dynamic Spectrum Access
DSB-AM	Double-Sideband Amplitude Modulation
DSP	Digital Signal Processing
ED	Energy Detection
EUROCAE	European Organization for Civil Aviation Equipment
FAA	Federal Aviation Authority
FC	Fusion Center
FCI	Future Communication Infrastructure

FD	Feature Detection
FDD	Frequency Division Duplexing
FFB	Fast Filter Banks
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
FL	Forward Link
FPGA	Field-Programmable Gate Array
GS	Ground Stations
ICAO	International Civil Aviation Organization
IFFT	Inverse Fast Fourier Transform
LDACS	L-band Digital Aeronautical Communication System
LRT	Likelihood ratio test
MIMO	Multiple-Input Multiple-Output
NU	Noise Uncertainty
OFDM	Orthogonal Frequency Division Multiplexing
PL	Programmable Logic
QPSK	Quadrature Phase-Shift Keying
PU	Primary User
RA	Random Access (RA)
RL	Reverse Link
RMSE	Root Mean Square Error
SCD	Single-Cycle cyclostationary Detection
SEAR	Single European Sky ATM Research
SNR	Signal to Noise Ratio
SU	Secondary User
SVM	Support Vector Machine
VDL	VHF digital Link
WEAS	Weighted Energy Averaging Scheme

Chapter 1

Introduction

Air traffic has seen tremendous growth over the past decade, with trends pointing towards continuing growth in the future. The increase in the number of aircrafts leading to a saturation state for the current Air Traffic Management (ATM) system within the next 10 years, primarily in Europe and US-the world most dense air-traffic regions. This exponential increase in air traffic demands a modernization of the ATM for improving air-traffic efficiency with improved safety [1].

The current state of the art of the aeronautical communications still using the analog voice communications for connecting the ground controllers to the pilots in the aircraft. They are using DSB-AM (Double-Sideband Amplitude Modulation) and is deployed in the VHF band from 118 to 137 MHz. The DSB-AM is capable of ensuring reliable communication between the aircraft and the ground controllers. However, this technology is very spectrum inefficient, and voice communication is not able to satisfy most of the future needs. In the early 1990s, the International Civil Aviation Organisation (ICAO) has standardized the first digital link in the VHF band called the VDL (VHF digital Link). There are 3 modes for the system called the VDL Mode 2/3/4, out of which only VDLMode 2 is used for current aeronautical communications. VDL provides a very limited data capacity of the order of 31.5Kbps, which cannot satisfy the needs for the future aeronautical communication systems [2].

To address these challenges, the ICAO has recommended the Future Communications Infrastructure (FCI) that integrates the existing technologies and new data link protocols for enhancing air-to-air, air-to-ground, and satellite-based links. For the air-to-ground links, the L-band Digital Aeronautical Communications System (LDACS)

is gaining traction as the preferred model for final deployment. LDACS is proposed as an inlay approach with legacy L-band systems like Distance Measuring Equipment and hence has stringent requirements on transmission and reception [2–4]. The LDACS system uses modern digital modulation schemes like Orthogonal Frequency Division Multiplexing (OFDM) for improved performance and is expected to operate on the lower half of the L-band from 960 MHz to 1164 MHz as an inlay system between the two neighboring Distance Measuring Equipment (DME) channels. The DME cause a substantial interference to LDACS1 due to the inlay deployment approach and narrow frequency separation between the two systems. DME is the radio navigation technology, which measures the slant distance between the aircraft and the ground station (GS) that operates in the UHF frequency spectrum between 960–1164 MHz. This part of the spectrum is already allocated for aeronautical communications on a secondary basis [2].

1.1 Cognitive Radio for Aeronautical Communications

The VHF band allocated for aeronautical communication systems has the bandwidth of 19 MHz with 760 DSB-AM channels of 25 kHz bandwidth each. Due to the high demand in Europe, these channels are divided again into 3 sub-channels of width 8.33 KHz each. The studies in Europe and US shows that there at least 2% increment in the aviation industry annually. The current spectrum resources cannot handle the air traffic by 2020– 2025 [5, 6]. Moreover, the current aeronautical technology is very spectrum inefficient.

Cognitive Radio (CR) [7] is getting significant consideration as the enabling technology to accomplish Dynamic Spectrum Access (DSA) in licensed bands. The key thought behind CR is to make smart radios which are mindful of and can adjust to, their surroundings. Subsequently, in licensed bands, CR nodes monitor the primary user's (PUs) transmission to find the spatially and timely unused spectrum. The unused spectrum or the spectral holes are detected using spectrum sensing techniques. CR enabled aeronautical systems are proposed to overcome the spectrum inefficiency in the current aeronautical communication systems [8–10]. However, due to its stringent spectrum requirements and spectrum scarcity, applying CR concepts to the current state of the art of aeronautical communication is not considered feasible[11, 12].

FIGURE 1.1: Cognitive Radio enabled architecture for future Air-to-Ground Communication system.

CR integrated schemes are proposed for future aeronautical communication systems such as LDACS, to improve the spectrum efficiency and communication capacity further[11, 12]. The CR architecture proposed for future A/G communication [11, 12] is demonstrated in Figure. 1.1. The proposed system consists of a secondary system in addition to the primary system. The centralized spectrum broker (CSB) in the ground station allocates the licensed spectrum to the primary radio system. The primary radio supports the communication between pilots and controllers on the ground and remains untouched for safety reasons. On the other hand, the secondary radio system attached to a system with cognitive capabilities enabled by different sensors and configurable hardware. The system is compact to handle the changing environments of the aeronautical channel by combining the cognitive algorithms and reconfigurable hardware. These characteristics enable the secondary radio to detect the spectrum holes and this information can be collected by the data center in the ground station. The unused spectral holes can be used by the secondary radio for

transmitting multimedia messages such as aircraft health parameters from the aircraft to the ground station. As mentioned, the main responsibility of the CR system is to find the spectrum holes. There is a major concern about the accuracy of the spectrum sensing algorithm as the aeronautical communication is a safety-of-life problem. Any interference towards the PU is more dangerous as it profoundly affects the seamless communication between the pilot on-board and the ground controller. At the same time, the CR system requires less false alarm rates to maintain the throughput of the secondary radio.

1.2 Spectrum Sensing

The most crucial step in DSA is the identification of spectrum holes, that can be done only by spectrum sensing. Once the information of the vacant channels is obtained, the secondary user's (SU's) may use the channel for communications. Spectrum sensing is performed either based on the received signal strength from the PU signal or some known features of the PU signals. The spectrum sensing is identified as a binary classification problem with two states of primary users, either they are active or idle. We cannot assume a noiseless transmission through a channel. Primary signal detection with the presence of noise can be identified with the help of a binary hypothesis testing problem in which Hypothesis 1 ($\mathcal{H}_1$) and Hypothesis 0 ($\mathcal{H}_0$), represents the presence and absence of PU signal respectively [13, 14]. Many spectrum sensing algorithms are available in the literature to detect the presence/absence of the PU signal. The major spectrum sensing techniques are summarised below.

The main spectrum sensing techniques are Energy Detection(ED) [15], matched filter detection [16], cyclostationary feature detection [17], and eigenvalue detection.

- **Energy Detection:** In energy detection (ED), the energy of the received signal in the frequency band of interest is estimated and is then compared with the predefined threshold for the decision of the presence/absence of the PU signal [15, 18]. If the energy comes above the threshold, then the detector concludes that the primary user is present; otherwise, the PU is absent. ED is widely accepted because of its simplicity and incoherent nature. The main drawback of

ED is that the performance of the detector is highly sensitive to the noise variance and there exists a Signal to Noise Ratio (SNR) wall for the satisfactory performance of the detector, ie. The detector fails under low SNR regimes [18, 19].

- **Matched Filter Detection:** Matched filter uses the prior knowledge of the PU signal for the detection process [16]. Though it is considered as the optimal detector for maximizing SNR in the presence of additive noises, this scheme is not widely used due to its higher computational complexity and synchronization issues.
- **Cyclostationary feature detection (CFD):** This technique uses the periodicity in the primary signal received to recognize the presence/absence of PUs [17, 20]. In this, the known periodic properties of the PU signal is used in the detection process. The periodicity can be seen generally with sinusoidal carriers, spreading codes, pulse trains, cyclic prefixes (CP) or hopping sequences of PU signal. The statistical parameters of received signals such as mean and autocorrelation may vary periodically. These statistical properties of the PU signal can be used in cyclostationary detection. By extracting the cyclostationary properties of the received signal and comparing with the pre-knowledge PU, the signal can be detected easily because the noise does not possess any cyclostationary features. CFD is considered as a robust detector under noise uncertainty, and it works well in low SNR region. At the same time, it needs high sampling rates, a large number of samples, and it is challenging to implement [21].
- **Eigenvalue detection:** In this detection topology, the maximum-minimum ratio of the eigenvalues of the covariance matrix of the received signal vector is compared to detect the absence or presence of the PU signal. The detector does not require prior knowledge about the PU signal. The main shortcoming of the detector is that its computational complexity to find the covariance matrix and eigenvalue decomposition. The threshold selection also a challenging task [22, 23].

1.3 Motivation

The future aeronautical communication needs more spectral resources due to the exponential growth forecasted for the air traffic. The dynamic allocation of the spectrum can increase spectrum efficiency. The usage of the CR technology in aeronautical communication systems is proposed in [8–12, 24] to enable the dynamic spectrum access in an opportunistic manner. As mentioned, in a CR enabled communication system, the secondary radio system is required to identify the spectrum holes using spectrum sensing techniques. Considering the safety criticality of the target domain, a secondary radio in aeronautical communication system should be able to detect the primary user signal in a more effective way to avoid any interference towards the PU. In this context, the significant performance matrices of the spectrum sensing are the probability of detection and the probability of false alarms. The spectrum sensing unit should be able to produce the best trade-off between the probability of detection and the probability of false alarms to improve the spectral efficiency while providing sufficient safety to the primary user. The main challenges for the spectrum sensing in aeronautical systems are summarized as,

- Channel conditions between the communicating entities can change very rapidly, which requires much more complex processing relative to the terrestrial CR systems.
- Aeronautical communication systems deal with the safety-of-life problem; the accuracy of sensing is an essential element to provide a reliable outcome in a short period.
- Perfect noise estimation is essential for accurate decision making of a detection algorithm. Intelligent threshold selection also required to ensure interference avoidance.
- Fast sensing, decision making and channel assignment are desired to cater to the changing environment.
- Aeronautical systems are power-limited systems; thus, the low-complexity realization of the spectrum sensing and subsequent processing units are imperative for this domain.

1.4 Major Contributions

The significant contributions of this thesis are summarised as follows:

- An innovative spectrum sensing technique for LDACS based on an energy difference algorithm is proposed in this research. It is done by exploiting the spectral shape of OFDM after removing DME pulses from the neighborhood channels. The scheme detects the spectral holes from the wideband of interest by checking the spectral shape irregularities with the aid of an energy-difference algorithm. A wideband sensing simulation model is presented, and a simulation model is developed to evaluate the performance of the proposed scheme. Simulation studies show that the proposed scheme provides better detection accuracy than conventional ED schemes.
- An adaptive ED scheme is proposed to reduce the computational complexity of the energy difference detection. In this scheme, the historical sensing information is adaptively used to reduce the variance of test statistics. An energy difference algorithm is introduced to control the weight of the adaptive ED. The technique considerably improves the detection performance without incurring additional computational resources. An unbiased noise variance estimation technique also incorporated to reduce the effects of the noise uncertainty. The proposed spectrum sensing scheme is implemented, and it is integrated into the baseband of the cognitive radio platform on an FPGA board for the practical evaluation of the resource overheads.
- Proposed the use of multiplierless correlators to enable spectrum sensing in LDACS air-to-ground links, and its integration into the onboard LDACS system. The structure mimics a transpose-direct form filter where the multiplication operation at each tap is replaced by a multiplexer, that selects one among its many inputs based on the synchronization symbol value at that tap. The technique achieves a 28.3% reduction in energy consumption over the multiplier-based approach. The proposed technique provides better detection accuracy than the ED techniques, cyclostationary feature detection schemes, and auto-correlation aided sensing schemes.

- The multiplier-less correlator requires varying sensing duration depends upon the starting of the sensing epoch, and it can go up to 58.32 ms. In this context, this thesis discusses the design and implementation of cyclostationary detection schemes to reduce the sensing duration and to reduce the computational complexity of sensing further. In this work, a Likelihood Ratio Test (LRT) based cyclostationary detection scheme is presented in which the autocorrelation property of Cyclic Prefix (CP) of the OFDM signal is used to detect the spectrum occupancy. The scheme is further optimized by using a sliding correlator and a real-time noise variance estimation technique. Results show that the scheme provides comparable detection accuracy with the multiplierless correlator sensing by using about 1/3 of computational resources and fixed sensing duration.
- In order to reduce computational complexity and to enhance the energy efficiency of the proposed system, a Finite Impulse Response (FIR) filter bank based wideband sensing scheme which uses a one-bit quantizer is proposed in this research. In the proposed scheme, the sampling and quantization unit is reduced to a high-speed comparator, and the multiplication in each filter tap is replaced by a sign changer which is implemented using a 2's complement circuit and a 2:1 multiplexer. The scheme considerably reduces the computational complexity of the conventional filter bank based sensing by using a sign changer instead of a multiplier. The scheme provides an improved accuracy-complexity-throughput trade-off among the state of the art spectrum sensing schemes.

1.5 Outline of the Thesis

The rest of the thesis is organized as follows. Chapter 2 presents an overview of the future aeronautical communication system and different techniques for spectrum sensing. A literature review of numerous spectrum sensing techniques is provided with corresponding merits and demerits. Chapter 3 presents two energy detection techniques for spectrum sensing in the aeronautical domain named energy-difference detection and adaptive energy detection to lower the SNR wall for accurate detection. In Chapter 4, a low power correlator based detection scheme is presented to improve the detection accuracy and to reduce the noise uncertainty issues. Chapter

5 presents a low complexity cyclostationary feature detection scheme. Mathematical foundations, simulation model, and the FPGA implementation of the scheme is provided with illustrative examples. The techniques described in chapter 3- chapter 5 are concentrating on the optimization of narrow-band sensing. In chapter 6, a power efficient spectrum sensing scheme is presented to get the best accuracy-complexity-throughput trade-off. Chapter 7 concludes the thesis with some possible future directions.

Chapter 2

Spectrum sensing for aeronautical communication: A literature review

The air-traffic is increasing day by day, and it is expected to maintain its growth in the future. Due to the increased air-traffic, the current aeronautical communication system appears to be inadequate to support the traffic of the future years. Severe congestion is expected in some areas of the world, mainly in the United States(U.S) and Europe. To catle this issue, the FCI integrates the existing technologies and the new promising and optimal data link protocols for the aeronautical communication systems. In this chapter, a brief review of the evolution of the aeronautical communication systems starting from analog technologies to the L-band techniques such as LDACS for air-to-ground communication is provided. CR enabled aeronautical communication is getting traction as a promising technology to improve spectrum efficiency. Spectrum sensing and channelization play a major role in CR systems. This chapter also provides a review of the various spectrum sensing techniques and the different filter architectures which aids sensing and channelization.

2.1 Evolution of aeronautical communication systems

Aeronautical communication in the current days mainly operates by the combination of the two systems in the VHF band. The first system is in use for more than half a century and is based on an analog communication system for voice transmissions. The second one is the digital links in the same band introduced in the early 1990's

for enabling data transmission. However, they are not capable of meeting the future needs of the aeronautical communication systems due to the increased traffic. Recent studies show that the current system experience different congestion issues in different places around the world due to increased traffic [1]. The quality of service is likely to be degraded if the frequency congestion is not managed correctly. A Future Communication Infrastructure (FCI) program initiates to solve these issues. The FCI comprises of both the current and new data-link technologies to improve the links such as air-to-ground, air-air, and satellite communications among others. The development of FCI is under two programs: 1) the Next Generation Air Transportation System by the U.S [25] and 2) the Single European Sky ATM Research (SESAR)[26].

2.1.1 Future communication infrastructure activities

As mentioned, the FCI activities are mainly under two programs, namely NextGen and SESAR. The FCI expansion is based on three consecutive phases. Figure. 2.1 summarizes the shared roadmap developed by NextGen and SESAR to structure the implementation and development of aeronautical communications concerning traffic demands. The primary stage is to identify the most promising technologies to back future needs [27–29]. The identified technologies are required to be developed from the concept to implementation in the second stage. The third and crucial one is building new infrastructure supporting the technologies. From 2004-2007, EUROCONTROL and Federal Aviation Authority (FAA) evaluated different technologies, and their findings were submitted to ICAO for global acceptance. The most fitting frequency bands for different aeronautical communications were identified depending upon the propagation characteristics. The C-band is identified to support airport communications due to small distance and high data rate requirements [2, 30, 31]. For Air-to-ground communications, the L-band is included in addition to the VHF band. The L-band is recommended due to the availability of the band and the suitable propagation properties. L-band is also suggested for remote and oceanic communications. Nextgen and SESAR developed the same technology recommendations for the various flight domains. Those are summarized in Table. 2.1.

A brief description of the different components of the FCI shown in Figure. 2.2 and are summarized below.

FIGURE 2.1: Aeronautical communication evolution in Europe and the United States: From the early 2000s to the next 30 years.

TABLE 2.1: Technology recommendations for different flight domains.

Fight domain	Technology	Frequency band
Airport surface	AeroMACS (IEEE 802.16e)	C-band
Oceanic and other remote communications	Sattelite communications	AMS(R) band
Air-to-Ground communications	LDACS (in addition to VHF systems)	L-band

- **AeroMACS(Aeronautical mobile communication system)[30, 31]:** This data link technology is anticipated to complement the LDACS in large airports. It is foreseen to adopt the WiMAX standard and to deploy in the frequency range 5091-5150 MHz. The standardization of the AeroMACS is already initiated by the ICAO jointly with the European Organization for Civil Aviation Equipment (EUROCAE).
- **The satellite component:** The satellite component is for the communication of the aircraft in oceanic and remote areas. It can able to complement in air/-ground communication during necessary conditions [32].

FIGURE 2.2: FCI: Different Components.

- LDACS:** For air-to-Ground communications, ICAO recommended the development and feasibility study of two LDACS systems, namely LDACS1 and LDACS2 [2, 3]. LDACS1 is based on a broadband scheme with OFDM as the modulation scheme. It follows the modern transmission concepts as like in fourth-generation mobile systems. The LDACS is expected to operate on the lower half of the L-band from 960 MHz to 1164 MHz as an inlay system between the two adjacent DME channels. The LDACS1 channel of bandwidth 0.5MHz is placed at 0.5 MHz and 1 MHz from the adjacent DME and LDACS1 channels respectively. LDACS2 is based on Global System for Mobile Communications (GSM) technology, and it is based on a narrow band single-carrier system with 200KHz of Bandwidth and Time division duplex (TDM). The transmission capacity of LDACS2 is in the range of 70-115 kbps. LDACS1 is considered as the most promising and matured candidate for the future air-to-ground communication system as it performs far better than LDACS2 in terms of data rate and spectrum efficiency. Nowadays, the term LDACS itself is used to represent LDACS1 as it is chosen for deployment [3, 4].
- Air-to-air data link:** the development of this link is outside the scope of SESAR and NEXTGen currently. We can expect the development of an ad-hoc type of network with aircraft as nodes [2].

2.2 LDACS System Specifications

2.2.1 LDACS deployment

LDACS is a cellular communication system involving a network of Ground Stations (GS) and Airborne Stations (AS). It is a Frequency Division Duplexing (FDD) based system with Orthogonal Frequency Division Multiplexing (OFDM) as the modulation scheme with adaptive coding and will operate in the frequency range 960-1164 MHz. The system is proposed to be deployed as an inlay system between neighboring DME channels (that measures aircraft's distance from the ground station). The scheme uses OFDM as the modulation scheme with FFT block size 64 and a total bandwidth of 0.5 MHz for each channel. It uses 50 sub-carriers for transmission with a spacing of 9.8 kHz, which are further separated into two banks of 25 subcarriers each, which are used for Ground-to-Air and Air-to-Ground communication. LDACS defines these links as Forward Link (FL) and Reverse Link (RL) respectively. The LDACS1 channel of bandwidth 0.5MHz is placed at 0.5 MHz and 1 MHz from the adjacent DME and LDACS1 channels, respectively. The LDACS1 deployment as an inlay approach is shown Figure. 2.3. LDACS1 can achieve data rates from 561 kbps to 2.6Mbps under weak and robust coding scenarios, respectively [2–4, 33–37]. The OFDM design parameters of LDACS are summarized in Table. 2.2. [2, 38]

FIGURE 2.3: LDACS deployment: An inlay approach.

TABLE 2.2: OFDM design parameters of LDACS.

Parameter	Value
FFT size	64
Sampling Time	$1.6 \mu s$
Sub-carrier Spacing	$9.8 kHz$
Useful symbol time	$102.4 \mu s$
Cyclic prefix ratio	11/64
Cyclic prefix time	$17.6 \mu s$
OFDM symbol time	$120 \mu s$
Guard time	$4.8 \mu s$
Windowing time	$12.8 \mu s$
Used subcarriers	50
Lower frequency guard bands	7
Higher frequency guard bands	6

2.2.2 Physical frame characteristics of LDACS

The OFDM transmission symbols are arranged as frames. The frames are marked according to the data to be transmitted and are represented in the time-frequency plane[3, 4, 38]. The FL and RL frame structure is shown in the below subsections.

2.2.2.1 FL frame structure

The time-frequency tiling of the FL frame schematic is shown in Figure 2.4. The frame in the figure is shown for a time duration of 6.48ms, i.e., it consists of 54 OFDM symbols. Out of 54 symbols, the first two are synchronization symbols, and the rest are data and pilot symbols arranged in a particular fashion, as shown in the figure. The yellow color symbols in the left, right, and the center represents the null symbols which are termed as guard symbols.

2.2.2.2 RL frame structure

A hierarchical arrangement of the communication in the RL link is as shown in Figure. 2.5. Communication is organized into a cyclic structure of superframes, each

FIGURE 2.4: Forward link communication: Frame Structure.

FIGURE 2.5: Reverse link communication : Frame duration.

having a duration of 240ms. Each superframe has one Random Access (RA) slot, used by the aircraft to request cell entry and 4 multi-frames. Each multi-frame is composed of variable-sized Dedicated Control (DC) segment and a data segment. The DC segment starts with a tile structure which contains synchronization symbols, pilot symbols, AGC preamble, and null symbols. The data tiles contain only pilot symbols, null symbols, and data symbols. The RL DC frame structure is shown in Figure. 2.6.

FIGURE 2.6: LDACS frame structure: Reverse link.

FIGURE 2.7: Air station spectral mask of LDACS signals.

2.2.2.3 Spectral Mask of air station Tx LDACS signal

The spectral density characteristics of the air station transmitted LDACS signals are given in Figure. 7. As shown in the figure, the main lobe bandwidth is limited to 0.5 MHz, and the attenuation at the out of band is restricted to very lower values to avoid the mutual interference between DME. The power spectral density is arranged in such a way that if all 50 subcarriers are used more than 96% of the power lies within the 0.5KHz [3, 4].

FIGURE 2.8: LDACS frequency deployment.

2.2.2.4 LDACS frequency allocation

LDACS is deployed as an inlay system between DME channels in the frequency range 960-1164 MHz. The FL and RL frequency ranges are identified as 985-1009 MHz and 1048-1072 MHz, respectively. Also, each LDACS central frequency is placed 1 MHz apart from the adjacent LDACS channels. The frequency allocation is schematically shown in Figure. 2.8 [3, 4].

2.2.3 Airborne radio system for LDACS

The air station radio comprises transmitter and receiver which operates simultaneously in the frequency division duplexing mode through single antenna via a T_x/R_x duplexing unit. The front end of the radio is supported by the DSP or FPGA to perform baseband operations. The different units shown in the Figure 2.9 can be separated units or a combination of all. The dotted line represents the control interfaces, and the thick line represents the data interfaces. The number of subcarriers in the RL transmission, excluding RA frames, can be either 50 or 25. Therefore the adequate bandwidth of RL transmission is 500 kHz or less. On the other hand, the bandwidth of FL transmission is always 500 kHz as all the subcarriers are used during FL [3, 4].

FIGURE 2.9: Airborne radio architecture of LDACS system.

2.3 Cognitive Radio(CR) for Dynamic Spectrum Access

2.3.1 Definitions of cognitive radio

Different definitions are available in the literature for the term cognitive radio as it is a general concept and has several meanings in different contexts [7]. Mitola has introduced the term cognitive radio. According to him, cognitive radio is “*an intelligent radio which is aware of its surrounding environment and capable of changing its behavior to optimize the user experience*” [7]. Simon Haykin also defined the term cognitive radio based on DSA and is given as; “*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*” [39].

2.3.2 Operating modes of cognitive radio

Different operating modes of CR are discussed in the literature to improve the spectral efficiency by dynamically using unused licensed spectrum without letting unnecessary interference to the licensed users (aka primary users). CR networks can be

divided into three categories based on the spectrum access criteria and their time-frequency allocation. The three different modes are summarized as [40–58]

- Interweave mode [45–47]: In this mode, CR users required to identify the spectrum holes for transmission. The CR users transmit only through the vacant spectrum, and their transmission ends when the sensing algorithms indicate the PU is resuming.
- Underlay mode [51–54]: In this mode, both PU's and SU's transmits together in the same frequency slots without waiting for spectral holes. However, the interference towards PU must be less than a particular threshold. To reduce/avoid interference towards PU, SU devices need to reduce its transmit power, cancel interference, and transmit in the guard regions using the prior information.
- Overlay mode [55–58]: This mode also allows simultaneous PU and SU transmissions. However, the PU data sequence information can be used to cancel the PU interference on SU receivers. Another way is that a cooperative transmission using SU nodes as relays.

2.3.3 Functionalities of cognitive radio

The following functionalities help to achieve the DSA in CR.

2.3.3.1 Spectrum sensing

Spectrum sensing refers to the detection of the vacant spectrum. The spectrum sensing should be conducted continuously so that the PU arrival can be detected accurately. Spectrum sensing helps to identify the traffic of the channel, interference in the channel, and help to adjust the parameters such as transmitting power levels, spreading codes, transmitting frequencies to avoid mutual interference [13, 59–67].

2.3.3.2 Spectrum Management and Decision making

This functionality refers to selecting the best channel for transmission from the available spectrum holes, concerning several factors such as available bandwidth, modulation scheme, transmitting power. The factors such as interference towards PU,

CR throughput, channel capacity, frequency of channel switching are considered before deciding on available spectrum holes. The spectrum access is usually done by one among the three access decisions, namely centralized, distributed, and cluster-based decision making. In centralized decision making a fusion center collects all the sensing information along with the location, and the allocation is based on this information. The main advantages of this strategy are the overall throughput can be maintained, a priority-based allocation is possible, mobility issues can be addressed, and overall resulting in an interference-free communication. This scheme is identified as suitable for aeronautical communication due to the safety of life and mobility issues. In distributed decision making, the SU has complete authority over decisions. Though the SU does not need to wait for the instruction from the fusion center, the decisions may not be optimal when looking in a network perspective. More than that, a misdetection at the SU receiver can produce interference for PU communication, that is not at all acceptable. In cluster-based decision making nearby SUs can form a cluster; it has the advantages of both centralized and distributed schemes. However, the cluster needs to be kept small for the easy conveying of the control information [68–73].

2.3.3.3 Spectrum sharing

Fair allocation of spectrum among different CR users are essential to maintain the throughput of the entire network. The allocation is scheduled based on time, frequency, location, and even coding schemes. Spectrum sharing also can be centralized and distributed. In central controlled one the fusion center does the job of spectrum management and access decisions. On the other side, for the distributed scheme individual SUs take the decisions according to the local rules [74–76].

2.3.3.4 Spectrum mobility

The ability of a SU to hop among different spectrum holes seamlessly depending on the PU traffic and spectrum conditions is called spectrum mobility [77, 78].

The main aim of this thesis is to explore different spectrum sensing techniques for future aeronautical communication systems. The spectrum sensing techniques discussed in the literature are given in Section 2.4.

FIGURE 2.10: Different spectrum sensing techniques: an overview.

2.4 Spectrum Sensing Techniques

The spectrum sensing techniques can be categorized into two, namely narrowband or wideband sensing based on the number of frequency channels sensing at a time. In narrowband sensing, only one frequency channel is sensed at a time while wideband sensing gives the information about multiple frequency channels at a time. The major narrowband sensing schemes are energy detection[15, 79–87], cyclostationary feature detection [16, 17, 20, 21, 88], matched filter detection [89, 90], and Eigenvalue detection [22, 23], among others. In wideband sensing, the wideband spectrum is divided into narrow bands either using filter banks or wavelet decomposition, and then the narrowband sensing schemes are used to identify the spectrum holes. It can be either simultaneous or sequential. Sequential sensing is not effective as it takes a long time to complete the sensing. Higher sampling rate requirements also reduces its practicality. On the other hand, simultaneous sensing requires a large number of sensors in parallel and thus increased complexity for real-time implementation. Compressive

sensing also used to find the spectrum holes of a wideband, exploiting the sparse nature of the frequency channels. An overview of different spectrum sensing techniques is given in Figure. 2.10.

2.4.1 Narrowband sensing

The narrowband sensing is the process to find the state of a single frequency channel. The spectrum sensing problem can be modeled as a binary hypothesis problem with two hypothesis $\mathcal{H}_0$ and $\mathcal{H}_1$ to represent absence and presence of the signal in the channel respectively.

$$x(n) = \begin{cases} w(n) & \mathcal{H}_0 \\ h(n)s(n) + w(n) & \mathcal{H}_1 \end{cases}, \quad (2.1)$$

where $h(n)$, $s(n)$ and $w(n)$ represents channel gain, signal and additive white Gaussian noise(AWGN) respectively, and N is the number of signal samples used for the detection process. The hypothesis $\mathcal{H}_0$ represents the presence of noise samples only and $\mathcal{H}_1$ represents the presence of the PU signals with noise.

An ideal spectrum sensing device should be able to choose the hypothesis $\mathcal{H}_1$ whenever the PU signal is present, and it goes for $\mathcal{H}_0$ otherwise. The performance of a detection algorithm is evaluated using two probability measures, namely the probability of detection P_d and the probability of false alarm P_{fa} . A missed detection occurs when the PU signal is present in the particular band and the detector chooses the hypothesis $\mathcal{H}_0$, which may cause harmful interference to PU signal transmission. Similarly, a false alarm occurs when the channel is idle, and detector chooses the hypothesis $\mathcal{H}_1$. A schematic representation of the P_d , P_{md} , and P_{fa} are given in Figure. 2.11 . These probabilities are mathematically expressed as,

$$\begin{aligned} P_d &= P(\mathcal{H}_1 / \mathcal{H}_1) \\ P_{md} &= 1 - P_d = P(\mathcal{H}_0 / \mathcal{H}_1) \\ P_{fa} &= P(\mathcal{H}_1 / \mathcal{H}_0) \end{aligned} \quad (2.2)$$

From the figure, it is observed that there is a trade-off between the probability of detection and false alarm. More specifically, when the threshold is increased, the false

FIGURE 2.11: Schematic representation of the performance matrices of spectrum sensing: the probability of detection, the probability of missed detection, and the probability of false alarms.

alarm rate reduces, and it results in a reduction in the probability of detection and vice versa.

2.4.1.1 Energy detection

In Energy Detection (ED) based spectrum sensing [15, 79–87, 91], the received energy of a specified frequency channel over a time period is used as the test statistic for the detection process. The main components to evaluate the test static are a noise pre-filter, an analog to digital converter (ADC), a squaring device, and a summing node. The block diagram of the energy detector is given in Figure. 2.12. The main advantages of ED are low complexity and incoherent nature and its disadvantages are low SNR wall and noise uncertainty issues.

FIGURE 2.12: Experimental setup of conventional ED.

Test statistic The test statistic of ED is proportional to $\sum_{n=1}^N |x(n)|^2$, where $y(n)$ is the n th sample. The test statistic of classical energy detector is defined as [91]

$$T_i = \sum_{n=1}^N |x(n)|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\geq}} \lambda, \quad (2.3)$$

where T_i is the test statistic, λ is the decision threshold, and $\mathcal{H}_0$ and $\mathcal{H}_1$ represent hypothesis 0 and hypothesis 1, respectively.

Theoretical performance The closed-form expressions for the probability of detection (P_d) and the probability of false alarm (P_{fa}) can be derived based on the statistics T_i . Though the exact distribution of T_i is chi-square, for a large number of signal samples ($N = 10000$), the distribution of T_i can be approximated to normal distribution. This approximation makes the analysis simpler and helps to optimize the required number of signal samples. The distribution of T_i is given as [91–97]

$$T_i \sim \mathcal{N} \begin{cases} N\sigma_w^2, 2N\sigma_w^4 & \mathcal{H}_0 \\ N(\sigma_s^2 + \sigma_w^2), 2N(\sigma_s^2 + \sigma_w^2)^2 & \mathcal{H}_1 \end{cases}, \quad (2.4)$$

where σ_w^2 is the noise variance, σ_s^2 is the signal variance, N is the number of signal samples, and $\mathcal{N}(\mu, \sigma^2)$ is the Normal distribution with mean μ and variance σ^2 . The algorithm for the working of conventional energy detection is given in Algorithm. 2.1.

The probability of false alarm and detection for AWGN noise is given as [91]

$$P_{fa} = Q\left(\frac{\lambda - N\sigma_w^2}{\sqrt{2N\sigma_w^2}}\right) \quad (2.5)$$

$$P_d = Q\left(\frac{\lambda - N(\sigma_s^2 + \sigma_w^2)}{\sqrt{2N(\sigma_s^2 + \sigma_w^2)}}\right) \quad (2.6)$$

Algorithm 1 Algorithm for conventional energy detection.

Input: $\lambda \in R^+, N \in N$

- 1: **for** each sensing event i **do**
- 2:   Estimate $T_i \leftarrow$ Energy of N samples
- 3:   **if** ($T_i \geq \lambda$) **then**
- 4:   Channel is occupied
- 5:   **else**
- 6:   Channel is vacant
- 7:   **end if**
- 8: **end for**

As mentioned, the ED takes the decision based on a comparison of the received energy from the particular band of interest with a threshold. Conventionally, the decision threshold is defined as a function of noise variance, the number of signal samples used for the detection, and the permitted probability of false alarm. The decision threshold is defined from (2.5)

$$\lambda = \left(Q^{-1}(P_{fa}) \sqrt{2N} + N \right) \sigma_w^2. \quad (2.7)$$

After some rearrangements and substituting λ in (2.5) the P_d is obtained as

$$P_d(\gamma) = Q \left(Q^{-1}(P_{fa}) - \sqrt{\frac{N}{2}} \gamma \right), \quad (2.8)$$

where $\gamma = \frac{\sigma_s^2}{\sigma_w^2}$, is the signal to noise ratio (SNR).

Design Parameters The primary design parameters are the number of signal samples (N) and the decision threshold (λ). The performance of the energy detector depends upon the SNR of the received signal, but we have only little control over SNR because these depend upon the transmission channel. The decision threshold controls the performance of the detection algorithm. The threshold can vary from 0 to ∞ , and the selection criterias are very much crucial as it is the deciding factor. The threshold should be chosen in such a way to increase the performance metric of a particular objective. The well-known objective is to keeping high P_d while keeping the P_{fa} as low as possible (e.g., as IEEE 802.22). For a known value of N and σ_w^2 , the conventional way of threshold selection is based on a constant false alarm rate.

The number of signal samples The number of signal samples used for signal detection has a significant role in decision accuracy. The decision accuracy is better for an increased number of signal samples used for detection. The desired number of signal samples to get the desired accuracy can be expressed in terms of P_d , P_{fa} , and SNR using (2.5) and (2.6).

$$N = 2 \left[Q^{-1}(P_{fa}) - Q^{-1}(P_d)(1 + \gamma) \right]^2 \gamma^{-2} \quad (2.9)$$

The N_{min} increases exponentially with the decrease in SNR and is shown in Figure. 2.13. However, there are limitations for ED in practical scenarios for achieving the desired performance in low SNR regimes, even with enough number of signal samples because there exists an SNR wall for the correct decision. Several alternative forms of ED are discussed in the literature to lower the SNR wall for conventional ED with increased complexity.

FIGURE 2.13: Minimum number of samples required for the desired performance i.e., $P_d = 0.9$ and $P_{fa} = 0.1$.

FIGURE 2.14: Schematic representation of the double threshold ED scheme.

2.4.1.2 Alternative forms of ED

Double threshold ED In conventional ED, the hypothesis selection is carried out with the help of a single decision threshold λ . Decision threshold highly depends on the noise variance and therefore, noise uncertainty issues profoundly affect the detection performance. To address this issue, double threshold ED is proposed in [98–103]. Double threshold energy detection works based on two thresholds around the conventional threshold; they are the upper threshold λ_1 and the lower threshold λ_2 . These thresholds and the confusion region are schematically represented in Figure 2-15. The λ_1 and λ_2 can be defined as [99]

$$\lambda_1 = (1 + \rho)\lambda \quad (2.10)$$

$$\lambda_2 = (1 - \rho)\lambda \quad (2.11)$$

where ρ is the uncertainty parameter. The decision making of the double threshold ED is mathematically expressed as

$$\begin{aligned} \mathcal{H}_0, \quad T_i &\leq \lambda_2 \\ \text{No decision,} \quad \lambda_2 &< T_i < \lambda_1 \\ \mathcal{H}_1, \quad T_i &\geq \lambda_1 \end{aligned} \quad (2.12)$$

The double threshold energy detection suffers from sensing round repetitions to take a decision. Let q be the probability that the observed energy falls in confusion region. The expression for q is given as [98]

$$q = P(\mathcal{H}_1) (P_d(\lambda_2) - P_d(\lambda_1)) + P(\mathcal{H}_0) (P_d(\lambda_1) - P_d(\lambda_2)) \quad (2.13)$$

The average number of sensing rounds N_s required to take a decision is given as

$$N_s = \sum n q^{n-1} (1 - q) = \frac{1}{q} \quad (2.14)$$

The sensing repetition problem can be minimized by employing alternative forms of energy detection or feature detection methods into the confusion region. In [104], a two-stage detection scheme with ED as a detection technique in the first stage and pilot assisted feature detection as the second stage is proposed. In [99], a double threshold energy detection scheme with sequential energy detection in the confusion region is proposed to limit the sensing rounds to a maximum of 2.

Adaptive threshold-based ED The main challenge in energy detection is the setting of an appropriate decision threshold. The threshold in conventional ED is based on constant false alarm rates. A large number of signal samples are required to meet the required performance in a wide range of SNR as per the FCC norms in conventional energy detection. The adaptive threshold makes the best trade-off between the P_d and P_{fa} [105–110]. The threshold is chosen adaptively to minimize the average error rate. In this scheme, the optimized threshold is represented as a function of SNR and is given as

$$\lambda = 2N\sigma_w^2 \frac{(1 + SNR)}{2 + SNR} \quad (2.15)$$

The threshold is adaptively chosen based on SNR and noise variance. The scheme improves the detection accuracy with the aid of this adaptive threshold. However, the estimation of SNR is a computationally intensive task making it inappropriate for the practical implementation.

Improvements in ED schemes Several approaches are discussed in the literature to improve the detection performance of the conventional ED schemes. In [111], an iterative updating threshold-based ED scheme is proposed to achieve the desired detection accuracy. In [109], authors proposed a discrete Fourier transform (DFT) filter bank-based sensing scheme, which adaptively chose the decision threshold to minimize the average error. An image-binarization based sensing scheme [110] is proposed in to characterize the state channel. In this scheme, the adaptive threshold is calculated by the historical decisions, SNR , and target P_d . In [112], a normalized ED scheme is used to improve the detection performance. The authors claim that their scheme reduces the errors in detection using the likelihood ratio test (LRT) and the

cooperative fusion of sensing results. In [113], the authors formulated an adaptive threshold for fading channels. In [114], a blind Ed scheme is proposed to reduce the noise uncertainty issues. The scheme uses the spatial information and the maximum-minimum energy ratio to find the occupancy of the frequency channel. In [115] and [86], a history assisted energy-efficient sensing schemes are proposed. The schemes show that the use of historical sensing information can enrich the spectrum sensing accuracy. A tree search-oriented recursive ED scheme is proposed in [116] that can detect even bursting PUs. In [117], a likelihood ratio test based hybrid of ED and autocorrelation scheme is proposed to improve the detection accuracy and to reduce the noise uncertainty issues.

2.4.1.3 Cyclostationary feature detection(CFD)

In this method of detection, the statistical features of the received signal are exploited for the detection. The features include periodic properties such as mean and autocorrelation. In some cases, cyclostationary features are inserted to assist the spectrum sensing [17, 20, 88]. The key feature of the CFD is that it can differentiate the noise and the PU signals effectively [16, 21]. Moreover, cyclostationary features can be used to distinguish different types of transmissions and PU signals. The Cyclic Spectral Density (CSD) function of the received signal can be represented as [118]

$$R_x^\alpha = \frac{1}{N} \sum_{n=0}^{N-1} R_x(n, N_d) e^{-j2\pi\alpha n}, \quad (2.16)$$

where α is the cyclic frequency, and $R_x(n, N_d)$ is defined as,

$$R_x(n, N_d) = x(n)x^*(n + N_d). \quad (2.17)$$

The test statistic $T(\alpha)$ is defined as

$$T(\alpha) = |R_x^\alpha|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda, \quad (2.18)$$

where λ is the decision threshold. In multicycle detectors, the test statistic is carried out at a selected number of cycle frequencies (α) and lags(N_d) [119]. Their mean value is considered for decision making. At the same time, to reduce the computational

complexity and to get a suboptimal solution single cycle detector (SCD) schemes are proposed [17, 20].

Performance analysis The test statistic is chi-square distributed [17], and the probability of false alarm and the probability of detection are given as [17]

$$P_{fa} = e^{-\lambda N \sigma_w^4} \quad (2.19)$$

$$P_d = Q_1 \left(\frac{\gamma}{v}, \frac{\sqrt{\lambda}}{\gamma} \right), \quad (2.20)$$

where Q_1 is first degree marcum-Q function, $\gamma^2 = |E[R_y^\alpha] / \mathcal{H}_1|^2$ and $v^2 = \text{var}(R_y^\alpha / \mathcal{H}_1)$. Unlike the ED schemes, the CFD schemes are immune to noise uncertainty. Though the desired detection accuracy can be obtained by observing a large number of signal samples, high computational complexity, and the large sensing time requirements are considered as its disadvantages.

Improvements in CFD In [120], a sequential CFD scheme is proposed to reduce the sensing duration. However, the scheme works only for PUs with low PU activity changes (i.e., the PU remains the same state for a long time). In [121], a joint cyclic frequency and autocorrelation based CFD is proposed. The authors claim that the scheme provides better detection accuracy than the conventional CFD schemes. However, the computational complexity limitations are not addressed in this scheme. A low-complexity CFD scheme using multiple antenna technique is discussed in [122]. The scheme reduces the computational complexity of CFD schemes using the local cyclic features of the cyclic autocorrelation function. However, the sensing duration optimization and the noise variance estimation is not addressed in this scheme. A pilot assisted autocorrelation based CFD scheme is proposed in [123]. Though this scheme improves the detection accuracy, the scheme requires the knowledge of the channel, noise variance information, and the carrier frequency offset.

In [124], an SCD scheme is proposed to reduce the sensing time and implementation complexity. In this scheme, the cyclostationarity property is artificially induced by intentionally altering the waveform signal before transmission, to facilitate detection and identification. Though the detection ability is improved, the proposed scheme is application-specific and cannot apply in a generic environment. In [125], a log-likelihood ratio test (LRT) based SCD scheme is proposed in which the test statistic

is the ratio with two different cyclic frequencies. However, prior knowledge of all the cyclic frequencies is a strict requirement for this scheme and thus not be practical for most of the spectrum sensing scenarios. In [126], an SCD scheme is proposed to improve the performance of the SCD scheme by using a sliding correlator approach. Though this scheme outperformed the SCD schemes till the time, noise variance estimation and implementation aspects are not discussed in this paper.

2.4.1.4 Matched filter detection

Matched filter is considered as the optimum filter to improve the SNR of the received signal in the presence of additive noise. In matched filter detection, the cross-correlation of the received signal and the known pilots are used to compute the test statistic [13, 89]. The test statistic is then compared to a pre-computed decision threshold to choose the appropriate hypothesis. A block diagram representation of matched filter detection is shown in Figure 2.15. The test statistic is defined as,

$$T_i = \frac{1}{N} \sum_{n=1}^N x(n)P^*(n), \quad (2.21)$$

where $y(n)$ is the received signal, and $P^*(n)$ is the saved pilots. Matched filtering requires significant computational resources as several multipliers require to be implemented in parallel. Also, the exact prior-information about the transmitted signals are always not available. Knowledge of receiver timing synchronization is also considered as a drawback.

FIGURE 2.15: Block diagram of matched filter detection

FIGURE 2.16: Block diagram of Eigenvalue detection

2.4.1.5 Eigenvalue detection

Eigenvalue detection [22, 23, 127–129] is also an incoherent detection technique in which the maximum to minimum ratio of eigenvalues of the covariance matrix of the received signal is compared with a threshold to determine the presence/absence of communication in the current channel. The sample covariance matrix is evaluated from the received signals. Then the eigenvalues are extracted using the singular value decomposition. The ratio of maximum eigenvalue to the minimum eigenvalue is used for the detection process. Though the scheme is incoherent, it requires computation of a covariance matrix and eigenvalue decomposition of the received signal, which are computationally complex tasks. Furthermore, the threshold selection for eigenvalue detection is also a challenging problem. The block diagram representation of eigenvalue detection is given in Figure. 2.16.

2.4.1.6 Learning-based sensing techniques

The ability to interpret data patterns of machine learning algorithms is gaining interest in spectrum sensing also. Different approaches are discussed in the literature [130, 131] to classify a specified frequency channel into vacant or occupied. In [130], a K-means and support vector machine (SVM) based detection scheme is proposed. In the scheme, the K-means algorithm is used as the first step to analyze the patterns of the PU signals, and then the SVM is used for the classification. Some machine learning-oriented works [131] are used for the compressive wideband sensing. The selection of the proper features is an essential factor in these techniques to get a reliable decision. However, the real-time performance in a standalone system, huge data requirements for training, and high complexity are considered as its disadvantages.

Advantages and disadvantages of the narrowband sensing scheme are summarised in Table. 2.3.

TABLE 2.3: Narrowband sensing techniques: Advantages and disadvantages

Spectrum sensing scheme	Advantages	Disadvantages
Energy detection	Less complex implementation Incoherent nature	Low SNR wall Noise uncertainty
Cyclostationary feature detection	Immune to noise uncertainty Able to distinguish signals and noise Low P_{fa}	Large sensing duration requirement High computational complexity
Matched filter detection	Better detection accuracy Optimum for SNR improvement	Prior-knowledge of transmitted signals required Synchronization issues
Eigenvalue detection	Incoherent Blind detection	Computationally intensive
Learning-based techniques	Using complex methods in an easy manner	Complex techniques Real-time performance is limited Feature selection highly affects the decision and it increases the complexity Huge data set requirements

2.4.2 Wideband Spectrum Sensing

High data rates and bandwidth are required to meet the needs of next-generation communication systems. In this context, the SUs are required to sense a wide range of frequencies to find the available spectrum holes. Wideband sensing is essential to get the spectrum hole information from a range of frequencies. Majority of the approaches split the wideband into several narrowband sensing, and the sensing is performed either sequential or simultaneous fashion. The simultaneous sensing requires considerable sensing duration, which affects the throughput of the SU. On the other hand, simultaneous sensing with the help of parallel sensor nodes increases the resource overheads and also have sensor node synchronization issues. As a choice, researchers proposed compressive sensing to reduce the high sampling rate requirements and to reduce the number of signal samples. However, ADCs with varying sampling rates is a challenging task to implement in practice also sparsity of the signal may not be available due to the less number of signal samples. Wideband sensing can be divided into two main classes based on the sampling rate, namely Nyquist rate based systems, and sub-Nyquist rate-based systems.

FIGURE 2.17: Block diagram of wavelet transform detection.

2.4.2.1 Nyquist rate based wideband sensing

In Nyquist rate based wideband spectrum sensing approach [13], the ADCs operates at Nyquist rate to get the sampled version of the received wideband signal. The major Nyquist rate sensing schemes are wavelet detection, filterbank based detection, and the FFT-power spectrum density detection. A brief of major techniques is given below.

Wavelet transform based detection Wavelet transform is used when the frequency locations and power spectral density are unknown in a wideband of interest. The wavelet transform is used to detect the edges of the occupied bands [132–135]. This is done by characterizing the local irregularities in the frequency domain. The block diagram representation of the wavelet transform is given in Figure. 2.17. However, splitting the bands into several channels, then sensing the individual channel requires a significant amount of time. To reduce the sensing duration, bank of narrowband filters, and then sensors can use simultaneously [132–135].

FilterBank based sensing In the filterbank spectrum sensing scheme, the individual channels are divided using a bank of filters, which are frequency-shifted versions of the low-pass filter. Each filter output is connected to a narrowband sensing scheme to find whether the channel is vacant or occupied. The schematic representation of filterbank based spectrum sensing is shown in Figure. 2.18. Different filters and filterbank architectures are discussed in the literature. The conventional filterbank structures use the polyphase decomposition of the prototype low pass filters [136–139]. Low complexity reconfigurable filter-architectures also discussed in the literature. The main reconfigurable structures are interpolation and masking [140–142] and coefficient decimation [143] techniques. A tree structure based fast filterbank [144] also proposed in the literature to reduce the computational complexity of the

FIGURE 2.18: Schematic representation of filterbank based spectrum sensing.

conventional filterbank architectures. A brief of the different approaches is given below.

Per-channel approach It is the simplest way of designing filterbank with parallel filters used to extract the subbands of desired subbands. When the number of desired subbands increases, the complexity of the per-channel approach also increases. The per-channel approach is not suitable for cognitive radio approach as the bandwidth of the subbands may change dynamically, and it requires vast memory to store the filter coefficients corresponding to different configurations[139].

Modulated filter banks In modulated filter banks, different subbands are obtained by modulating the low-pass prototype filters [145, 146]. The Discrete Fourier Transform (DFT) based approach is one of the main types of modulated filter banks. More details about the Discrete Fourier Transform filter bank (DFTFB) is available in [145], and it is suitable for the uniform filter bank realization.

Fast filterbanks (FFB) FFB [144, 147] uses interpolation and masking techniques in several stages to extract the desired sub-band, and it can be realized as a bank of filters arranged in a parallel tree structure. For a k -stage FFB, the prototype filter is interpolated by a factor of $2^k - 1$ in the i^{th} stage. A k -stage FFB gives 2^k sub-bands of equal bandwidths.

FIGURE 2.19: Block diagram representation of the FFT based sensing.

Coefficient decimation based filter banks In this approach, different subbands are obtained by using coefficient decimation operation and appropriate adding/subtracting the simultaneously obtained responses and their complementary responses or using a proper low complexity masking filters. Different coefficient decimation approach based filter banks are discussed in [143, 148–151].

Frequency response masking based filter banks Multiple subbands responses are obtained by interpolating the prototype filters and then proper masking [140–142]. Similar to coefficient decimation based filterbanks non-uniform bandwidths can be obtained by adding/subtracting the simultaneously obtained responses and their complementary responses.

FFT power spectral density detection In this technique, the state of multiple frequency channels is analyzed simultaneously rather than analyzing one at a time. The block diagram representation of the FFT based sensing is given in Figure. 2.19. The process contains a serial to parallel converter according to the desired frequency resolution, followed by the FFT of the windowed signal. Narrowband detection analysis is carried out in each frequency bins to get the state of that particular channel [152].

2.4.2.2 Sub-Nyquist rate based detection

Nyquist rate wideband sensing has limitations like high sampling rate and large power consumption, which are not acceptable for future communication systems, especially limited power budget systems like aeronautical communications. Compressive sensing is identified as a paradigm to solve the issues associated with high sampling rates [153–155]. Compressive sensing for wideband analysis is getting traction as a promising candidate to use the sparse nature of the wideband signal in the frequency domain because of the presence of vacant frequency channels. In compressive sensing, the sparsity of the signal in some domain is used for the detection. The main components are the sparse representation, measurements, and sparse recovery. Compressive sensing can be classified into two subgroups, namely Non-blind and blind sensing techniques. The Non-blind techniques require the knowledge of the sparsity level of the wideband signal, whereas the blind detection technique does not require the knowledge of the sparsity level of the wideband signal.

Non-blind compressive sensing The Non-blind techniques require the knowledge of the sparsity level of the wideband signal, whereas the blind detection technique does not require the knowledge of the sparsity level of the wideband signal. In Non-blind approaches, the parameters of the wideband signal such as sparsity, occupancy information, and the required measurements are performed before starting the measurement procedure. The literature describes several methods to determine the mentioned parameters [156, 157]. For example, in [156], the authors proposed two-stage compressive sensing to minimize the sampling rate requirements further. In this scheme, the sparsity level is estimated at the first stage, and the number of measurements in the sampling is done in the next stage.

Blind compressive sensing Sparsity estimation is a complex task because it needs more data exchanges between the sensing nodes and an external database for the analysis. Different approaches are described in the literature, which does not require prior knowledge about the sparsity. In [158], discrete cosine transform (DCT) is used to get the energy of the wideband signal from a few samples. As another example, the technique described in [157], blindly determine the vacant channel locations. It requires only the maximum possible number of active subbands and its maximum bandwidth.

2.4.3 Cooperative spectrum sensing in cognitive radios

In cooperative spectrum sensing schemes, the information from the spatially distributed cooperative nodes is combined at the fusion center (FC) to decide the absence or presence of PU signal [40, 41, 159–161]. The sensed information from the multiple SU nodes has been reported in two ways, either data fusion or decision fusion.

2.4.3.1 Data fusion

Data fusion based on amplify-and-forward (AF) scheme in which the received signal from PU is amplified and forwards to the fusion center. The detection complexity at the cooperative nodes is very less compared to the decision fusion due to the centralized decision making policy. However, there is a requirement of large bandwidth in the reporting channel (the channel between SU and FC). The major data fusion schemes are maximal ratio combining and equal gain combining [41].

2.4.3.2 Decision fusion

In the case of decision fusion, the hard decision regarding the presence/absence of the PU signal has taken by the individual nodes, and then the binary decision (0/1) is reported to the fusion center (FC), and the FC takes the cooperative decision regarding the PU activity. Generally, the decision device of the FC is based on any one of the $k - out - of - n$ Rule. This rule corresponds that out of the total n cooperating nodes how many give the individual decision as detected according to the number k . Mainly there are three types of hard decision rules, namely OR rule, AND rule and Majority rule for $k = 1, n$ and $n/2$, respectively.

2.4.4 Implementation of spectrum sensing schemes

While the implementation of spectrum sensing is concerned, computational complexity and power utilization are the most sensitive factors [19, 162]. Spectrum sensing requires real-time processing and decision making. The fast processing of complex algorithms requires huge computational resources and power consumption. Power

utilization is a significant concern for systems like aeronautical communications. Also, the delay in decision making matters the throughput of the secondary radio. In this section, implementation of various spectrum sensing algorithms and their issues are summarized.

The ED consists of two multipliers (for squaring real and imaginary parts of the signal) and a digital integrator [80–85]. ED is the lowest complex methods and can be used as a reference for the implementation complexity of other detectors. In ED, 85% of the total power is consumed for the multiplication operation. Though ED is considered as simplest among all the detectors, noise uncertainty issues are severe for this scheme [13]. For autocorrelation based detection schemes, memory elements are additionally required to implement the autocorrelation delay. The scheme also requires division operations, which are implemented using the inverse matrix operation and requires additional multipliers and memory elements [79, 163]. The implementation of cyclostationary feature detection is highly complex due to the requirement of decimator, FFT, and autocorrelation estimation. Radix-2² architecture is used for the FFT computation unit, the frequency shift is realized using the CORDIC algorithm, and the decimator is implemented cascaded integrator-comb. The FFT operation is very complex, and it bears more than 40% of used computational resources [162].

Cognitive radio platforms like GNU Radio [164], and Iris [165] focussed on software-driven platforms and modularity. However software-based approach facilitates the baseband and the medium access control adaption easy; the computational complexity due to software-based radios on general-purpose platforms limits their usability in power-constrained environments like aircraft. FPGAs have been widely used in CR research owing to their hardware level adaptability, processing capabilities and parallelism. While platforms like CRUSH [166] and CRKIT [167] aimed to leverage the computational capabilities of FPGAs for implementing complex baseband modules, platforms like WARP [168] and Iris [169] used hardware-level flexibility to adapt properties of baseband modules based on channel conditions. Recent hybrid FPGA platforms have renewed interest in building adaptive radios on FPGAs as they offer close coupling of a processor for high-level cognitive software and hardware fabric for high throughput baseband processing. Software APIs can enable detailed reconfiguration of the hardware (the entire baseband or parts of it) from within the cognitive layer [170]. Such architectures have been demonstrated for LDACS [171]. We integrated the proposed spectrum sensing algorithms into this platform and evaluate the

performance in actual hardware in addition to software simulations.

2.5 Summary

An overview of the recent developments in aeronautical communication system is presented in the first and second sections of this chapter. The overview includes the evolution of the aeronautical communication systems and the limitations of the state of art of the current systems, future activities to modernize the ATM systems, upcoming schemes to handle the various aeronautical communication links. The specifications of the LDACS oriented air-to-ground communication system is given in detail as this thesis is more focused on CR enabled air-to-ground communication systems. The third section is detailing the CR concepts and the different components associated with it. In this section, definitions, operating modes, and functionalities of CR is briefed. As this thesis mainly focuses on the development of spectrum sensing techniques for aeronautical communication systems, a more detailed explanation of the various existing spectrum sensing schemes are also presented in this section. A detailed review of the significant spectrum sensing techniques like energy detection, matched filter detection, cyclostationary feature detection, and Eigenvalue detection is also provided. Their test statistic, advantages and disadvantages, and various challenges are also provided in detail. The next chapters present the proposed low complexity spectrum sensing schemes to improve sensing accuracy, reduce complexity, and reduce the noise uncertainty issues. Efficient implementation of the proposed sensing schemes is also presented in this thesis to show the practicability of the proposed schemes.

Chapter 3

Improved Energy Detection Schemes: Energy-difference Detection and Adaptive Energy Detection

3.1 Introduction

Unlike terrestrial systems, spectrum sensing in LDACS offers unique challenges as channel conditions and signal quality can vary rapidly due to the non-stationary nature of aircrafts around a fixed ground station. Also, aircraft systems operate on limited energy budget and hence necessitates the use of low complexity spectrum sensing schemes to meet strict power consumption limitations¹. Though feature detection techniques like matched filtering and cyclostationary detection schemes offer better detection accuracy at low SNR regimes, high complexity and long sensing duration requirements of these techniques make it less attractive for aeronautical communications. Energy Detection (ED) based techniques are suited for this scenario due to their low complexity and incoherent nature. However, conventional ED relies on accurate estimation of noise variance to meet performance requirements and also suffers from inability to distinguish between primary and other (malicious) users [19]. Also, detection accuracy of conventional ED deteriorates significantly at lower SNR

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¹The work in this chapter has been published in [1,5]

regimes. While alternative forms of ED have been investigated to address these shortcomings, they achieve such improvements at the cost of much higher computational complexity and hence power consumption.

In this chapter, two improved energy detection schemes are presented to reduce the SNR wall and to reduce the problems associated with the noise uncertainty issues of conventional energy detection schemes. The first scheme is based on energy difference-detection scheme in which the spectrum shape irregularities are analyzed to locate the spectrum holes. An adaptive energy detection scheme is introduced in the second part of this chapter to reduce the computational complexity of the energy-difference detection scheme without compromising the sensing accuracy. In the adaptive scheme, the historical sensing information is used to improve the sensing accuracy and has reduced complexity than the first scheme. A real-time noise variance estimation also introduced to reduce the effect of noise uncertainty issues. The adaptive ED scheme can be considered as a hybrid detection scheme as it uses two features of the received signals such as power and autocorrelation.

3.2 Energy-difference Detection based Spectrum Sensing Scheme

LDACS is proposed to deploy as an inlay system between the Legacy systems like DME. DME sends a series of pulse-pairs at regular intervals to find the distance between the aircraft and the ground station. The LDACS wideband spectrum attains a unique spectrum shape (with regular spectral gaps of DME) after removing the DME pulses from the received wideband signal. The energy-difference detection exploits this advantage to locate the spectral holes of interest [172, 173].

3.2.1 Motivation for proposing energy-difference algorithm

LDACS is proposed to deploy as an inlay system in the spectral gaps between two adjacent DME channels. The power of DME pulses would be considerably high at LDACS receiver, and it significantly affects the LDACS performance. The performance of conventional energy detection also gets affected by DME interference. The out-of-band radiation from the DME pulses may lead to false alarm (the detector may

choose the hypothesis $\mathcal{H}_1$ even if the LDACS signal is absent). To reduce the false alarm rate, we need to pass the wideband signal through a DME interference mitigation system. Several pulse interference mitigation techniques are discussed in the literature [172, 173]. To reduce the overhead in spectrum sensing, it is advised to use simple interference mitigation systems such as pulse blanking or clipping techniques. In pulse blanking technique, the signal component is compared with a predefined threshold, and if the amplitude of the pulse is above the threshold, that component is blanked. It is observed that along with DME signals, some parts of LDACS signals are also removed by the DME interference mitigation system which results in a reduction in SNR. If conventional energy detection is used, this reduction in SNR degrades the detection performance. However, the unique spectral shape of OFDM after removing DME pulses from the neighborhood channels can be exploited for better detection performance. A typical spectrum scenario in L-band is shown in Figure 3.1. Two different cases are demonstrated in the figure:

1. LDACS+DME with mutual interference
2. LDACS channels after removing DME Pulses using pulse-blanking technique [172]

It is clear from the Figure. 3.1 (a) that the energy due to DME pulses is very high compared to the LDACS signals, and it offers considerable interference towards LDACS channels. The out-of-band interference from DME pulses causes false alarms while using conventional ED for spectrum sensing. It is observed in Fig. 3.1 (b), there is a reduction in power spectral density of LDACS channels after DME removal, which results in a reduction in SNR. As shown in Fig. 3.1. (b), if an OFDM signal is present in the LDACS channel, there should be a considerable difference in power levels of LDACS1 channel and DME channel (after removing DME pulses). These unique characteristics motivated us to think about an energy-difference detection algorithm for spectrum sensing. Moreover, the energy difference algorithm in the proposed technique avoids the problem of SNR degradation by considering the difference in energy values of adjacent channels (LDACS channel and DME channel) which reduces the effect of noise.

FIGURE 3.1: LDACS spectrum Scenario: (a) With DME interference (b) After DME removal.

FIGURE 3.2: Wideband spectrum sensing using energy-difference detection.

3.2.2 Proposed energy-difference detection based spectrum sensing Scheme

The steps involved in the proposed technique is as follows: The wideband signal of interest is scanned and passed through a DME interference mitigation system to avoid false alarms which may arise due to the presence of DME pulses [172, 173]. A low-complexity FFB [144, 147] is then used to simultaneously scan the frequency bands corresponding to different LDACS and DME channels. FFB gives sharp frequency response at relatively low complexity, and it uses interpolation and masking techniques in several stages to extract the desired sub-band and can be realized as a bank of filters arranged in a parallel tree structure. For a k – stage FFB, the prototype filter is interpolated by a factor of 2^{k-1} in the i^{th} stage. A k – stage FFB gives $N = 2^k$ sub-bands of equal bandwidths. Energy values are computed for the filtered outputs of each of the frequency bands obtained using the FFB. In the final decision-making stage, the absolute difference of the energies obtained from the LDACS channel and the nearby DME channels (after removing DME pulses) are compared with a predefined threshold. The LDACS signal is detected if the energy difference is above the predefined threshold. The schematic diagram of the energy difference based spectrum sensing is shown in Figure 3.2.

3.2.3 Analysis of the Test statistic of Energy-difference Detection Algorithm

The test statistic of conventional energy detection is explained in section 2.4.1.1. The test statistic of the energy-difference detection also derived using the same assumptions (Central Limit Theorem). The distribution of the test statistic for the LDACS channel and the DME channel under $\mathcal{H}_1$ is different because there is no PU signal present in the DME channel. The closed-form expressions for the probability of false alarm (P_{fa}) and probability of detection (P_d) can be obtained from the test static T_i . Note that T_i follows the central (under $\mathcal{H}_0$) and non-central (under $\mathcal{H}_1$) chi-square distribution with $2N$ degrees of freedom. For low SNR regimes, to get acceptable performance, we need to use a large number of signal samples ($N \gg 1$). When N is large enough (say $N = 10000$), T_i can be assumed to follow Normal distribution by using the central limit theorem [92–95]. The test statistic (or the energy) of each LDACS

channel follows the Normal distribution as

$$T1_i \sim \mathcal{N} \begin{cases} N\sigma_{w1}^2, 2N\sigma_{w1}^4 & \mathcal{H}_0 \\ N(\sigma_{s1}^2 + \sigma_{w1}^2), 2N(\sigma_{s1}^2 + \sigma_{w1}^2)^2 & \mathcal{H}_1 \end{cases}, \quad (3.1)$$

where σ_{w1}^2 and σ_{s1}^2 are noise and signal variances, respectively for a particular LDACS channel. The received energy of the DME channel after removing the DME pulses follows the distribution as

$$T2_i \sim \mathcal{N}(N\sigma_{w2}^2, 2N\sigma_{w2}^4), \quad \mathcal{H}_0 \text{ \& } \mathcal{H}_1, \quad (3.2)$$

where, σ_{w2}^2 is the noise variance of DME channel.

For the energy-difference detection scheme, the test statistic T_i follows $T_i \sim T1_i - T2_i$. If the random variables $x_1, x_2, \dots, x_k$ are independent, if x_i has a normal distribution with mean and variance, and if $a_1, a_2, \dots, a_k$ and b are constants with at least one $a_i \neq 0$. Then the new random variable $a_1x_1 + a_2x_2 + \dots + a_kx_k + b$ follows the random distribution with mean, $\mu = a_1\mu_1 + a_2\mu_2 + \dots + a_k\mu_k + b$ and with variance $\sigma^2 = a_1^2\sigma_1^2 + a_2^2\sigma_2^2 + \dots + a_k^2\sigma_k^2$ [174]. Then the test statistic for the energy-difference detection method follows Normal distribution, which is given as

$$T_i \sim \mathcal{N} \begin{cases} N(\sigma_{w1}^2 - \sigma_{w2}^2), 2N(\sigma_{w1}^4 + \sigma_{w2}^4) & \mathcal{H}_0 \\ N(\sigma_{s1}^2 + \sigma_{w1}^2 - \sigma_{w2}^2), 2N((\sigma_{s1}^2 + \sigma_{w1}^2)^2 + \sigma_{w2}^4) & \mathcal{H}_1 \end{cases}, \quad (3.3)$$

The probability of false alarm and the probability of detection can be derived from (3.3)

$$P_{fa} = Q \left(\frac{\lambda - N(\sigma_{w1}^2 - \sigma_{w2}^2)}{\sqrt{2N(\sigma_{w1}^4 + \sigma_{w2}^4)}} \right) \quad (3.4)$$

$$P_d = Q \left(\frac{\lambda - N(\sigma_{s1}^2 + \sigma_{w1}^2 - \sigma_{w2}^2)}{\sqrt{2N((\sigma_{s1}^2 + \sigma_{w1}^2)^2 + \sigma_{w2}^4)}} \right) \quad (3.5)$$

where λ is the decision threshold.

Threshold setting In energy detection based spectrum sensing techniques, the threshold is set either for a fixed P_{fa} rate or a target P_d . Decision threshold based on a target P_d requires the knowledge of noise and signal powers. The noise power can be estimated, whereas the signal power is difficult to estimate because it depends on factors

such as propagation and transmission characteristics. Conventionally, the threshold is chosen to limit the P_{fa} to an acceptable value, as it requires only the knowledge of noise power. In (3.6), the decision threshold λ is chosen for a fixed probability of false alarm. If the energy difference is more than that of the decision threshold, the proposed algorithm chooses the hypothesis $\mathcal{H}_1$. Otherwise, the algorithm chooses the hypothesis $\mathcal{H}_0$.

$$\lambda = Q^{-1}(P_{fa})\sqrt{2N(\sigma_{w1}^4 + \sigma_{w2}^4)} + N(\sigma_{w1}^2 - \sigma_{w2}^2) \quad (3.6)$$

where Q^{-1} is the inverse Q function, and P_{fa} is the permissible false alarm rate. For $\sigma_{w1}^2 = \sigma_{w2}^2 = \sigma_w^2$, the threshold is reduced to,

$$\lambda = Q^{-1}(P_{fa})\sqrt{4N\sigma_w^4} \quad (3.7)$$

Similar to conventional ED schemes, the energy-difference detection scheme also suffers from noise uncertainty problem as the threshold is a function of noise variance. The errors in the noise variance estimation affect detection performance. However, the issues of noise uncertainties are not addressed in the following simulation studies.

3.2.4 Simulation results of energy-difference detection scheme

3.2.4.1 Simulation setup

The performance of the proposed scheme is analyzed using simulation studies. LDACS signal generated according to the LDACS prototype specifications [4] and the DME pulses are generated using the mathematical model of DME [172]. The DME signals can be modeled as a pair of Gaussian pulses and are given as

$$P(t) = e^{-\frac{\alpha t^2}{2}} + e^{-\frac{\alpha(-\Delta t)^2}{2}} \quad (3.8)$$

The parameters α and t defines the width of the pulse and spacing between the pulses. The value of alpha gives a pulse width of $3.5\mu s$ at 50% of the maximum amplitude. A signal of 8 MHz bandwidth (satisfying interleaved LDACS and DME channels of 0.5 MHz) is considered for simulations. A 4-stage FFB [144, 147] is used for the simultaneous extraction of 16 channels, each having 0.5 MHz bandwidth and the energy

FIGURE 3.3: Detection performance comparison of proposed energy difference algorithm and conventional energy detection technique [91] (SNR Vs probability of detection).

FIGURE 3.4: Detection performance comparison of proposed energy difference algorithm and conventional energy detection technique [91] using ROC curves (Probability of false alarm Vs Probability of detection).

corresponding to the each channel is calculated. The performance of the proposed scheme in AWGN channel is analyzed by using 10000 Monte Carlo simulations. The simulation parameters are summarized in Table. 3.1.

TABLE 3.1: Simulation parameters of the energy-difference detection scheme.

Parameter	Value
Width of Gaussian pulse (α)	$3.5 \mu s$
Signal bandwidth	8 MHz
Number of signal samples	10000
SNR range	-20 dB to 0 dB

TABLE 3.2: Computational complexity comparison of the energy difference detection and the conventional ED schemes

Item	Conventional ED	Energy-difference detection
No of channels required to be scanned	1 channel	2 channels
Complex Multiplications	N	2N
Noise variance estimation required	1 channel	2 channels

3.2.4.2 Analysis of detection performance

The performance of the proposed scheme and the conventional energy detection is compared by analyzing the probability of detection over a range of SNR values. In Figure. 3.3, the detection performance is analyzed for SNR ranging from $-20dB$ to $0dB$ for constant false alarm rates ($P_{fa} = 0.1$ and 0.01). The detection performances are compared with conventional ED schemes. The results show that the proposed energy difference algorithm-based scheme offers a better detection performance than the conventional energy detection method at the low SNR values and identical performance at relatively high $SNRs$. In Figure. 3.4 the detection performance of the proposed and conventional schemes are analyzed using ROC curves. The ROC curves are plotted for $SNR = -10$ dB. From the ROC curves, it is clear that the proposed scheme offers better performance than the conventional scheme. For example, when $P_{fa} = 0.1$, the proposed scheme gives about 35% improvement in the probability of detection when compared to the conventional scheme. However, the energy differ-

ence scheme improves the detection performance of the conventional ED, the computational complexity of the scheme is relatively higher (2 times) than that of conventional ED as energies from two channels required to be estimated for decision making. A Comparison of the computational complexity of the energy difference scheme and the conventional ED is given in Table 3.2.

3.3 Adaptive Energy Detection Scheme with Real-time Noise Variance Estimation

Different approaches are discussed in the literature to reduce the SNR wall and to alleviate the noise uncertainty issues. Though the energy-difference detection scheme discussed in Section 3.2 improves the detection accuracy, the algorithm required to extract two channels (one LDACS channel and one DME channel) and find their energy differences. Compared to the conventional ED scheme, the computational resource requirement is almost 2 times for the energy-difference scheme. Also, the applicability of the proposed scheme is limited to the LDACS scenario as the scheme exploits the unique spectrum characteristics in the spectrum of interest.

A modified approach of ED, utilizing the historical sensing information is used to improve the detection accuracy with relatively less computational complexity. Also, a real-time noise variance estimation technique presented to alleviate the noise uncertainty issues. In this approach, an energy difference based Weighted Energy Averaging scheme (WEAS) is used to reduce the effective variance of the test statistic and thereby lower the SNR wall with minimal computational overhead. The weighted sum of the current and the past energy values are considered as the test statistic in the proposed scheme. An energy-difference algorithm is used to detect channel state changes, and is combined with the weighted averaging scheme with dynamically tuned weights to counter performance degradation issues. The energy-difference algorithm takes the difference of received signal energy from the current and the previous sensing slots and compares it with a predefined threshold for detecting state changes. The algorithm further tunes the weights for the energy values based on state change information and estimated noise variances, thus alleviating the performance issues in state of the art WEAS schemes.

The main contributions of this scheme are as follows:

- An adaptive energy detection scheme is proposed which switches between WEAS and conventional ED by adaptively controlling the weight w based on a novel energy difference algorithm.
- A novel method is proposed to compute optimised weights dynamically is proposed based on received signal history.
- Mathematical formulation(s) of the decision threshold for WEAS and energy difference schemes are derived, which aims at improving accuracy in decision making.
- An enhanced real-time noise variance estimation technique is developed with the aid of cyclic prefix in the LDACS signals. The noise variance can be estimated effectively in real-time irrespective of primary signal being on or off.
- A wideband spectrum sensing scheme is developed in which the detector is able to choose to scan the desired LDACS channel from a wideband.
- The proposed technique is integrated into a cognitive radio platform on a field-programmable gate array (FPGA) platform to quantify resource overheads.

3.3.1 Proposed Spectrum Sensing Scheme

The performance metric in energy detection can be improved by reducing the effective variance of the test statistic. In this work, the correlation between the current and past energy measurements is exploited for lowering the SNR wall to achieve the desired detection accuracy. The sensing and transmission slots in a typical CR communication is represented in Figure 3.5. The flow chart for the proposed scheme is given in Fig. 3.6. The proposed scheme calculates the energy difference between the current and previous sensing slots ($E_d = E_i - E_{i-1}$). This energy difference is compared with a pre-specified threshold (The details of threshold calculation is given in

FIGURE 3.5: Utilizing historical information for improved spectrum sensing.

FIGURE 3.6: Flowchart of the energy difference incorporated weighted energy averaging scheme.

Section 3.3.1.4). This energy difference algorithm is used to identify the sudden rise or drop of the received energy in the consecutive sensing intervals. A state change (either $\mathcal{H}_0 \rightarrow \mathcal{H}_1$ or $\mathcal{H}_1 \rightarrow \mathcal{H}_0$) is indicated if $|E_d| > \lambda_d$. In that case, only the received energy from the current sensing slot is considered for decision making ($w = 1$). On the other side, when the PU is identified as static (either $\mathcal{H}_0 \rightarrow \mathcal{H}_0$ or $\mathcal{H}_1 \rightarrow \mathcal{H}_1$), the weighted sum of the received energy ($0 \leq w \leq 1$) from the current and previous time slots is considered for the decision making. This adaptive switching is controlled by adaptively applying the weights for current and previous sensing slots ($0 \leq w \leq 1$). The weight w is optimized to reduce the false alarm rate by giving higher priority to the sensing interval whose noise variance is less. The details of the weight optimization is explained in Section 3.3.1.3.

Incorporating the past energy observations into the decision making improves the detection performance in static PU, as it reduces the variance of the test statistics.

FIGURE 3.7: The probability distribution for the test statistic. (a) Conventional ED (b) WEAS.

The probability distribution plots for the test statistic for this weighted energy averaging scheme (WEAS) and the conventional ED is shown in Fig. 3.7. The simulations have been carried out with 10000 signal samples at $SNR = -10$ dB. The results from the 10000 iterations are summarised in the probability distribution curves. It is clearly visible from the Fig. 3.7 that the common area shared by $\mathcal{H}_0$ and $\mathcal{H}_1$ (ie, the probability of error) is less for WEAS when compared to conventional ED. On the other hand, WEAS lead to performance degradation during frequent state changes. To address this, an energy difference algorithm is employed to detect the state changes. The proposed algorithm adaptively controls the weights of the current and past energy observation in the calculation of the test statistic thereby adaptively switch between the WEAS and conventional ED depends upon the static and frequent state change conditions respectively.

3.3.1.1 The channel state model

Different approaches [14, 86, 175, 176] are available in the literature to model the intermittent PU activity in cognitive radio. In this work, two state Markov chain model is adopted to create a practical scenario. Let α be the probability of the channel changes from busy ($\mathcal{H}_1$) to idle ($\mathcal{H}_0$) state and β be the probability of the channel changes its state from idle to busy. The channel state change is modeled as a two state Markov chain and is shown in Fig. 3.8. The values of α and β can be expressed as a function of

FIGURE 3.8: The channel state change model using two state Markov chain.

the state probabilities $P(\mathcal{H}_1)$ and $P(\mathcal{H}_0)$ of the channel with the aid of Markov model. The values of $P(B)$ and $P(I)$ are obtained from the historical data.

$$P(\mathcal{H}_1) = (1 - \alpha)P(\mathcal{H}_1) + \beta P(\mathcal{H}_0) \quad (3.9)$$

$$P(\mathcal{H}_0) = \alpha P(\mathcal{H}_1) + (1 - \beta)P(\mathcal{H}_0) \quad (3.10)$$

$$P(\mathcal{H}_1) = \frac{\beta}{\alpha + \beta} \quad (3.11)$$

$$P(\mathcal{H}_0) = \frac{\alpha}{\alpha + \beta} \quad (3.12)$$

3.3.1.2 Weighted Energy Averaging Scheme (WEAS)

The proposed spectrum sensing scheme considers the received energy of the previous time slots along with the current energy values. The test statistic T_i for the WEAS is defined in (3.13).

$$T_i = wE_i + (1 - w)E_{i-1} \quad (3.13)$$

where E_i and E_{i-1} are the received signal energy from the current sensing slot and previous sensing slot respectively. The E_i and E_{i-1} follow normal distribution according to CLT [92, 95], as explained in section 2.4.1.1, equation (5.1). The equation is revisited and is given as

$$E_i \sim \mathcal{N} \left\{ \begin{array}{ll} N\sigma_{w_i}^2, 2N\sigma_{w_i}^4 & \mathcal{H}_0 \\ N(\sigma_{s_i}^2 + \sigma_{w_i}^2), 2N(\sigma_{s_i}^2 + \sigma_{w_i}^2)^2 & \mathcal{H}_1 \end{array} \right. , \quad (3.14)$$

As mentioned, a two-state Markov chain is used to represent the state transitions. As shown in Fig. 3, there are four possibilities of state transitions in the WEAS ($\mathcal{H}_0 \rightarrow$

$\mathcal{H}_0, \mathcal{H}_0 \rightarrow \mathcal{H}_1, \mathcal{H}_1 \rightarrow \mathcal{H}_0$ and $\mathcal{H}_1 \rightarrow \mathcal{H}_1$). The distribution of the test statistic of WEAS for all possible state transitions are derived using (3.14) and is given in (3.15).

$$T_i \sim \begin{cases} \mathcal{N}\left(N\left(w\sigma_{w_i}^2 + (1-w)\sigma_{w_{i-1}}^2\right), \right. \\ \left. 2N\left(w^2\sigma_{w_i}^4 + (1-w)^2\sigma_{w_{i-1}}^4\right)\right) & \mathcal{H}_0 \rightarrow \mathcal{H}_0 \\ \mathcal{N}\left(N\left(w(\sigma_{w_i}^2 + \sigma_{s_i}^2) + (1-w)\sigma_{w_{i-1}}^2\right), \right. \\ \left. 2N\left(w^2(\sigma_{w_i}^2 + \sigma_{s_i}^2)^2 + (1-w)^2\sigma_{w_{i-1}}^4\right)\right) & \mathcal{H}_0 \rightarrow \mathcal{H}_1 \\ \mathcal{N}\left(N\left(w\sigma_{w_i}^2 + (1-w)(\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)\right), \right. \\ \left. 2N\left(w^2\sigma_{w_i}^4 + (1-w)^2(\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)^2\right)\right) & \mathcal{H}_1 \rightarrow \mathcal{H}_0 \\ \mathcal{N}\left(N\left(w(\sigma_{w_i}^2 + \sigma_{s_i}^2) + (1-w)(\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)\right), \right. \\ \left. 2N\left(w^2(\sigma_{w_i}^2 + \sigma_{s_i}^2)^2 + (1-w)^2(\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)^2\right)\right) & \mathcal{H}_1 \rightarrow \mathcal{H}_1 \end{cases} \quad (3.15)$$

where σ_{s_i} and $\sigma_{s_{i-1}}$ are the signal variances and σ_{w_i} and $\sigma_{w_{i-1}}$ are the noise variances of sensing slots i and $i-1$, respectively.

The first term of (3.15) indicates the distribution of the test statistic when the PU is idle for both i^{th} and $i-1^{th}$ sensing intervals ($\mathcal{H}_0 \rightarrow \mathcal{H}_0$). The second term corresponds to a state change from idle to busy ($\mathcal{H}_0 \rightarrow \mathcal{H}_1$), third term is used to represent the state change from busy to idle ($\mathcal{H}_1 \rightarrow \mathcal{H}_0$) and the last term is the distribution of the test statistic when the PU is busy on both the sensing intervals ($\mathcal{H}_1 \rightarrow \mathcal{H}_1$). The average probability of false alarm and the probability of detection can be derived from (3.15).

Probability of false alarm The average probability of false alarm has been derived from the first and third terms of (3.15). During $\mathcal{H}_0 \rightarrow \mathcal{H}_0$, the probability of false alarm P_{fa} is,

$$\begin{aligned} P_{fa}(WEAS/\mathcal{H}_0 \rightarrow \mathcal{H}_0) &= P\left(T_i > \lambda_{WEAS}/(\mathcal{H}_0 \rightarrow \mathcal{H}_0)\right) \\ &= Q\left(\frac{\lambda_{WEAS} - N(w\sigma_{w_i}^2 + (1-w)\sigma_{w_{i-1}}^2)}{\sqrt{2N(w^2\sigma_{w_i}^4 + (1-w)^2\sigma_{w_{i-1}}^4)}}\right) \end{aligned} \quad (3.16)$$

Similarly for $\mathcal{H}_1 \rightarrow \mathcal{H}_0$, the probability of false alarm, P_{fa} is obtained from third term of (3.15),

$$\begin{aligned} P_{fa}(WEAS/\mathcal{H}_1 \rightarrow \mathcal{H}_0) &= P\left(T_i > \lambda_{WEAS}/(\mathcal{H}_1 \rightarrow \mathcal{H}_0)\right) \\ &= Q\left(\frac{\lambda_{WEAS} - N\left(w\sigma_{w_i}^2 + (1-w)(\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)\right)}{\sqrt{2N\left(w^2\sigma_{w_i}^4 + (1-w)^2(\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)^2\right)}}\right) \end{aligned} \quad (3.17)$$

The average probability of false alarm of the WEAS is given as,

$$\begin{aligned} P_{fa}(WEAS) &= (1-\beta)P\left(T_i > \lambda_{WEAS}/(\mathcal{H}_0 \rightarrow \mathcal{H}_0)\right) \\ &\quad + \alpha P\left(T_i > \lambda_{WEAS}/(\mathcal{H}_1 \rightarrow \mathcal{H}_0)\right) \end{aligned} \quad (3.18)$$

where $1-\beta$ is the probability of the transition $\mathcal{H}_0 \rightarrow \mathcal{H}_0$ and α is the probability of the transition $\mathcal{H}_1 \rightarrow \mathcal{H}_0$ as shown in Fig. 3.8.

Probability of detection The average probability of detection has been derived from the second and fourth terms of (3.15). During $\mathcal{H}_0 \rightarrow \mathcal{H}_1$, the probability of detection is obtained from second term of (3.15),

$$\begin{aligned} P_d(WEAS/\mathcal{H}_0 \rightarrow \mathcal{H}_1) &= P\left(T_i > \lambda_{WEAS}/(\mathcal{H}_0 \rightarrow \mathcal{H}_1)\right) \\ &= Q\left(\frac{\lambda_{WEAS} - N\left(w(\sigma_{w_i}^2 + \sigma_{s_i}^2) + (1-w)\sigma_{w_{i-1}}^2\right)}{\sqrt{2N\left(w^2(\sigma_{w_i}^2 + \sigma_{s_i}^2)^2 + (1-w)^2\sigma_{w_{i-1}}^4\right)}}\right) \end{aligned} \quad (3.19)$$

Similarly, for $\mathcal{H}_1 \rightarrow \mathcal{H}_1$, the probability of detection obtained from fourth term of (3.15) and is given in (3.20).

$$\begin{aligned} P_d(WEAS/\mathcal{H}_1 \rightarrow \mathcal{H}_1) &= P\left(T_i > \lambda_{WEAS}/(\mathcal{H}_1 \rightarrow \mathcal{H}_1)\right) \\ &= Q\left(\frac{\lambda_{WEAS} - N\left(w(\sigma_{w_i}^2 + \sigma_{s_i}^2) + (1-w)(\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)\right)}{\sqrt{2N\left(w^2(\sigma_{w_i}^2 + \sigma_{s_i}^2)^2 + (1-w)^2(\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)^2\right)}}\right) \end{aligned} \quad (3.20)$$

The average probability of detection of the WEAS is given as,

$$P_d(WEAS) = \beta P\left(T_i > \lambda_{WEAS} / (\mathcal{H}_0 \rightarrow \mathcal{H}_1)\right) + (1 - \alpha) P\left(T_i > \lambda_{WEAS} / (\mathcal{H}_1 \rightarrow \mathcal{H}_1)\right) \quad (3.21)$$

The decision threshold The decision threshold λ_{WEAS} for the WEAS is calculated from (3.16) for a fixed false alarm rate and assuming no state change.

$$\lambda_{WEAS} = \sqrt{2N(w^2\sigma_{w_i}^4 + (1-w)^2\sigma_{w_{i-1}}^4)} Q^{-1}(P_{fa}) + N(w\sigma_{w_i}^2 + (1-w)\sigma_{w_{i-1}}^2) \quad (3.22)$$

When $\sigma_{w_i}^2 = \sigma_{w_{i-1}}^2$, $\lambda_{WEAS} = \lambda_{avg}$ and is given in (3.23).

$$\lambda_{avg} = \left(Q^{-1}(P_{fa})\sqrt{N} + N\right)\sigma_{w_i}^2 \quad (3.23)$$

When the PU state changes (either $\mathcal{H}_0 \rightarrow \mathcal{H}_1$ or $\mathcal{H}_1 \rightarrow \mathcal{H}_0$), the detection schemes proposed in [91] and [86] degrade its performance (refer (3.17) and (3.19)). The state changes of the PU are not considered in these schemes. In proposed energy detection scheme, an energy difference algorithm is used to find the state changes. The energy-difference $|E_D|$ ($E_D = E_i - E_{i-1}$) is compared with predefined threshold λ_d to find the state change. As explained in the flow chart of the proposed scheme, when state change happens, decision will be made using received energy of the current slot only (i.e., $w = 1, \lambda_{WEAS} = \lambda_i$ and $T_i = E_i$).

3.3.1.3 Weight Optimization

The weight optimization is required when there is no state change ($\mathcal{H}_0 \rightarrow \mathcal{H}_0$ and $\mathcal{H}_1 \rightarrow \mathcal{H}_1$). In this work, the weight optimization is carried out on the basis of $\mathcal{H}_0 \rightarrow \mathcal{H}_0$ as it requires knowledge about noise variance only. To do this, the first term of (3.15), i.e., $\mathcal{N}\left(N(w\sigma_{w_i}^2 + (1-w)\sigma_{w_{i-1}}^2), 2N(w^2\sigma_{w_i}^4 + (1-w)^2\sigma_{w_{i-1}}^4)\right)$ is considered. The variance in the above distribution needs to be minimised to reduce the effective false alarm rate. The optimal value of w by minimizing $2N(w^2\sigma_{w_i}^4 + (1-w)^2\sigma_{w_{i-1}}^4)$ and is obtained by,

$$\frac{\partial}{\partial w} 2N(w^2\sigma_{w_i}^4 + (1-w)^2\sigma_{w_{i-1}}^4) = 0 \quad (3.24)$$

The optimal value of w is obtained from (3.24) is given as

$$w = \frac{\sigma_{w_{i-1}}^4}{\sigma_{w_i}^4 + \sigma_{w_{i-1}}^4} \quad (3.25)$$

From (3.25) it is clear that more weight is given to the time slot having less noise variance that results in better decision accuracy. For $\sigma_{w_i}^2 = \sigma_{w_{i-1}}^2$, the optimal weight is 0.5, and is observed in the simulation results too.

3.3.1.4 Energy-Difference Algorithm

The state change can be detected with the energy-difference algorithm. The difference of the received energy for the current and previous time slots ($E_d = E_i - E_{i-1}$) is compared with the predefined thresholds for the state change detection. The distribution of the test statistic of the energy-difference for different state changes is derived using the distribution given in (3.14) and is given as.

$$E_d \sim \begin{cases} \mathcal{N}\left(N(\sigma_{w_i}^2 - \sigma_{w_{i-1}}^2), \right. \\ \left. 2N(\sigma_{w_i}^4 + \sigma_{w_{i-1}}^4)\right), & \mathcal{H}_0 \rightarrow \mathcal{H}_0 \\ \mathcal{N}\left(N((\sigma_{w_i}^2 + \sigma_{s_i}^2) - \sigma_{w_{i-1}}^2), \right. \\ \left. 2N((\sigma_{w_i}^2 + \sigma_{s_i}^2)^2 + \sigma_{w_{i-1}}^4)\right), & \mathcal{H}_0 \rightarrow \mathcal{H}_1 \\ \mathcal{N}\left(N(\sigma_{w_i}^2 - (\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)), \right. \\ \left. 2N(\sigma_{w_i}^4 + (\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)^2)\right), & \mathcal{H}_1 \rightarrow \mathcal{H}_0 \\ \mathcal{N}\left(N((\sigma_{w_i}^2 + \sigma_{s_i}^2) - (\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)), \right. \\ \left. 2N((\sigma_{w_i}^2 + \sigma_{s_i}^2)^2 + (\sigma_{w_{i-1}}^2 + \sigma_{s_{i-1}}^2)^2)\right), & \mathcal{H}_1 \rightarrow \mathcal{H}_1 \end{cases} \quad (3.26)$$

From the distribution, the mean of the energy-difference can be defined as $\mu_d = N(\sigma_{w_i}^2 - \sigma_{w_{i-1}}^2)$ and $\sigma_d^2 = 2N(\sigma_{w_i}^4 + \sigma_{w_{i-1}}^4)$ during static channel conditions (No state changes) assuming signal power remains unchanged during the consecutive sensing durations. The differential threshold λ_d is derived from (3.26) and is given in (3.27).

$$\lambda_d = \sqrt{2N(\sigma_{w_i}^4 + \sigma_{w_{i-1}}^4)}Q^{-1}(P_{fa}) + N(\sigma_{w_i}^2 - \sigma_{w_{i-1}}^2) \quad (3.27)$$

Note that no state change happens if the absolute value of energy-difference is less than λ_d . The proposed spectrum sensing scheme uses an energy-difference algorithm and the weighted energy averaging scheme (WEAS) as explained in the flowchart in Fig. 3.6 and section 3.3.1.

3.3.2 Noise Variance Estimation

The decision threshold in the ED based systems are highly dependent on the noise level. The detection performance degrades drastically even with minor errors in the noise variance estimation. In this scheme, we use an unbiased noise variance estimator, which exploits the pre-knowledge of cyclic prefix in the LDACS signal. Fig. 3.9 shows the LDACS signal frame structure. As shown in the figure, the insertion of CP induces an autocorrelation property. This property is utilized for the consistent estimation of noise variance, irrespective of the state of the channel and the presence of primary user signal.

Let the total number of signal samples, $N = K(N_{CP} + N_D)$, where K represents the total number of OFDM symbols used for the sensing, N_{CP} is the cyclic prefix length in samples per symbol and N_D is the data length of OFDM symbol. Let define two terms E_x and ρ_x as,

$$E_x = \frac{1}{K(N_{CP} + N_D)} \sum_{n=1}^{K(N_{CP} + N_D)} |x_i(n)|^2 \quad (3.28)$$

$$\rho_x = \frac{1}{KN_{CP}} \sum_{n=1}^{K(N_{CP} + N_D)} \Re[x_i(n)x_i(n + N_D)] \quad (3.29)$$

where $\Re[.]$ represents the real part of the term. E_x represents the energy estimate and ρ_x is the autocorrelation strength of the received signal samples. The distribution of

FIGURE 3.9: Frame structure of OFDM based LDACS signals.

FIGURE 3.10: RMSE of estimated noise power versus SNR.

E_x and ρ_x are given in (3.30) and (3.31) respectively.

$$E_x \sim \begin{cases} \mathcal{N}\left(\sigma_{w_i}^2, \frac{2\sigma_{w_i}^4}{K(N_{CP}+N_D)}\right), & \mathcal{H}_0 \\ \mathcal{N}\left((\sigma_{s_i}^2 + \sigma_{w_i}^2), \frac{2(\sigma_{s_i}^2 + \sigma_{w_i}^2)^2}{K(N_{CP}+N_D)}\right), & \mathcal{H}_1 \end{cases} \quad (3.30)$$

$$\rho_x \sim \begin{cases} \mathcal{N}\left(0, \frac{\sigma_{w_i}^4(N_{CP}+N_D)}{2KN_{CP}^2}\right), & \mathcal{H}_0 \\ \mathcal{N}\left(\sigma_{s_i}^2, \frac{(\sigma_{s_i}^2 + \sigma_{w_i}^2)^2(N_{CP}+N_D) + \sigma_{s_i}^4 N_{CP}}{2KN_{CP}^2}\right), & \mathcal{H}_1 \end{cases} \quad (3.31)$$

The unbiased estimate of noise variance is defined using E_x and ρ_x as (the derivation is given in Appendix A)

$$\hat{\sigma}_{w_i}^2 = E_x - \rho_x \quad (3.32)$$

From (3.30) and (3.31), the distribution of $\hat{\sigma}_{w_i}^2$ is derived and is given as.

$$\hat{\sigma}_{w_i}^2 \sim \begin{cases} \mathcal{N}\left(\sigma_{w_i}^2, \frac{2\sigma_{w_i}^4}{K(N_{CP}+N_D)} + \frac{\sigma_{w_i}^4(N_{CP}+N_D)}{2KN_{CP}^2}\right) & \mathcal{H}_0 \\ \mathcal{N}\left(\sigma_{w_i}^2, \frac{2(\sigma_{s_i}^2 + \sigma_{w_i}^2)^2}{K(N_{CP}+N_D)} + \frac{(\sigma_{s_i}^2 + \sigma_{w_i}^2)^2(N_{CP}+N_D) + \sigma_{s_i}^4 N_{CP}}{2KN_{CP}^2}\right) & \mathcal{H}_1 \end{cases} \quad (3.33)$$

TABLE 3.3: Simulation Parameters for LDACS Signal Generation

Parameter	Value
FFT size	64
Sampling time	1.6 μs
Sub-carrier spacing	9.765625 KHz
Cyclic prefix ratio	11/64
Used subcarriers	50
Lower frequency guard sub-carriers	7
Higher frequency guard sub-carriers	6

It can be observed from (3.33) that the variance of $\hat{\sigma}_{w_i}^2$ asymptotically turns to zero. Hence, the consistency and unbiased nature of the proposed noise variance technique is proved. The root mean square error (RMSE) of the estimated noise power is plotted in Fig. 3.10 for both the hypotheses. RMSE is relatively higher when the PU signal is present because the variance of $\hat{\sigma}_{w_i}^2/\mathcal{H}_1$ is high compared to $\hat{\sigma}_{w_i}^2/\mathcal{H}_0$ (refer (3.33)).

3.3.3 Simulation Set-up and FPGA Implementation

3.3.3.1 Simulation Set-up

LDACS signal generation A wideband spectrum sensing scheme is developed to scan multiple LDACS spectral holes from a range of frequencies. For the simulation study, we consider the sampling frequency of 4 MHz and that enables to scan any LDACS channel within this 4 MHz range (Include 4 LDACS and 4 DME channels each having a bandwidth of 0.5 MHz). To imitate the real-world scenario, we have generated the LDACS baseband signals according to the specifications given in [4], and the Matlab code for the same is provided by DLR (German space agency) [177]. The parameters used to simulate LDACS signals are given in Table 3.3.

Filter architecture A digital filter bank is used to split the wide band into several sub-bands. In this work, the fast filter bank (FFB) based channeliser proposed in [144, 147] is used for obtaining uniform sub-bands meeting the stringent LDACS spectral

FIGURE 3.11: Higher level architecture of the proposed system: Integration of spectrum sensing logic into the receive path of the LDACS radio platform.

mask specifications with low complexity. An 8-channel FFB design is used in the spectrum sensing unit. Out of these 8 channels, 4 alternative channels used to scan LDACS channels.

3.3.3.2 FPGA Implementation

To evaluate the resource overheads, the proposed spectrum sensing scheme is implemented and it is integrated into the baseband of the cognitive radio platform on the Xilinx Zynq ZC706 board [24]. Figure 3.11 shows the integration of the spectrum sensing scheme into the receive path of our radio platform. As shown in the figure, to enable the strong coupling between the software and hardware, an ARM processor, and a Programmable Logic (PL) are integrated into the Zynq architecture. Channelization, spectrum sensing, and the RF interfaces are implemented in the PL region of Zynq. The PL has dedicated interfaces to communicate with software functionalities running on the ARM core. Dedicated memory access (DMA) enables high-speed interfaces between the baseband modules and software. The parametric and the partial reconfiguration techniques initiated through simple software APIs offers high-speed dynamic adaptability.

FIGURE 3.12: Hardware architecture of the proposed sensing scheme.

The higher level architecture of the sensing scheme is shown in Figure. 3.12. The implementation strategy is to minimise the resource consumption by using building boxes that gets reused within the respective computational stages using a hierarchical state-machine. These building boxes are built around the DSP block primitive to compute complex multiplication, multiply-accumulate and division operations that are required in the estimation. We use 16-bit fixed-point representation for inputs and 32-bit fixed point representation for intermediate steps, with rounding to fit wider intermediate results back to 32-bits. The received information from the antenna is post-processed (RF domain) and fed into the channeliser that provides 4 alternative LDACS channels which are fed into the receive path buffers. One of the channels is chosen at a time for spectrum sensing and is fed into an autocorrelation logic which computes the energy of the received signal over 10000 samples (E, σ_w^2). The autocorrelation logic is a shift-register delay chain of 64-elements, while complex multiplications at the tap outputs are mapped onto DSP blocks. Further, the state machine (marked SM) initiates the computation of differential threshold λ_d and the energy difference E_d . Based on the results of the energy difference algorithm, the SM initiates the weight optimization process. Once the optimized weight is estimated, the SM estimates the test statistic (T_i) and the decision threshold (λ_{WEAS}) and channel occupancy decision is made based on the statistical test. The information is passed to the cognitive logic in ARM cores which can initiate a transmission in

FIGURE 3.13: Detection performance of sequential ED: Probability of detection during Static channel ($\mathcal{H}_1 \rightarrow \mathcal{H}_1$) and during state change conditions ($\mathcal{H}_0 \rightarrow \mathcal{H}_1$)(at SNR=-16 dB).

the vacant channel or configure the hardware switch to evaluate other channels. The computed parameters are stored in dedicated per-channel registers in the hardware for use in subsequent scan intervals. The state machine transitions are controlled by the parameters like the number of samples to be observed, window the depth and so on, which are configured into the parameter memory. Thus the logic can perform detection by observing a larger number of samples to boost the detection accuracy at low SNR values by altering the register value(s).

3.3.4 Results and Discussions

The performance of the proposed scheme is analysed using simulation studies. The LDACS signals are generated according to the specifications and the detection performance is evaluated for different noise levels. The performances are evaluated for static PU and frequent state change conditions and the average detection performances are also evaluated. The signal energy and the noise variance are estimated from 10000 signal samples and the detection performance is average out from 10000 iterations. The state change probabilities α and β are set to 0.001 and 0.1 for static PU and frequent state change conditions respectively [86].

FIGURE 3.14: Average detection performance comparison of the Conventional ED [91], IED [91], sequential ED [86] and the energy difference incorporated WEAS (proposed scheme) in static PU and frequent PU state cases.

The detection performances of WEAS with static PU and frequent state change conditions and the conventional ED are compared in Fig. 3.13. The receiver operating characteristic (ROC) curves are plotted for an SNR=-16dB. Results show that the WEAS without considering the state changes [86] under-performs when a state change occurs ($\mathcal{H}_0 \rightarrow \mathcal{H}_1$ here). At the same time, providing noticeably better performance for the static channel conditions. The proposed scheme intended to take this advantage during static channel conditions and not to lose the performance when there is a state change. The average detection performance of the proposed scheme is uplifted with the adaptive choice of the sensing scheme.

The average detection performance of the proposed scheme, conventional ED, IED [91], and the sequential ED [86] are compared in Fig. 3.14. For IED scheme, the parameters L and M set to 3 for imitating the static PU and $M=2$ for representing a state change. L corresponds to the total number of sensing information considered for averaging and M corresponds to the number of sensing intervals where PU is actually present. The parameters α and β are set to 0.001 and 0.1 for static PU and frequent state change conditions respectively for the sequential ED [86] and the proposed scheme. Results indicate that regular WEAS and the proposed scheme provides identical performance during static channel conditions. On the other hand, During

FIGURE 3.15: Detection performance comparison of the proposed technique (Matlab and hardware results) and Matched filtering based sensing.

FIGURE 3.16: Effect of weight in WEAS for different signal to noise ratios (SNR's).

frequent state change scenarios, the detection performance of the proposed scheme is better than that of sequential ED, IED and the conventional ED schemes. Here, the sequential ED also provides comparable performance during static channel conditions because of the optimised weights used for the computation of test statistic. In [86], the authors just averaged out the energies not considering the optimal weights.

FIGURE 3.17: Performance comparison of the proposed scheme Vs conventional ED [91] scheme with and without noise uncertainty (NU).

In our experiments, it was observed that the hardware implementation closely followed the accuracy set by the full precision Matlab models, when tested with actual LDACS frame structure. The Matlab and hardware simulation results are given in Fig. 3.15. A comparison of the detection performance of the proposed scheme and the matched filtering based sensing also shown in the same figure. Though matched filtering offers better detection accuracy at low SNR regions, the higher complexity, and long and variable sensing duration to achieve high accuracy limit the practicality of the scheme.

The advantage of weight optimization is demonstrated in Fig. 3.16. Same noise variance is considered for the analysis for the i^{th} and $i - 1^{th}$ sensing slots. So $w = \frac{1}{2}$ is the optimal weight. The same trend is observed in the simulation results also. we observed that when $w = 1$, (ie, equivalent to conventional ED), a steep drop in the probability of detection compared with $w = 0.5$. It is guaranteed that the performance of the proposed scheme does not fall below the level of conventional ED even if sudden state changes happens in the consecutive sensing intervals. The performance of the proposed scheme is analysed and are compared with the conventional ED for a range of SNRs in Fig. 3.17. It is observed that the conventional ED performance is highly sensitive to the noise variance uncertainty. A drastic drop of the probability of detection is noticed at $SNR = -10dB$ with 5% noise uncertainty (NU). The resulting false

alarms are also plotted in Fig. 3.17 (red color curves). A deviation from the assumed false alarms has been observed for the case with 5% NU because of the deviation of the threshold from the actual value. The real-time noise variance estimation technique used in this work enhanced the stability against NU. We observed that along with the proposed technique, the conventional ED also provides reasonable detection accuracy with the proposed noise variance estimation technique.

The various aspects of the performances are analysed and are compared in Fig. 3.13- Fig. 3.17. These analysis shows that the WEAS with optimised weight effectively separates the two hypotheses ($\mathcal{H}_0$ and $\mathcal{H}_1$) by reducing the effective variance of the test statistic. Also it was perceived that the energy difference incorporated WEAS prevents the performance degradation of regular WEAS when a state change happens. For the optimal w , the SNR wall to get $P_d = 0.9$ & $P_{fa} = 0.1$ is $-16.5dB$ whereas it is $-14.9dB$ for the conventional ED. For achieving better detection accuracy, the proposed method requires only two additional registers to store the previous energy and noise variance values and two additional multipliers to calculate the test statistic and the thresholds. Unlike the proposed scheme, conventional schemes use dedicated hardware for noise variance estimation which effectively reduces overall resource utilization.

Finally, the performance of the hardware model is validated using simulations in ModelSim. LDACS frames generated in MATLAB were quantised to 16-bit fixed point values, which were mapped into the receiver FIFO in the hardware model for validation. The energy-detection block looks at the FIFO status and reads out samples as soon as it becomes available to start the computation. With frame data available at every clock edge, the sensing logic was able to compute the outcome of sensing (decide between $\mathcal{H}_0$ or $\mathcal{H}_1$) in 10116 cycles. We observe that with 16-bit fixed-point representation for inputs, the hardware implementation offers comparable performance as the MATLAB simulation (see Fig. 3.15) across all simulation conditions (different SNR conditions).

Further, the design is integrated into the radio platform discussed in [24] to estimate the resource overheads incurred by the hardware model. Table 3.4 shows the resource consumption of the radio platform (both transmit and receive chains) after integrating the spectrum sensing logic. The channel filter (transmit path) and channeliser

TABLE 3.4: Resource utilisation of the Zynq radio platform after integrating the spectrum sensing logic.

Sub-module	FFs	LUTs	BRAMs(36/18)	DSPs
Channel Filter	1,336	1,397	0/0	23
Channeliser	1,581	2,161	4/0	46
Sensing logic	6,179	5,220	0/3	55
RF I/F	22,781	21,970	6/4	77
Reconfig	697	767	1/1	0
Total Utilisation	32,092	30,919	11/8	178
% Utilisation	7.3	14.1	2.75	19.78
Operating Frequency	140 MHz			

(recieve path) are integrated as reconfigurable modules since only one of them is active at any given time. It can be observed that the state-machine driven approach results in an efficient implementation with very minimal overhead of general purpose resources (1% in Lookup Tables (LUTs), 3% in FlipFlops of the entire device). Also, while the current design consumes 55 DSP blocks, a fully flattened approach would infer 76 additional Digital Signal Processing (DSP) blocks, resulting in over $2\times$ higher DSP resources and energy consumption. The individual building blocks are also extensively pipelined to achieve an operating frequency of 140 MHz in the integrated design. The results shows that the proposed scheme offers significant improvement in the detection process and can be efficiently deployed in hardware for application in LDACS air-to-ground communication. A comparison of the resource overheads of the proposed scheme, conventional matched filtering, and conventional ED is given in Table 3.5. Results show that matched filtering offers better detection accuracy with more resource overheads. At the same time, the proposed scheme offers better detection accuracy than the conventional ED with comparable resource utilization. While analyzing power consumption, the proposed design consumes a mere 112 mW in operation (dynamic power), with a device static power of 299 mW, compared to the 3,166mW consumed by the matched filter based detection scheme, making it an ideal choice for deployment on aircraft onboard systems with limited energy budget. Apart from the resource utilization and power consumption, the matched-filter requires a higher sensing period relative to other schemes (as high as up to 58.3 ms) which need

TABLE 3.5: Resource utilization comparison of the proposed scheme, conventional matched filtering, and energy detection.

Sensing logic	FFs	LUTs	DSP
Proposed scheme	6179	5220	55
Conventional matched filtering	11968	6112	1500
Conventional ED [178]	6592	12038	48

FIGURE 3.18: Overview of the energy-difference detection and adaptive energy detection schemes.

to be varied depending on channel conditions, restricting the throughput of the secondary radio.

3.4 Summary

In this chapter, two ED based spectrum sensing schemes were proposed. The first scheme is based on energy-difference detection, which utilizes the unique spectrum shape after removing DME pulses. Though the scheme offers better detection accuracy (around 35% improvement), higher computational complexity and LDACS limited applicability are considered as its disadvantages. An alternative form of ED

scheme is introduced to reduce the computational complexity, which is based on an energy difference incorporated weighted energy averaging. The weighted energy averaging helps to reduce the effective variance of the test statistic by adaptively choosing the weights based on current and past energy observations. The scheme also addresses the shortcomings of regular WEAS by incorporating an adaptive energy difference scheme into the WEAS. The technique allows the algorithm to switch between WEAS and conventional ED based on channel state change information derived from the energy difference computation. Also, an unbiased noise variance estimation technique is proposed to reduce the noise uncertainty issues. The proposed method can be considered as a hybrid scheme as it uses both energy and autocorrelation features for spectrum sensing. Apart from this, the resource overhead of the proposed scheme is evaluated by implementing the scheme on an FPGA platform. The overview of the two contributions of this chapter is schematically shown in Figure 3.18.

Chapter 4

An Efficient Spectrum Sensing Scheme Using Low-Power Correlators

4.1 Introduction

Use of cognitive radio (CR) based dynamic spectrum access has been proposed for LDACS, which would enable opportunistic and on-demand access to the L-band channel(s) while meeting the reliability and safety requirements imposed by the standard [11, 12, 171]. However, introducing dynamic spectrum access for LDACS presents unique challenges over terrestrial CR systems; aircraft in the range of the system are in constant motion resulting in an evolving network structure, while the channel conditions between communicating entities can change very rapidly, requiring more effective sensing compared to terrestrial CR systems. Furthermore, while ground-based systems can employ powerful computational systems to support the processing demands, implementations for aircraft must be compact and power efficient to satisfy weight, space, and power budgets¹.

Though the energy detection based spectrum sensing schemes proposed in Chapter 3 are relatively less computationally intensive than the feature detection schemes, the detection performance drastically drops even with slight errors in noise variance estimation. The noise variance estimation technique proposed in Section 3.3 are vulnerable to noise uncertainty issues compared to feature detection techniques. As LDACS

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¹The work in this chapter has been published in [2]

signal properties are priorly available, feature detection technique like matched filtering is a good choice for detecting the spectrum holes. However, implementing a matched filter on hardware is a computationally tedious task due to the requirement of a series of multipliers on a raw.

In this chapter, an approach for spectrum sensing using low power correlators that also serve as the receiver synchroniser for the OFDM baseband is proposed. The multiplierless correlator architecture presented for IEEE 802.16d in [179] is enhanced to cater to the longer preamble structure of LDACS air-to-ground transmissions. Further, an enhancement of the computational precision to improving performance in very low signal-to-noise ratio (SNR) conditions, which are likely in the LDACS scenario due to diverse channel conditions, limited transmission power, and the mobile nature of the aircraft is performed. Results show that the proposed approach outperforms traditional energy detection (ED) as well as feature detection (FD) based spectrum sensing schemes even when the ED technique incorporates highly accurate noise prediction. The multiplierless approach also results in improved power consumption, making it an ideal choice for on-board implementation. The proposed correlator is implemented on a Xilinx Zynq FPGA to evaluate the performance in hardware.

4.2 Multiplierless Correlator for Spectrum Sensing

The synchronization information in a multi-frame of LDACS signals is known a priori, allowing the use of cross-correlation for spectrum sensing and synchronization. Though cross-correlation based techniques offer good detection accuracy even at low SNR values, high implementation complexity makes it inadequate for aeronautical applications. Multiplierless correlators address this challenge by replacing the multiplication operation with shift-add blocks and representing the known preamble as a sum of powers-of-2 [179, 180]. It has been shown that they can maintain the same synchronization accuracy as multiplier-based correlators while consuming significantly fewer resources [179]. In this chapter, a modified algorithm based on the multiplierless correlator approach described in [179] has been analyzed in the context of spectrum sensing for LDACS air-to-ground band. The correlator is enhanced to cater for the very low SNR conditions that may be encountered in aeronautical systems and

FIGURE 4.2: Variation of detection accuracy with quantisation levels of multiplierless correlator for LDACS-1 frame.

The high-level architecture of the multiplierless correlator is shown in Fig. 4.1, which extends the correlator used in [179] for the IEEE 802.16d standard. The structure mimics a transpose-direct form filter where the multiplication operation at each tap is replaced by a multiplexer, that selects one among its many inputs based on the synchronisation symbol value at that tap (Sync[n]). Like in [179], our architecture uses a single shared *shift-add* block to optimise resource consumption; however, our design supports higher quantization levels to improve performance under very low SNR conditions. This shared *shift-add* block receives the **I** and **Q** components from the RF front-end and computes all possible multiples of the input sample corresponding to the 375 synchronisation samples. While the design in [179] uses a 64 sample preamble structure, the long synchronisation tile in LDACS creates a long critical path through the multiplexers. To mitigate this, we introduce a pipeline stage at the output of the tap multiplexers to increase the operating frequency of the design. Finally, to re-use the correlator for synchronisation of the FL frames (unique to our application), which rely on the synchronisation symbols alone instead of a full tile, the input multiplexers of taps 1–75 have an additional select line, which can bypass the *shift-add* inputs for ‘0’. In this case, the output of tap 225 is used for synchronisation purposes.

To optimise the quantisation level for the design, we simulated the multiplierless correlator in MATLAB using different quantisation levels and observed that there is no

FIGURE 4.3: Integrating the multiplierless correlator into the LDACS processing chain.

appreciable gain beyond 6-bit quantisation, as shown in Fig. 4.2. Hence during implementation, the quantised values of the synchronisation tile ($\text{Sync}[n]$) were hard-coded with 6-bit quantization and I and Q sample wordlength of 16 bits. This allows the tools to optimize most of the multiplexers (except 1–75) into fixed logic during the implementation process, reducing the resource consumption further. The multiplexers corresponding to taps 1–75 were optimized to 2-to-1 multiplexers, also lowering resource consumption. Though this results in an inflexible design, the contents of the synchronisation tile are fixed in LDACS, allowing them to be computed off-line and loaded into the system at design time.

4.2.2 Proposed Correlator in the LDACS Processing Chain

Fig. 4.3 shows a simplified block diagram of the LDACS baseband, with the proposed multiplierless correlator integrated into the datapath. In the receive direction, the digitised signals are passed through a programmable channeliser that can extract and isolate the LDACS channels from the adjacent DME pulses. The binary data from the selected channel is fed to the correlator (part of receiver synchroniser), which attempts to estimate the symbol timing offset by detecting the start of a ground-to-air frame (signal cross correlation approach). The remainder of the receive channel

baseband mimics a typical OFDM receiver – the FFT module transforms the received frame to the frequency domain, which is then equalised, demodulated and decoded to obtain the actual transmitted information. The LDACS standard also suggests the use of time- and frequency-domain interference mitigation techniques and adaptive equalisation to ensure robust and reliable reception.

When the station needs to transmit information, the spectrum sensing chain is activated and the cognitive logic configures the channeliser to scan the LDACS RL bandwidth. In this configuration, the correlator tries to detect the presence of a synchronisation tile in the data received from the channeliser output, and the information is relayed to the cognitive logic. Once a suitable channel is detected, the transmit chain is activated and the cognitive logic configures the RF modules to use the selected channel for transmission. The baseband modules map the information using Quadrature Phase-Shift Keying (QPSK) modulation, applies the IFFT, and inserts the cyclic prefix to form the LDACS frame. The spectral masking filter transforms the signal to maintain the stringent LDACS specification, before feeding it to the Digital to Analog conversion and RF modules.

4.2.3 Integration into LDACS Radio Platform

The simplified diagram in Fig. 4.4 shows the architecture of our radio platform for LDACS [171] on a Xilinx Zynq device. The Zynq architecture integrates a dual core ARM processor and a programmable fabric on the same chip, enabling tight coupling between software and hardware processing blocks. The baseband functionality (LDACS channelizers and filters) and interfaces to the antenna are implemented in the programmable logic (PL) region of the Zynq with dedicated interfaces to interact with the cognitive software tasks running on the ARM core. Dedicated direct memory access (DMA) controllers offer high speed data movement between the baseband modules and software (or external interfaces). The platform offers high speed dynamic adaptability through parametric reconfiguration (for tuning parameters) and high-speed partial reconfiguration, which can be initiated through simple software APIs. An Analog Devices AD-FMCOMMS4-EBZ board (based on the AD9364) connects to the antenna interface to complete the RF front-end (see [171] for more details of the LDACS radio platform).

FIGURE 4.4: Integrating multiplierless correlator into the radio platform on Zynq.

The LDACS standard allows transmission of air-to-ground information over 23 channels and places stringent requirements on the pulse shape of the transmitted signal. This results in the use of complex filters for channelization during reception and pulse shaping during transmission. This non-concurrent functionality is implemented using partial reconfiguration to reduce the area overheads and power consumption; the channelization module is loaded on the fly during spectrum sensing, while the channel filter module is loaded during actual transmission. The PR approach optimises resource utilisation, leaving behind enough resources to implement other complex baseband modules, like the correlator in this case.

As shown in Fig. 4.4, the correlator module (marked as Mless-corr) interfaces with the output of the partially reconfigurable region (PRR) that holds either the channelizer or the channel filter (depending on the operating mode). The filter-bank based spectrum sensing scheme in [171] is replaced with an optimal channelizer for LDACS and the channel filter proposed in [182] to reduce multiplication complexity. During a sensing operation, the channelizer output is also read by the correlator module that can determine the presence of an LDACS air-to-ground frame transmitted in the channel. Four such channels are available simultaneously through the channelizer,

and are sequentially fed into the correlator module under software control. The result of sensing is read by the cognitive software to determine the best channel for transmission. During a normal receive operation, the software configures a register bit in the correlator module allowing it to be reused as a receiver synchroniser for the OFDM demodulator stage. The parametric configuration changes as well as the mode switch through reconfiguration are performed using simple function calls from the cognitive software, such as `set_basesband(spectrum_sense)`. Our framework handles all the low-level steps need to manage the change in parameters or physical reconfiguration operation in response to these function calls.

4.3 Results

4.3.1 Implementation Results

To evaluate the resource requirements of the proposed correlator and to estimate its power consumption, the correlator is implemented in isolation on a Xilinx Zynq XC7Z045 FPGA. The detailed resource consumption of the sub-modules of the multiplierless correlator is shown in Table 4.1. The design achieves an operating frequency of 190 MHz on the moderate-grade fabric of the XC7Z045, and the complete design consumes only 14% of the resources on the Zynq design allowing the rest of the baseband modules to be integrated on the same device.

For comparison, an optimised multiplier-based correlator design (in isolation, transpose direct form) also implemented, which could only fit on the larger XC7Z100 device (same architecture, but offers more resources) due to the large number of DSP blocks required. The optimised structure maps the delay elements using the internal pipeline registers within the DSP block to maximize performance with minimal fine-grained resource usage. The results of the different implementations are shown in Table 4.2. The multiplier-based design consumes nearly 2% of LUTs and Flip-flops (FFs) and 76% of the DSP blocks available on the larger XC7Z100 device. The lower resource utilisation of the multiplierless approach enables a more compact implementation (and a smaller device with less static power consumption), making our architecture better suited for on-board systems, while also leaving sufficient resources available for the rest of the baseband functions. The pipelined structure ensures that both designs offer similar compute throughput (one output per clock cycle) and latency (376

TABLE 4.1: Detailed resource consumption of the multiplierless correlator on a Zynq XC7Z045 device as a standalone module.

Sub-module	FFs	LUTs	Slices	DSPs
<i>shift_add</i>	242	180	67	0
tap mux	0	5,961	1,766	0
add-delay chain	23,726	23,754	5,957	0
Total Utilisation (%)	24,000	29,895	7,806	0
% Utilisation	5.5	13.7	14.2	0
Frequency	195 MHz			

TABLE 4.2: Resource comparison of proposed correlator on the Zynq XC7Z045 and the multiplier-based correlator on the Zynq XC7Z100 device.

Design	FFs	LUTs	Slices	DSPs	F _{Max}
Multiplierless	24,000	29,895	7,806	0	195
Multiplier-based	11,968	6,112	1,528	1,500	406
Adaptive ED (Chapter 3)	6179	5220	1112	55	140

cycles); however, the higher operating frequency achievable using multiplier-based correlators make them suited for use in LDACS ground stations for managing/monitoring spectrum allocation across all aircraft.

We also evaluate the power consumption of the design using the XPower Analyser tool from Xilinx. A post place-and-route simulation dump was used to generate the activity rates with actual LDACS frame data as the input to the correlator in each clock cycle. The simulation was performed at the design clock frequency of 125 MHz. The tool computed the total power consumption of the multiplierless correlator as 1,160 mW, with 1,038 mW contributed by the correlator operation (dynamic power) on the XC7Z045 device. The power analysis of the multiplier-based correlator at the same operating frequency resulted in an estimated consumption of 3,166 mW of dynamic power (contributed by the correlator in operation). The proposed design thus achieves a $3\times$ advantage in dynamic power consumption. The larger device requirement for the multiplier-based design also contributes to a much higher total power, further highlighting the advantage of the proposed approach.

TABLE 4.3: Resource utilisation of the Zynq radio platform after integrating the proposed correlator.

Sub-module	FFs	LUTs	BRAMs(36/18)	DSPs
Channel Filter	1,336	1,397	0/0	23
Channelizer	1,581	2,161	4/0	46
Mless-corr	24,000	29,895	0	0
RF I/F	22,781	21,970	6/4	77
Reconfig	697	767	1/1	0
Total Utilisation	49,913	55,594	11/5	123
% Utilisation	11.4	25.4	2.57	13.67

Finally, we evaluate the resource overheads of the design when integrated into our radio platform on the XC7Z045 device. The results of the implementation are shown in Table 4.3. It can be observed that the proposed correlator is logic intensive and contributes nearly 65% of the total LUT consumption of the system (without considering the baseband modules that are not integrated here). However, our correlator doubles up as the receiver synchronises in the LDACS OFDM baseband, a key functionality that is required to ensure accurate decoding of the received information (over the critical LDACS ground-to-air link). A standalone multiplierless cross-correlator to assist with receiver synchronisation would otherwise consume 9215 registers and 9574 LUTs more, and our proposed correlator effectively reducing the resource consumption by 16%. The overall design consumes less than 26% of resources on the device, leaving considerable general (LUTs, FFs) and specialised (DSP Blocks, BRAMs) resources for implementing baseband modules and other compute intensive processing for on-board LDACS systems.

4.3.2 Spectrum Sensing Effectiveness

To determine the effectiveness of the proposed correlator approach in detecting the presence/absence of transmissions under different SNR conditions, we generate LDACS frames in MATLAB and emulate different received conditions by adding Additive White Gaussian Noise (AWGN) components. For the proposed correlator-based approach and the multiplier-based approach, we use a single frame size (4950 samples) as the

(A) Actual LDACS RL frame with no noise.

(B) Received LDACS RL frame at -10 dB SNR.

FIGURE 4.5: Frequency plots of generated LDACS RL frames under different SNR conditions.

detection window. This frame size corresponds to the minimal RL frame recommended by the standard. The frequency response plot of our test input frames are shown in Fig. 4.5; sub-plot 4.5a shows the actual LDACS RL frame when it was transmitted (zero noise condition), while sub-plot 4.5b shows the case when the frames are received at SNR conditions of -10 dB. It can be observed that the noise significantly affects the frequency response signature and noise power level of the transmitted LDACS frame, limiting the scope of simple energy detection-based techniques. An effective spectrum sensing scheme should be able to accurately determine the presence of LDACS transmission under such diverse conditions.

For the evaluation, these received frames are used as inputs to the hardware implementation (as preloaded RAM contents), simulation model of the proposed multiplier-less correlator (MATLAB simulation), and the multiplier-based model (in hardware). The inputs are quantized to 16-bit signed-magnitude fixed-precision format for hardware implementation while the MATLAB simulation model is tested with MATLAB's native accuracy (double precision floating point). The output of the proposed correlator (hardware evaluation) corresponding to received LDACS frames at different

FIGURE 4.6: Correlator output at SNR of 0dB and -10 dB.

noise conditions ($SNR = 0$ dB, $SNR = -10$ dB) is plotted in Fig. 4.6. The presence of frame is determined by detection of a significant peak (more than $1.33\times$ all others in the current frame) at sample index 375, corresponding to the LDACS RL preamble. Though the plots vary significantly due to the difference in input noise levels, the proposed correlator achieves significant peaks at index 375 most of the time, resulting in positive frame detection.

The detection accuracy of the proposed correlator under different noise conditions with SNRs ranging from -20 dB to 0 dB is also evaluated in hardware, by loading the test frames into BlockRAMs on the FPGA. The performance is averaged over 1000 LDACS frames (4950 samples each) for each SNR condition, with each frame having a different noise signature at the same SNR. We also compare against the performance of a simulation model of the proposed correlator in MATLAB and a multiplier-based correlator in hardware (at 16-bit precision), to compare against the proposed correlator with the same input frames. The results are plotted in Fig. 4.7. The hardware model achieves almost identical accuracy to the multiplier-based equivalent (same truncation mechanism) and the simulation model in MATLAB (minor deviations due to rounding), with 100% positive frame detection in conditions up to -12 dB.

The detection performance of the proposed approach is compared against the traditional ED-based technique (in MATLAB) under different noise variance estimation conditions. The performance of ED based detection is largely determined by the noise variance estimation, which is complex to compute and is often assumed to be a known parameter while evaluating the algorithm. For our evaluation, we consider three cases of noise variance estimation: with no error (ideal condition), with 1% error and with 5% error (practical condition). We have used a 4950 sample observation window and 1% probability of false alarm as the parameters for determining

FIGURE 4.7: Comparison of detection accuracy of the proposed scheme using different detection techniques: Conventional ED [91], Low complexity CFD [126], Single cycle CFD [17], and autocorrelation scheme [163].

the decision threshold in ED. With perfect noise estimation, it can be observed that the percentage detection of ED reduces rapidly beyond an SNR of -11dB , while the proposed approach can achieve close to 90% positive detection even at an SNR of -15dB . As the quality of noise estimation deteriorates to 1% and 5% error, the performance of ED deteriorates significantly compared to the proposed approach. The results show that the proposed correlator based technique offers better detection accuracy over the ED technique without incurring the computational complexities associated with highly accurate noise estimation. Finally, the proposed technique is compared against cyclostationary feature detection (CFD) and autocorrelation based schemes from the literature. A low-complexity cyclostationary technique for sensing spectrum in a femtocell design for LTE networks [126], a cooperative cyclostationary technique for spectrum sensing in low SNR conditions in generic OFDM systems (which we have adapted to a single-cycle CFD scheme for LDACS) [17], and an autocorrelation technique described in [163] relies on the detection of autocorrelation coefficient for spectrum sensing in generic OFDM systems are considered together with the properties of LDACS RL-DC frame and simulated the performance in MATLAB, under different noise conditions with SNRs ranging from 0dB to -20dB . The results, shown in Fig. 4.7, clearly shows that the proposed technique offers higher detection accuracy, even while running at lower computational precision. It should be noted that the detection accuracy of techniques which rely on periodic properties of the signal will improve further as the detection window size is increased, which is

FIGURE 4.8: Overview of the multiplier-less correlator based sensing scheme.

mandatory for the detection across multiple timeslots in the LDACS RL-DC segment.

4.4 Summary

In this chapter, the use of multiplierless correlation for spectrum sensing is proposed in the LDACS digital front-end, with the added benefit of the same hardware being used for timing synchronization in the LDACS OFDM receiver. Results show that the proposed architecture offers three times energy reduction over multiplier-based correlators and better detection of LDACS RL frames in air-to-ground channels even at low SNR values, compared to traditional ED systems and other feature detection techniques. Moreover, the observation window for spectrum sensing can be as small as the minimal RL frame structure, enabling faster turn-around from sensing to start of transmission. Our results show that the proposed correlator based spectrum sensing offers 90% detection accuracy even -15 dB SNR without requiring noise estimation, reducing the computational complexity in on-board implementation. An overview of the proposed sensing scheme is given in Figure 4.8. Figure summarizes how the

sensing scheme gets improved detection accuracy and how the scheme reduces its computational complexity compared to the multiplier based correlators.

Chapter 5

Design and Implementation of a simplified cyclostationary feature detection scheme

5.1 Introduction

As mentioned, spectrum sensing plays a significant role in CR-based communications systems. Though different approaches have been explored to sense the LDACS reverse link spectrum efficiently in previous chapters, they suffer from higher computational complexity, noise uncertainty, low detection accuracy, and high power consumption¹.

The primary aim of this chapter is to propose a sensing scheme that gives a complexity-accuracy trade-off. The statistical properties of the received signals such as mean and autocorrelation can be utilized for the detection process. Cyclostationary detection (CD) is getting important consideration as the technique that uses statistical properties of the signal to detect the spectrum holes. However, the CD schemes are highly complex to implement, and long sensing duration is required to detect the spectrum. Single-cycle cyclostationary detection (SCD) is gaining traction as the technique of choice in this context since it can perfectly distinguish PU signals from noise and interference even at low SNR regimes. Moreover, SCD is more immune to noise uncertainty issues and has lower computational complexity compared to conventional CD

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¹The work in this chapter has been published in [6] and submitted to [3].

schemes. Similar to conventional CD schemes, SCD also exploits the dominant Cyclostationary features due to the periodicity within the signal or its statistical properties to assist spectrum sensing. The detection process uses the Fourier series expansion of the cyclic autocorrelation as a test statistic for the decision making. Though SCD schemes are less sensitive to noise uncertainty, the dependence of decision threshold to noise variance leads to performance degradation. Also, real-time updating of the threshold makes the implementation even harder compared to other simple schemes. Some of the recent literature proposed innovative methods [17, 126] to improve the efficiency of the SCD schemes. But none of these methods deals with real-time noise variance estimation and noise uncertainty. Alternatively, likelihood ratio test (LRT)-based spectrum sensing techniques [119, 163] are introduced to improve the stability against noise uncertainty. These techniques normalize the test statistic with the signal variance to reduce the dependence of the noise estimation errors on the detection performance. Though the normalization improves the stability against noise uncertainty, the signal variance increases when the PU is present, and it reduces the probability of detection. Also, such techniques consider the absolute value of the autocorrelation while estimating the correlation coefficient, which biases the test statistic and leads to performance degradation. Moreover, many prior research rely on knowledge of noise variance, either as a known factor or deduce an approximation based on pilot channels. However, in a practical system, regular estimation and updating of the noise variance is required to maintain the sensing accuracy. The technique proposed in this chapter aims to overcome such drawbacks in the existing spectrum sensing techniques.

A novel and efficient technique for spectrum sensing using the cyclostationarity property of the received signals in the LDACS scenario is discussed in this chapter. The proposed method addresses the problem of noise uncertainty by using the noise variance estimation technique proposed in section 3.3 from the known features of the received signal samples. The technique is equally suitable for the estimation of the noise variances independent on the presence of primary user communication.

The key contributions of this chapter are given below;

- A low complexity cyclostationary feature detection scheme is proposed to detect the spectrum holes for aeronautical LDACS.
- A novel method to get the best estimate of the time-varying autocorrelation coefficient is proposed.

- An unbiased and consistent method for noise variance estimation is integrated along with the spectrum sensing unit.
- The proposed scheme is implemented on a field programmable gate array (FPGA) platform to evaluate the overall resource consumption.

The estimator uses the autocorrelation property induced by cyclic prefix (CP) of the received signal to maintain accuracy. The test statistic is designed in such a way that the detector is less sensitive to noise estimation errors and the decision threshold is independent of the noise variance. The results show that the proposed scheme provides better detection accuracy compared to conventional cyclostationary detection (CD) and energy detection (ED) schemes with minimal overheads. Furthermore, noise estimation is performed concurrently on the same frequency band, overcoming the issues associated with noise uncertainty. The proposed approach also lends itself to an efficient hardware implementation and the resource overheads are evaluated by implementing the proposed scheme on an FPGA platform.

5.2 System Model

In a CR-aeronautical communication system, the secondary radio is required to find the spectrum holes for additional resources. These vacant channels can be used for sending multimedia messages and aircraft health parameters upon approval from the ground control station. The secondary radio analyses the received signals of the frequency of interest to detect the spectral holes.

The n^{th} sample of the baseband signal transmitted by the primary communication is given as

$$s(n) = \sum_{m=-\infty}^{\infty} \sum_{k=0}^{N-1} d_m(k) g(n - mT_s) e^{\frac{j2\pi k(n - mT_s - T_{cp})}{N}}, \quad (5.1)$$

where N is the number of OFDM subcarriers, $d_m(k)$ is the data transmitted on the k^{th} subcarrier of the m^{th} OFDM symbol, and $g(n)$ is the rectangular shaping window with duration T_s equal to the sum of useful symbol time T_u and the cyclic prefix (CP) time T_{cp} . An autocorrelation property is present in the transmitted signal $s(n)$ due to the insertion of CP, which is demonstrated in Figure 5.1. The secondary receiver has to detect the presence/absence of a primary signal on a given carrier by observing the received signal $x(n)$. A test has to perform to decide between the hypotheses $\mathcal{H}_0$

FIGURE 5.1: The autocorrelation induced by the cyclic prefix in OFDM signals.

and $\mathcal{H}_1$, i.e., the absence and the presence of the signal $s(n)$ respectively. Revisiting the system model for the stastical hypothesis test from Section 2.4.1, equation 2.1 and is given as

$$x(n) = \begin{cases} w(n), & \mathcal{H}_0 \\ h(n)s(n) + w(n), & \mathcal{H}_1 \end{cases}, \quad (5.2)$$

where $w(n)$ is the additive white Gaussian noise and $h(n)$ represents the channel. The channel coefficients are assumed to be constant over one sensing period.

5.3 Proposed Spectrum Sensing Scheme

5.3.1 Test statistic definition

In the proposed method, the idle carriers in the allowed frequency range are identified by exploiting the cyclostationary feature of the transmitted signal from the primary transmitter. A wideband spectrum sensing scheme is used to find different spectrum holes in the band of interest. Each channel is extracted using a fast filter bank (FFB) [144], then the spectrum sensing is performed individually in all the required channels. The transmitted signal exhibits periodicity in the time-varying autocorrelation $R_x(n, N_d)$ with a period T_s due to the insertion of CP. The fourier series expansions of $R_x(n, \tau)$ are [17, 126]

$$R_x^\alpha(N_d) = \frac{1}{T_s} \sum_{n=-\infty}^{\infty} R_x(n, N_d) e^{-j2\pi\alpha n}, \quad (5.3)$$

where $\alpha = k/T_s$, the cyclic frequency. For a window of M signal samples, $R_x^\alpha(N_d)$ is expressed as

$$R_x^\alpha(N_d) = \frac{1}{M} \sum_{n=0}^{M-1} R_x(n, N_d) e^{-j2\pi\alpha n}, \quad (5.4)$$

where N_d is the number of useful data samples in one OFDM symbol.

In conventional methods, $R_x^\alpha(N_d)$ can be expressed as,

$$R_x^\alpha(N_d) = \frac{1}{M} \sum_{n=0}^{M-1} x(n)x(n+N_d)e^{-j2\pi\alpha n}, \quad (5.5)$$

where $x(n)$ is the received signal sample. The autocorrelation of the received signal due to the presence of the cyclic prefix is used here for the detection. Unlike the conventional methods, a sliding window correlation based estimation of $R_x^\alpha(N_d)$ in a recursive way is used in the proposed method. Also, as a consequence, the independent nature of the real and imaginary parts of $x(n)$ are also exploited for the consistent estimation of $R_x(n, N_d)$. For a sliding window of length L , $\hat{R}_x(n, N_d)$ is defined as

$$\begin{aligned} \hat{R}_x(n, N_d) &= \frac{1}{L} \sum_{i=n}^{n+L-1} \Re[x(i)x^*(i+N_d)], \\ &= \frac{1}{L} \sum_{i=n}^{n+L-1} x_R(i)x_R(i+N_d) + x_I(i)x_I(i+N_d), \end{aligned} \quad (5.6)$$

where $\Re[\cdot]$ indicates the real part of a complex number, x_R and x_I are the real and imaginary parts of the signal $x(n)$ respectively. From (5.4) and (5.6), $R_x^\alpha(N_d)$ is defined as

$$R_x^\alpha(N_d) = \frac{1}{ML} \sum_{n=0}^{M-1} \sum_{i=n}^{n+L-1} \Re[x(i)x^*(i+N_d)]e^{-j2\pi\alpha n}. \quad (5.7)$$

In this work, we consider a Likelihood ratio test (LRT) for hypothesis testing. In general, the Likelihood ratio Λ_x^α is defined as

$$\Lambda_x^\alpha = \frac{\theta_1/x}{\theta_0/x}. \quad (5.8)$$

In conventional LRT schemes[119, 163], the term is the signal variance (σ_x^2). Note that this approach is biased as the θ_0 is an overestimate when the received signal contains noise+ primary user signals ($\sigma_x^2 = \sigma_s^2 + \sigma_w^2$), which leads to performance degradation. In the proposed scheme, $\theta_1/x = R_x^\alpha(N_d)$ and $\theta_0/x = \sigma_w^2$, the noise variance of the particular channel. So (5.8) is rewritten as

$$\Lambda_x^\alpha = \frac{R_x^\alpha(N_d)}{\sigma_w^2}. \quad (5.9)$$

Here, an unbiased noise variance estimator, which exploits the apriori knowledge of cyclic prefix in the LDACS signal is used for the consistent estimation of noise variance from the received signal samples, irrespective of the state of the channel. Please note that the details of noise variance estimation are given in Section 5.3.3.

For a particular cyclic frequency α , the statistical test is defined as

$$T(\alpha) = |\wedge_x^\alpha|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\geq}} \mathcal{T}_h, \quad (5.10)$$

where $\mathcal{T}_h$ is the decision threshold.

5.3.2 Analysis

The analysis of the theoretical performance of the statistical test ($T(\alpha)$) is given in this section. The analysis starts with the derivation of mean and variance of $\wedge_x^\alpha$ for both the hypothesis $\mathcal{H}_0$ and $\mathcal{H}_1$. Then the probability of false alarm, probability of detection, and the deflection coefficient are derived.

5.3.2.1 Analysis of the statistical properties of $\wedge_x^\alpha$

The mean and variance of $\wedge_x^\alpha$ are calculated according to the distribution of the received signal $x(n)$ under hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$.

Mean and variance of $\wedge_x^\alpha / \mathcal{H}_0$: In this case, $x(n) = w(n)$ and is distributed as $\mathcal{N}(0, \sigma_w^2)$, i.e., $E[w(n)w(n + N_d)] = 0, \forall N_d \neq 0$. $E[\wedge_x^\alpha / \mathcal{H}_0]$ is calculated as

$$E[\wedge_x^\alpha / \mathcal{H}_0] = 0. \quad (5.11)$$

Similarly, the variance of $\wedge_x^\alpha / \mathcal{H}_0$ is given as

$$\text{var}[\wedge_x^\alpha / \mathcal{H}_0] = E[|\wedge_x^\alpha|^2 / \mathcal{H}_0] - \left| E[\wedge_x^\alpha / \mathcal{H}_0] \right|^2 \quad (5.12)$$

$$E[|\wedge_x^\alpha|^2 / \mathcal{H}_0] = \frac{1}{M^2 L^2 \sigma_w^4} \sum_{n=0}^{M-1} \sum_{m=0}^{M-1} e^{j2\pi\alpha_k(n-m)} \sum_{i=n}^{n+L-1} \sum_{j=m}^{m+L-1} E[\Re[w(i)w^*(i + N_d)] \Re[w^*(j)w(j + N_d)]]. \quad (5.13)$$

For $M \gg T_s$, ($T_s = N_{cp} + N_D$), where N_{cp} is the cyclic prefix length in data samples in one OFDM symbol.

$$\sum_{n=0}^{M-1} \sum_{m=0}^{M-1} e^{j2\pi\alpha_k(n-m)} = \sum_{n=0}^{M-1} \sum_{m=0}^{M-1} \delta(n-m) = M. \quad (5.14)$$

Taking into account that the noise samples are independent and identically distributed Circularly Symmetric Complex Gaussian(i.i.d CSCG),

$$E\left[\Re[w(i)w^*(i+N_d)]\Re[w^*(j)w(j+N_d)]\right] = \delta(i-j)\frac{\sigma_w^4}{2}. \quad (5.15)$$

From (5.12)-(5.15) $\text{var}\left[\Lambda_x^\alpha/\mathcal{H}_0\right]$ is obtained as

$$\text{var}\left[\Lambda_x^\alpha/\mathcal{H}_0\right] = E\left[|\Lambda_x^\alpha|^2/\mathcal{H}_0\right] = \frac{1}{2ML}. \quad (5.16)$$

Mean and variance of $\Lambda_x^\alpha/\mathcal{H}_1$: Under hypothesis $\mathcal{H}_1$, $x(n) = h(n) \otimes s(n) + w(n)$. Initially, we consider only the AWGN channel, i.e., $x(n) = s(n) + w(n)$, For sufficiently long signal samples ($M \gg T_s$), $s(n)$ and $w(n)$ are distributed as $s(n) \sim \mathcal{N}(0, \sigma_s^2)$ and $w(n) \sim \mathcal{N}(0, \sigma_w^2)$ respectively. $\Lambda_x^\alpha/\mathcal{H}_1$ is expressed as

$$\Lambda_x^\alpha/\mathcal{H}_1 = \frac{1}{ML\sigma_w^2} \sum_{n=0}^{M-1} \sum_{i=n}^{n+L-1} \left[\Re[(s(n) + w(n))(s^*(i+N_d) + w^*(i+N_d))] e^{-j2\pi\alpha_k n} \right] \quad (5.17)$$

Let us consider the term $\Re[(s(n) + w(n))(s^*(i+N_d) + w^*(i+N_d))]$ in (5.17), their expectation is obtained after removing all the uncorrelated terms

$$E\left[\Re[(s(i) + w(i))(s^*(i+N_d) + w^*(i+N_d))]\right] = E\left[s_R(i)s_R(i+N_d) + s_I(i)s_I(i+N_d)\right], \quad (5.18)$$

where $s_R(i)$ and $s_I(i)$ are the real and imaginary parts of the transmitted signal $s(n)$. Using (5.6) and (5.18), $R_s(n, N_d)$ is defined as

$$\hat{R}_s(n, N_d) = \frac{1}{L} \sum_{i=n}^{n+L-1} E\left[s_R(i)s_R(i+N_d) + s_I(i)s_I(i+N_d)\right] \quad (5.19)$$

Substituting (5.19) in (5.6), $E[R_x^\alpha(N_d)/\mathcal{H}_1]$ is expressed as

$$E[R_x^\alpha(N_d)/\mathcal{H}_1] = \frac{1}{M} \sum_{n=0}^{M-1} \hat{R}_s(n, N_d) e^{-j2\pi\alpha n}. \quad (5.20)$$

Using extensive computer simulations, we observed that $\hat{R}_s^\alpha(N_d) - R_s^\alpha(N_d) \rightarrow 0$, and we have $E[R_x^\alpha(N_d)/\mathcal{H}_1] = R_s^\alpha(N_d)$.

In order to derive the probability density function (pdf) of the statistical test defined in (5.10), we need to estimate the $\text{var}(|\wedge_x^\alpha|/\mathcal{H}_1)$. For that, $E[|\wedge_x^\alpha|^2/\mathcal{H}_1]$ is computed using (5.21).

$$E[|\wedge_x^\alpha|^2/\mathcal{H}_1] = \frac{1}{M^2 L^2 \sigma_w^4} \sum_{n=0}^{M-1} \sum_{m=0}^{M-1} e^{j2\pi\alpha_k(n-m)} \sum_{i=n}^{n+L-1} \sum_{j=m}^{m+L-1} E[\mathcal{R}[x(i)x^*(i+N_d)]\mathcal{R}[x^*(j)x(j+N_d)]] \quad (5.21)$$

In (5.21), the expectation of the term when $i = j$ is obtained as

$$E[\mathcal{R}[x(i)x^*(i+N_d)]\mathcal{R}[x^*(j)x(j+N_d)]]_{i=j} = \frac{(\sigma_s^2 + \sigma_w^2)^2}{2}, \quad (5.22)$$

where σ_s^2 and σ_w^2 are signal and noise variances respectively. $E[|R_x^\alpha(N_d)|^2/\mathcal{H}_1]$ is expressed as

$$E[|\wedge_x^\alpha|^2/\mathcal{H}_1] = \frac{1}{M^2 L^2 \sigma_w^4} \sum_{n=0}^{M-1} \sum_{m=0}^{M-1} \left[e^{j2\pi\alpha_k(n-m)} \left(L \frac{(\sigma_s^2 + \sigma_w^2)^2}{2} + \sum_{i=n}^{n+L-1} E[s_R(i)s_R(i+N_d) + s_I(i)s_I(i+N_d)] \sum_{j=m}^{m+L-1} E[s_R(j)s_R(j+N_d) + s_I(j)s_I(j+N_d)] \right) \right]. \quad (5.23)$$

From (5.19), it is observed that $\sum_{i=n}^{n+L-1} E[s_R(i)s_R(i+N_d) + s_I(i)s_I(i+N_d)] = LR_s(n, N_d)$, and $\sum_{n=0}^{M-1} \sum_{m=0}^{M-1} e^{j2\pi\alpha_k(n-m)} = M$ (see (5.14)). Using these results, $E[|R_x^\alpha(N_d)|^2/\mathcal{H}_1]$ is simplified as

$$E[|\wedge_x^\alpha|^2/\mathcal{H}_1] = \frac{|R_s^\alpha(N_d)|^2}{\sigma_w^4} + \frac{1}{2ML\sigma_w^4} (\sigma_s^2 + \sigma_w^2)^2. \quad (5.24)$$

Then the variance of $|R_x^\alpha(N_d)|/\mathcal{H}_1$ is computed as

$$\text{var}(|R_x^\alpha(N_d)|/\mathcal{H}_1) = \frac{1}{2ML} (1 + \text{SNR})^2, \quad (5.25)$$

where $\text{SNR} = \frac{\sigma_s^2}{\sigma_w^2}$, the signal to noise ratio.

5.3.2.2 Probability of false alarm (P_{fa})

Besides, taking into account that the $\Lambda_x^\alpha/\mathcal{H}_0$ follows CSCG distribution, from (5.10), we have that $T(\alpha)/\mathcal{H}_0$ follows a chi-square distribution χ_2^2 with two degrees of freedom [126] with a pdf $f(x) = \lambda e^{-\lambda x}, \forall \mathbb{R}^+$, with $\lambda = ML$. At last, it is concluded straight forward that the probability of false alarm P_{fa} turns out to be,

$$P_{fa} = \int_{\mathcal{T}_h}^{\infty} e^{-xML} dx = e^{-\mathcal{T}_h ML} \quad (5.26)$$

From (5.26), the decision threshold $\mathcal{T}_h$ for a particular false alarm rate is given as,

$$\mathcal{T}_h = \frac{1}{ML} \ln\left(\frac{1}{p_{fa}}\right), \quad (5.27)$$

where $\ln(\cdot)$ is the natural logarithm. Unlike other approaches, the decision threshold is fixed and independent of noise variance which aids to diminish the noise uncertainty issues. Also, it results in a less complex implementation of the decision logic compared to the conventional SCD schemes as there is no requirement of updating the threshold during each decision making.

5.3.2.3 Probability of detection

The probability of detection for the AWGN channel and Rician fading channel is derived in this section with the aid of Section. 5.3.2.1.

Probability of detection-AWGN channel ($P_{d,AWGN}$): Assuming the hypothesis $\mathcal{H}_1$, Λ_x^α also follows CSCG distribution. This implies that the test statistic $T(\alpha)$ follows a non-central chi-square distribution with two degrees of freedom. Eventually, the distribution of $T(\alpha)/\mathcal{H}_1$ is given by [17, 20, 126]

$$f_{\mathcal{T}(\alpha)/\mathcal{H}_1} = \frac{1}{2v^2} e^{\frac{-(\gamma^2 + \mathcal{T}(\alpha))}{2v^2}} I_0\left(\sqrt{\mathcal{T}(\alpha)} \frac{\gamma}{v^2}\right), \quad (5.28)$$

where I_0 is the first-kind Bessel function of order zero, $\gamma^2 = |E[\Lambda(x)]/\mathcal{H}_1|^2$ and $v^2 = \text{var}[\Lambda(x)]/\mathcal{H}_1 = \frac{1}{2ML}(1 + \text{SNR})^2$. Using these results, the probability of detection P_d

is obtained as,

$$\begin{aligned} P_{d,AWGN} &= \int_{\mathcal{T}_h}^{\infty} \frac{1}{2\nu^2} e^{\frac{-(\gamma^2 + \mathcal{T}(\alpha))}{2\nu^2}} I_0\left(\sqrt{\mathcal{T}(\alpha)} \frac{\gamma}{\nu^2}\right) dT(\alpha), \\ &= \mathcal{Q}_1\left(\frac{\gamma}{\nu}, \frac{\sqrt{\mathcal{T}_h}}{\gamma}\right), \end{aligned} \quad (5.29)$$

where $\mathcal{Q}(a, b)$ is the first order Marcum $\mathcal{Q}$ -function.

Probability of detection-Rician fading channel ($P_{d,Ric}$): Recent studies shows that air-to-ground transmission is subject to Rician fading [183–187]. In this section, we investigate the performance of the proposed detector when the SNR variations follow a Rician channel. The pdf of instantaneous SNR in a Rician fading channel is given by [188]

$$f(\gamma) = \frac{K+1}{\bar{\gamma}} e^{-K-(K+1)\frac{\gamma}{\bar{\gamma}}} I_0\left[2\sqrt{\frac{K(K+1)\gamma}{\bar{\gamma}}}\right], \quad (5.30)$$

where $\bar{\gamma}$ denotes the average SNR and K denotes the shape (*Rice*) parameter. K is the ratio of the power in the direct path to the power in other scattered paths. The $P_{d,Ric}$ can be calculated by averaging $P_{d,AWGN}$ in (5.29) over the PDF of the instantaneous SNR in (5.30) and is given by

$$P_{d,Ric} = \int_0^{\infty} f(\gamma) \mathcal{Q}_1\left(\frac{\gamma}{\nu}, \frac{\sqrt{\mathcal{T}_h}}{\gamma}\right) d\gamma. \quad (5.31)$$

The detection performance of the proposed detector under Rician fading is analyzed using simulation studies and the results are presented in Section 5.5.1.

5.3.2.4 Deflection coefficient ($\mathcal{D}_{\mathcal{C}}$)

In hypothesis testing, the deflection coefficient ($\mathcal{D}_{\mathcal{C}}$) is a measure of how the two hypotheses are being separated from each other. The physical meaning of DFC is schematically represented in Figure. 5.2. The larger the $\mathcal{D}_{\mathcal{C}}$, more substantial is the differentiation between $\mathcal{H}_0$ and $\mathcal{H}_1$, resulting in better decision accuracy. $\mathcal{D}_{\mathcal{C}}$ is defined as

$$\mathcal{D}_{\mathcal{C}} = \frac{|E[\theta/\mathcal{H}_1] - E[\theta/\mathcal{H}_0]|}{\sqrt{\text{var}(\theta/\mathcal{H}_0)}}, \quad (5.32)$$

where θ denotes the test statistic. The $\mathcal{D}_\mathcal{C}$ for the proposed scheme is obtained as

$$\begin{aligned}\mathcal{D}_\mathcal{C} &= \frac{|\wedge_s^\alpha(N_d)|^2 + \frac{1}{2ML}(1 + SNR)^2 - \frac{1}{ML}}{\frac{1}{ML}} \\ &= ML|\wedge_s^\alpha(N_d)|^2 + \frac{1}{2}(1 + SNR)^2 - 1\end{aligned}\quad (5.33)$$

It is observed from (5.33) that $\mathcal{D}_\mathcal{C}$ increases with increase in SNR .

5.3.3 Analysis of the estimation of $\hat{\sigma}_w^2$

An unbiased noise variance estimator, which exploits the pre-knowledge of the cyclic prefix in the LDACS signal is used for the consistent estimation of noise variance from the received signal samples. The noise variance estimation technique is the same as that used in the adaptive energy detection scheme (refer Section 3.3.2). As described in Section 3.3.2, The estimation technique works irrespective of the state of the channel. i.e., without being dependent on the presence and absence of primary user. Re-visiting the crucial parts of the estimation, which is given as Let define two terms E_x and ρ_x as

$$E_x = \frac{1}{K(N_{cp} + N_d)} \sum_{n=1}^{K(N_{cp} + N_d)} |x(n)|^2, \quad (5.34)$$

$$\rho_x = \frac{1}{KN_{cp}} \sum_{n=1}^{K(N_{cp} + N_d)} \Re[x(n)x^*(n + N_d)], \quad (5.35)$$

where $\Re[\cdot]$ represents the real part of the term. E_x represents the energy estimate or signal variance and ρ_x is the normalized autocorrelation strength of the received signal samples.

FIGURE 5.2: The The physical meaning of the deflection coefficient.

From (3.30) and (3.31), an unbiased estimate of noise variance σ_w^2 is defined as

$$\hat{\sigma}_w^2 = E_x - \rho_x = \frac{1}{M} \sum_{n=1}^M |x(n)|^2 - \frac{1}{KN_{cp}} \sum_{n=1}^M \Re[x(n)x^*(n + N_d)] \quad (5.36)$$

Hence the likelihood ratio Λ_x^α can be rewritten as

$$\Lambda_x^\alpha = \frac{\frac{1}{ML} \sum_{n=0}^{M-1} \sum_{i=n}^{n+L-1} \Re[x(i)x^*(i + N_d)] e^{-j2\pi\alpha n}}{\frac{1}{M} \sum_{n=1}^M |x(n)|^2 - \frac{1}{KN_{cp}} \sum_{n=1}^M \Re[x(n)x^*(n + N_d)]} \quad (5.37)$$

5.4 FPGA Implementation

To analyze the resource overheads and to estimate the power requirements, the proposed scheme is implemented in Verilog and mapped it on a Xilinx FPGA device. The high-level overview of the computational logic is shown in Fig. 5.3. The incoming real and imaginary parts of the received frame are buffered into independent shift-register blocks, 65 cycles deep. The first and last outputs are used for computing the energy estimate and the autocorrelation strength of the incoming signals, following equations (5.34) and (5.35). The architecture instantiates 4 32-bit multipliers built on the Xilinx DSP48 blocks and shares them among the different computations by controlling the multiplexers that feed input to their input registers. When the input samples are received, the multiplexers feed the input shift-register outputs (1st and 65th tap) to the input registers (marked by the black paths) to accumulate the autocorrelation values, signal energy and time-varying autocorrelation. For the latter, the outputs

FIGURE 5.3: Hardware architecture of the proposed LRT based cyclostationary spectrum sensing logic for implementing on an FPGA platform.

from the multipliers are added and accumulated over a sliding window scheme using another 65-tap shift register. The result of this is then accumulated in a cyclic manner into a 75-element deep register bank to produce the accumulation over the entire sliding width.

Once sufficient samples have been observed (i.e., M), the multiplexers feed the accumulated value in the register bank along with the pre-computed exponent values from the *exp mem* block to the upper two multipliers, which are accumulated as real and imaginary parts of $R_x^\alpha(N_d)$ prior to normalization. This sequence is marked by the blue paths in the system. Subsequently, the accumulated values of energy, auto-correlation and $R_x^\alpha(N_d)$ are normalized by multiplying with the normalization factors, which are configured into the *config* register block. In a static system (i.e., when the optimal conditions are known apriori), these can be treated as constants based on the design choices of number of observed samples, sliding window depth and threshold. In our design, these are mapped into user configurable registers to allow the values to be tweaked at run-time. This phase of computation is marked by the paths denoted in red. To avoid a resource expensive division operation, the unbiased noise variance estimate $\hat{\sigma}_w^2$ is also scaled by the predetermined threshold value (stored in *config* block) to alter Eq.(5.10) to a comparison between the numerator and denominator terms of (5.9) to determine the state of the hypothesis. The final computation involves computing the square of the absolute values of the numerator and denominator parts of (5.9), which is marked by the green paths. Once computed, these two parts are compared to arrive at a decision on whether the channel is free or in use.

As mentioned, the multiplier blocks uses a 32-bit input precision and is implemented using a cascade of 4 Xilinx DSP48 blocks. The *exp mem* is mapped as a 16-bit wide read only block RAM memory, while *config* and the accumulation memory/registers are implemented as 32-bit wide and 64-bit wide register banks respectively. The inputs X_R and X_I have 16-bit precision, while the outputs of the multiplier blocks are accumulated at full precision (64-bit) except for the initial computation cycle that uses the inputs directly, and hence uses 32-bits. The accumulated values are trimmed to 32-bit before each multiplication phase to ensure that the overflow is contained, while also maintaining the representation format. All computations are performed using signed twos complement arithmetic.

The entire operation of the blocks is co-ordinated by a central state machine (CSM). The CSM switches from idle state at a first valid input and uses counters to keep track

of the number of incoming samples as well as exponent depth to determine when to switch between states. In each state, it generates the control signals for the multiplexers and the register blocks to determine which inputs are chosen to be fed into the input registers of the multipliers as well as which registers are enabled for accumulation. It also generates the addressing for reading/writing values into the accumulation register bank and exponent memory to sequentially perform the operations in the correct order. Once the computation is completed, the CSM also generates control signals to mark completion of the detection process and outputs the computed values for decision making by the cognitive logic in the radio system. The state machine transitions are controlled by the parameters like number of samples to be observed, window depth and so on, which are configured into the *config* memory. Thus the logic can perform detection by observing a larger number of samples to boost the detection accuracy at low SNR values by altering the register value(s).

5.5 Results

In this section, the performance of the proposed spectrum sensing scheme is compared with the existing methods and evaluated the resource consumption of the proposed design on a Xilinx Zynq XC7Z020 device on the ZC702 development platform. The performance of the proposed scheme is extensively analyzed using simulation studies. For the simulation studies, LDACS signals are generated using the specifications in [4, 189] and the MATLAB code released by German Aerospace Center (DLR). The simulation parameters to generate LDACS signals are summarized in Table 3.3.

The detection performance of the proposed scheme under various SNR conditions have been analyzed by adding the artificial noise (using Matlab's inbuilt command) to the LDACS signals. The input signals (after adding the noise) are quantized to 16-bit precision, and then the detection performances were analyzed using Matlab simulations. Hardware results were also verified using Xilinx Vivado simulator at functional and post-place and route level, with the same set of signals. The plots in figures 5.4 to 5.7 are generated using the MATLAB model at 16-bit quantization and closely matches the hardware simulation model results at 16-bit input precision and 64-bit data path (with negligible error (max 3%) due to the rounding scheme).

5.5.1 Results of Simulation Studies

This section presents the performance comparison of the proposed scheme against existing spectrum sensing schemes from literature such as SCD [126], Multiplier-less correlator (Chapter 4), and ED[13]. A detailed investigation of the influence of the Rician fading and the noise uncertainty issues on detection performance among various spectrum sensing schemes are presented. As discussed in Section 5.3, the detector estimates the noise variance from the same frequency band being sensed. Thus, unlike other SCD and CD schemes, we show that the detection performance is independent of the noise variance information and their estimation errors.

Fig. 5.4 analyses the receiver operating characteristic (ROC) curves of the proposed scheme for AWGN and Rician channels. The Rician Fading channel is simulated with a K factor of 12 dB and a Doppler shift of 1000 Hz. The analysis is conducted at $SNR = -10$ dB and for varying number of samples (M) ($M = 10000, 20000, 40000$). Results show that the fading has no effect on the detection performance. This can be attributed to the presence of a dominant LOS component. It is also observed that the detection performance increases with an increase in M , i.e., the desired detection performance can be achieved by increasing the sensing duration. From the ROC curves, it is obvious that $M=20000$ is sufficient to get the desired detection accuracy at low SNR regimes ($SNR = -10$ dB), which is relatively less compared to the recent spectrum sensing scheme for LDACS (Chapter 4).

Fig. 5.5. presents the effect of SNR and M on detection accuracy for both AWGN and Rician fading channels. The figure shows that the detection performance is not affected by the fading for wide range of SNR from -20 dB to 0 dB. The graph also shows a non-linear relationship between rate of change of P_d and M . At relatively low SNR values, i.e., when $SNR = -20$ dB to -13 dB, a considerable improvement is observed in the rate of change of P_d with an increase in M . Above this SNR region, the improvement in P_d does not scale in the rate when M is increased. For instance, with M varying from 10000 to 20000 and 20000 to 40000 (i.e., doubling in M) at SNR of -15 dB, the improvement in P_d achieved is 0.2 to 0.3 and 0.3 to 0.5 respectively. The observation is also valid at M is scaled to higher values. On the other hand, when $SNR = -12$ dB to -10 dB, with doubling in M , we observe a proportional improvement in P_d (i.e., nearly identical rate of improvement).

FIGURE 5.4: ROC curves of the proposed scheme for both AWGN and Rician fading channels P_{fa} Vs. P_d .

FIGURE 5.5: Detection performance of the proposed scheme for varying SNR (SNR Vs. P_d); both AWGN and Rician fading channels.

The detection performances of the competing spectrum sensing techniques from literature are analyzed in Fig. 5.6. It can be observed from the figure that the proposed scheme outperforms SCD [126] and ED [13, 190] based schemes, while offering comparable performance to the multiplier-less correlator (Chapter 4) based spectrum sensing. However, the multiplier-less correlator require variable sensing period up to the maximum duration of an LDACS multi-frame (58.32 ms) since the sensing window is not synchronised to the LDACS multi-frame. Also, as seen in Section 5.5.2,

FIGURE 5.6: Performance comparison of different spectrum sensing schemes includes the proposed scheme, multiplierless correlator (Mless correlator) (presented in Chapter 4), SCD scheme [126], ED-based schemes [13].

FPGA implementation results indicate that the power consumption of the multiplierless correlator is more than 3 times than that of the proposed scheme. We also observed that the proposed scheme outperforms the SCD and ED schemes even with half the number of signal samples.

Further, the effect of noise uncertainty against ED and SCD based schemes are also analysed and compared. The effect of noise uncertainty (NU) on detection performance on all schemes are plotted in Fig. 5.7. It can be observed that the detection performance of the proposed scheme is immune to NU, while SCD and ED-based schemes show minimal and profound impact respectively with uncertainty in noise estimation. While SCD shows gradual drop in detection accuracy, a sudden drop in P_d is observed in low SNR regimes for ED-based schemes even for 10% error in noise estimation. Thus, it can be concluded that the proposed scheme achieves higher detection accuracy for practical SNR ranges with low to moderate sensing duration.

Finally, the deflection coefficient of the proposed scheme is analyzed and compared them against conventional SCD scheme. The results of our simulation are plotted in Fig. 5.8, which indicate that the deflection coefficient increases with the increase in SNR. The figure also shows that the rate of increase of DFC is much higher for the proposed scheme, indicating a high interclass variability. Overall, the detection performance analysis shows that the proposed scheme is an attractive choice for LDACS

FIGURE 5.7: Analysis of the effect of noise uncertainty (NU) for different spectrum sensing schemes.

FIGURE 5.8: Deflection coefficient versus SNR.

spectrum sensing.

5.5.2 Hardware implementation Results

Table 5.1 shows the overall resource consumption of the proposed design on a Xilinx Zynq XC7Z020 device on the ZC702 development platform. The design choices allow us to generate an efficient implementation in terms of resource consumption, as observed from the table. The design consumes 7.3% of available DSP blocks on the small Zynq device with under 5% utilization of general purpose blocks like LUTs

TABLE 5.1: Resource consumption of proposed design on Zynq XC7020, compared to the multiplierless correlator-based spectrum sensing (Mless sensing), multiplier based correlators, and Eigenvalue detection schemes

Design	FFs	LUTs	Slices	DSPs
Proposed scheme	4545	2553	1461	16
Mless correlator (Chapter 4)	24,000	29,895	7806	0
Correlator with multipliers (Chapter 4)	11968	6112	1528	1500
Eigenvalue detection [191]	0	3276	0	93
Eigenvalue detection [192]	0	5177	1892	64

and Flip-Flops (FFs). implementation also easily achieves the desired operating frequency of 125 MHz, enabling seamless integration into our LDACS radio platform on the ZC702 platform. The compact design also alleviates the need for re-using the chip area by techniques like partial reconfiguration, which incurs area as well as complexity overheads in the design process. Further, a comparison of the resource overheads of the similar works discussed in the literature also presented in Table. 5.1. Results show that the proposed design consumes fewer resources than the state-of-the-art.

The power consumption of the proposed design is evaluated by using Xilinx Vivado's power analysis tools. For this, the implemented design is simulated with actual LDACS frame contents as inputs, at 16-bit input precision. The simulation was performed at 125 MHz with a sample fed into the design at every clock cycle; the detection window was set to 10000 samples. The tool estimates that the design consumes a mere 206 mW in operation (dynamic power) with a device static power of 106 mW, compared to the 1160 mW consumed by the multiplierless correlator-based (Chapter 4) sensing scheme, making it an ideal choice for deployment on aircraft on-board systems with limited energy budget.

5.6 Summary

In this chapter, a novel and efficient technique for spectrum sensing in the LDACS system using the cyclostationarity property of the received signals is proposed. The proposed system is extensively analyzed theoretically and through simulation studies. The system is further evaluated by implementing the algorithm on a hybrid FPGA

platform. From the evaluations, it is observed that the proposed scheme offers better detection accuracy than SCD and ED-based schemes and has comparable performance with multiplier-less correlator technique. The FPGA implementation of the proposed scheme also performed to evaluate the resource overheads and to estimate the power requirements. The results indicate that the scheme offers comparable performance with the multiplier-less correlator only consuming one-third of power. Besides, the proposed method achieves desired detection accuracy in a fewer number of samples that improves the throughput of the secondary radio. Finally, the hardware implementation shows that the design consumes only a fraction of the resources (DSPs 7.3%, LUTs 4.7% and FFs 4.9%) on a small FPGA device, making it ideally suited for deployment in energy-constrained systems. The significant contributions of chapter 5 and how they are achieved are summarized in Figure. 5.9.

FIGURE 5.9: The overview and contributions of Chapter 5.

Chapter 6

Design and Implementation of a Power-efficient Wideband Spectrum Sensing Scheme

6.1 Introduction

In the previous chapters, optimization of diverse spectrum sensing techniques such as ED, cyclostaoanry feature detection, and matched filtering have been presented to advance the detection accuracy, to overcome the noise uncertainty issues, and to reduce the implementation complexity. Though the proposed schemes achieve a good accuracy-complexity trade-off for narrow-band sensing, simultaneous wideband sensing using these techniques is not practical due to the requirement of overwhelmed resources. In these chapters, wideband sensing has been conducted serially to limit the usage of computational resources. This approach reduces the throughput of the secondary radio due to the prolonged sensing duration¹.

Different approaches are discussed in the literature to cattle the wideband spectrum sensing problem. Sub-Nyquist approaches [153–155] are identified to reduce the long sensing duration, and the computational complexity induced by Nyquist rate implementations. These approaches can be realized through compressive sensing [154], in which the features of the signals are represented by a fewer number of signal samples

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¹The work in this chapter is submitted to [4].

by exploiting the sparse nature of the signal in some domain. However, compressive sensing requires hardware support in the form of a new analog to digital converters (ADC) with dynamically varying sampling speed. Also, a non-optimum number of samples leads to the improper representation of the PU signal, leading to erroneous detection. In Nyquist rate systems, the spectrum sensing is composed of several narrowband sensing [13] where filterbank divides the spectrum into equal or unequal individual parts. A hypothesis test has to be performed for individual narrowbands to decide the presence/absence of PU signal. Wavelet transform can also be applied to analyze the individual slices of the spectrum. In the wavelet-based spectrum sensing scheme [13], irregularity of the power spectrum density across narrowbands are analyzed to classify the subbands as vacant or occupied.

Though conventional Nyquist rate based system uses different ways to balance the trade-off between the complexity and the accuracy, they demand high-resolution ADCs with very high sampling rates to get the desired detection accuracy. The high sampling rate and resolution (bit-width) also result in considerable power overhead for base-band processing. Also, unlike terrestrial systems, spectrum sensing in aeronautical domain has unique challenges such as limited power budget and varying channel characteristics. Nyquist rate wideband sensing is a tedious and computationally intensive task, and its high power consumption made it impractical in aeronautical systems. Though improved techniques like cross-correlator-based sensing without deploying multipliers, cyclostationary detection, and energy difference detection have been proposed in the previous chapters for spectrum sensing in LDACS, they require higher quantization rates that make it inappropriate for parallel wideband sensing.

In [193], it is shown that a low-resolution quantizer can operate at higher sampling rates consuming less power compared to a high-resolution quantizer operating at the same sampling frequency. For example, the power consumption of a one-bit ADC with higher sampling rates is much less than that of a higher resolution ADC with the same sampling frequency. Also, it is significantly hardware efficient because a one-bit ADC can easily be implemented with a high-speed comparator. Two different approaches of one-bit quantization based spectrum sensing are discussed in the literature. In the first approach, the conventional Fast Fourier transform (FFT) based wideband spectrum sensing is modified by introducing one-bit quantizer followed by sampling circuit [194]. In this approach, a sign change logic replaces the initial layer

of multipliers in the butterfly implementation, and thus achieves significant savings in computational complexity. In the second approach, the authors used a windowed autocorrelation followed by a Discrete Fourier transform(DFT) to estimate the power spectral density [195].

One-bit FFT [194] and autocorrelation [195] based spectrum require the analysis of the whole spectrum, to find the power spectral density of the individual frequency channels and are hence cannot be applied to the LDACS scenario. Also, these techniques are ideal for sensing the wideband of the order of GHz, while the proposed technique can be applied even to a wideband of the order of 10 MHz. Filter bank assisted wideband sensing is the ideal choice for detecting LDACS vacant channels since the required areas of the spectrum can be selected using only the desired channel responses. The filter-coefficients can be pre-computed as the channel location and bandwidth are already known, and the noise variance estimation is straight forward as all the channels are of the same bandwidth.

In this chapter, a filter bank (FB) based one-bit quantizer wideband sensing architecture is proposed. The main attraction of this architecture is its easiness in implementation. In this scheme, the implementation complexity is reduced by exploring one-bit quantized signals for the detection process. The complexity is reduced in various stages, such as ADC and signal processing. For this scheme, the ADC can be replaced with a high-speed sampler and a comparator, which compares only the signal sign. In the DSP stage, especially during channelization using FIR filters, the multiplier in each filter tap is replaced by a sign changer, which can be implemented using a 2's complement circuit and a 2:1 multiplexer. Similar to the other one-bit sensing schemes [194, 195], the autocorrelation property induced by the high sampling of a low baud rate signal provides the spectrum occupancy information. The main advantages of this scheme are low complex implementation exploiting the signal characteristics, the flexibility of dividing the spectrum into various bandwidths, number of channels, and localized scanning of the interested parts of the spectrum. For example, FFT-based scheme [194], the frequency resolution is limited by its butterfly structure and the FFT depth while with filterbanks, it is much easier to change the center frequency, bandwidth, and the number of channels by using reconfigurable filter coefficients. The one-bit autocorrelation-power spectral density scheme [195] also experiences the similar drawbacks of the FFT-based schemes[194]. Moreover,

both these schemes are suitable only for sensing a wide band, which consists of narrowband with equal widths, which may not be the practical scenario always.

6.2 Signal Model of the Wideband Spectrum

The wideband signal at the SU receiver is assumed to consist of M narrowband signals of equal bandwidths. The rate of change of the envelope of the narrowband signal is only $1/M$ times the sampling frequency F_s . The n^{th} sample of the discrete signal at the SU receiver can hence be determined by (6.1)

$$y(n) = \sum_{m=1}^M \left[A_{m, \lfloor \frac{n}{M} \rfloor} \cos\left(2\pi n \frac{f_m}{F_s}\right) - B_{m, \lfloor \frac{n}{M} \rfloor} \sin\left(2\pi n \frac{f_m}{F_s}\right) \right] + j \left[A_{m, \lfloor \frac{n}{M} \rfloor} \sin\left(2\pi n \frac{f_m}{F_s}\right) - B_{m, \lfloor \frac{n}{M} \rfloor} \cos\left(2\pi n \frac{f_m}{F_s}\right) \right] + w_R(n) + j w_I(n), \quad (6.1)$$

where A_m, B_m are independent Gaussian random variable with mean zero and variance $\frac{\sigma_m^2}{2}$, f_m is the carrier frequency of m^{th} narrowband, and M is the oversampling factor, $F_s = M f_m$.

6.3 Conventional Method: Filter Bank based Wideband Spectrum Sensing

Conventional filterbank (FB) based wideband spectrum sensing scheme is illustrated in Fig. 6.1a. As shown in the figure, in FB assisted wideband spectrum sensing, the wideband is split to various narrowband of equal or unequal bandwidths using a bank of filters, and then the decision algorithm is applied individually on each narrow band. The transposed direct form realization of an Finite impulse response (FIR) filter is shown in Fig. 6.1b. As shown in the figure, the realization requires large number of multipliers, which increases the implementation complexity. Various reconfigurable filter architectures such as coefficient decimation [143], and interpolation and masking [140–142], among others, are described in the literature to reduce the implementation complexity by using a fewer number of multipliers. Though all these techniques are computationally effective compared to the conventional per channel

FIGURE 6.1: (a). Filterbank assisted wideband spectrum sensing scheme. (b). Transposed direct form FIR filter structure.

approach and modulated filterbanks [145, 146], they still require a large number of multipliers to extract the different frequency responses in parallel. This makes them less suited for power-constrained implementations. Recent studies show that the spectrum occupancy information can be obtained by using low precision quantizer, and thereby, the computational resources can be limited. Similar to the schemes described [194] and [195], the autocorrelation property induced by the oversampling of the low-baud rate signal can be exploited for the spectrum sensing.

FIGURE 6.2: Proposed filterbank assisted one-bit quantizer wideband spectrum sensing scheme.

6.4 Proposed Sensing Scheme

6.4.1 Power-efficient architecture of the wideband sensing scheme

The block diagram representation of the proposed one-bit quantizer based wideband spectrum sensing scheme is shown in Fig. 6.2. At the receiver, the incoming signals are processed in the RF domain to increase signal gain and to reduce noise levels and are then down-converted to baseband for further processing/decoding [195]. The incoming signal is sampled using a high-speed sample and hold circuit; then the signal samples are quantized through a high-speed comparator that considers the sign of the input signal. Each quantized output signal will be a member of the set $\{1 + j, 1 - j, -1 + j, -1 - j\}$.

The output of the quantizer is connected to the inputs of the FB that consists of M parallel FIR filters. The Multiplier-less FIR filter design is schematically shown in Fig. 6.3. The Fig. 6.3 is a modified version of the filter architecture in Fig. 6.1b in which multipliers are replaced with 2:1 multiplexer and a 2's complement circuit. The one-bit quantized wideband signal at the input of the FB can be expressed as

$$y_Q(n) = \text{sgn}[y(n)], \quad (6.2)$$

where $\text{sgn}[\cdot]$ is the signum function of a real number. The effect of the quantization in the representation of the power spectral density is shown in Fig. 6.4. Here the power spectral densities are plotted for the received noisy signal at SNR=0 dB. It is observed from the figure that there is a power leakage due to the quantization. However, the spectral holes are still evident in the quantized version. As shown in [193], at low SNR regimes, the effect of low-resolution ADC towards spectral leakage is very less.

FIGURE 6.3: Multiplier-less FIR filter design for single bit input signal.

FIGURE 6.4: Illustration of the effect of one-bit quantization on the power spectral density.

The received energy over time from each narrowband is estimated using an autocorrelation based energy estimator. The soft energy measurements are given as inputs to a decision algorithm to classify the narrowbands into vacant and occupied ones. The proposed algorithm reduces the computational complexity by simplifying the design of filter architecture for sensing. Note that the proposed architecture is applicable only for spectrum sensing unit. In this design, the filter structure is same as a transpose direct form filter where the multiplication operation at each tap is replaced by a 2: 1 multiplexer and a 2's complement circuit that selects one among its two inputs $\{h_i, -h_i\}$ based on the input signal sign.

6.4.2 Detection Algorithm

The following aspects are considered while designing the detection algorithm.

- Algorithm lends itself to an efficient hardware implementation
- Practical constraints such as limited sensing window are accounted for, to improve spectrum efficiency and throughput.

- A real-time noise floor estimation is performed, assuming that not all channels are occupied simultaneously at any given time. The decision threshold is estimated from the noise floor value.
- It is assumed that all the subbands in the band of interests are of equal bandwidth.

In FB based sensing, the frequency channels of interest are filtered using precomputed/predetermined filter coefficients. The decision-making algorithm for one-bit quantizer based wideband spectrum sensing is given in Algorithm 6.1. Once the energy estimates $E(m)$ are computed for all M sub-channels, the decision algorithm evaluates the estimates to determine the ones with the lowest energy, which is assumed to be an unoccupied channel. The total noise variance is estimated by averaging the energies of the subbands, which are in a noise uncertain region $E_{min} \leq E(m) \leq \alpha E_{min}$, where α represents the uncertainty factor. Decision threshold is then computed as a function of false alarm and the estimated noise variance. Threshold is computed as $\left(Q^{-1}(P_{fa})\sqrt{\frac{Count}{N}} + 1\right)$ times the noise variance $\hat{\sigma}_w^2$, where P_{fa} is the false alarm rate, $Count$ is the number of channels in the noise uncertain region, and N is the number of signal samples used for detection. The function is chosen to limit the false alarm to acceptable limits while providing high detection probability.

6.4.3 FPGA Implementation

To evaluate the reduction in compute complexity and resource consumption in hardware, the proposed scheme is implemented using Verilog hardware description language and map it onto a radio platform based on the Xilinx Zynq hybrid system on chip [24]. The higher-level architecture of the radio platform is shown in Fig. 6.5. We focus on the receive interface and integrate the proposed scheme at the output of the wideband filterbank, which receives the downconverted signals from the RF interface logic interfacing with the analog devices radio front-end (AD-FMCOMMS4-EBZ). A quantiser logic within the filterbank generates the one-bit input samples required by the proposed scheme, based on the sign bit of the received sample. The samples and filter coefficients are represented using two's complement notation to reduce hardware overhead.

Algorithm 2 Decision-making algorithm for one-bit quantizer based wideband spectrum sensing

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Input: Estimated energy measurements $E(m), \forall m = 1 \dots M, E(m) = \frac{1}{N} \sum_{n=0}^{N-1} |y_m(n)|^2$

- 1: $E_{min} = \min\{E(m)\} \forall m = 1 \dots M$
  - 2: $E_{temp} = 0, Count = 0$
  - 3: **for** $i = 1$ to M **do**
  - 4:   **if** $(E(m) \leq \alpha E_{min})$ **then**
  - 5: $E_{temp} = E_{temp} + 1; Count = Count + 1$
  - 6:   **end if**
  - 7: **end for**
  - 8: Noise variance estimate, $\hat{\sigma}_w^2 = \frac{E_{temp}}{Count}$
  - 9: Decision threshold, $\lambda = \left(Q^{-1}(P_{fa}) \sqrt{\frac{Count}{N}} + 1 \right) \hat{\sigma}_w^2$
  - 10: **for** $i = 1$ to M **do**
  - 11:   **if** $(E(m) \geq \lambda)$ **then**
  - 12:   Channel m is occupied
  - 13:   **else**
  - 14:   Channel m is vacant
  - 15:   **end if**
  - 16: **end for**
-

FIGURE 6.5: Architecture of the cognitive radio enabled LDACS radio platform on the Xilinx Zynq FPGA.

The quantised input samples received by our logic is registered, the output of which fed as the select line of the chain of 2-to-1 8-bit multiplexers which select respective filter coefficients based on the sign. The filter coefficients themselves are stored as a bank of registers, and are mapped as addressable locations from the ARM cores to allow these to be altered at run-time. The output at each stage is accumulated along the chain as in the case of an FIR filter; the final accumulated output over the sensing period (configured by default to 10000 samples by the programmable *sample-depth* register) is squared to generate the estimate of the energy value. The quantisation width of registers were set to 8-bits since there was no appreciable gain observed in the sensing process at higher bit-widths to justify the higher resource overhead (discussed in the results section). The bit-width of the delay pipeline was chosen to ensure that the overflows are contained within the bitwidth for the sensing period configured at design time.

Multiple such sensing channels are attached to the outputs of each tap of the filterbank to perform wideband parallel sensing. Each channel computes the energy estimate independently and uses its own register space to store the filter coefficients independent of other channels. The output of all channels are evaluated by the cognitive logic simultaneously to determine the most appropriate channel for air-to-ground transmission at that instance. When the system operates in receiving mode (i.e., receiving information from ground stations or other aircrafts), the output from the chosen channel output of the filterbank is fed into the baseband logic downstream, bypassing the quantisation and sensing logic.

6.5 Results and Discussion

6.5.1 Simulation Results

For the simulation studies, LDACS signals are generated using the MATLAB code released by the German Aerospace Center (DLR) and the specifications in [4, 189]. The simulation parameters are summarized in Table 3.3. Wideband of 10MHz, which consists of 10 LDACS channels of bandwidth 0.5 MHz each, was considered for the performance analysis. After the one-bit quantization process, the 10 LDACS channels are extracted using the bank of filters. The filter coefficients are estimated using the Parks-McClellan algorithm. To optimize the essential quantization level requirement

for filter coefficients, we analyzed the performance using different quantization levels ($n = 6, 8, 10$ and 12) and observed that there is no appreciable gain beyond 8-bit quantization, which is demonstrated in Fig. 6.6. It is observed for a bit width of 8, the detector provides 100% accuracy even at -12 dB SNR. The simulation parameters to generate LDACS signals are summarized in Table 3.3.

Fig. 6.7 shows the detection and false alarm performances of the proposed scheme for different uncertainty values(α). The curves are plotted for a wide range of SNR from -24 dB to 0 dB . As shown in the figure, the performance is analyzed for three different values of α ($\alpha = 0.1, 0.2$ and 0.3 dB). When lower values of noise uncertainty are assumed, an increased probability of detection is observed. As a trade-off, the false alarm rate is increased for low SNR regimes. For larger values of α , the detection rate is reduced along with the false alarm reductions. It is to be noted that, for $\alpha = 0.1\text{ dB}$, the false alarm rates are still within the permissible limits. In Fig 6.8, the detection performance of the proposed scheme is compared with the conventional spectrum sensing schemes [190, 196] and the one-bit autocorrelation [195] based schemes. It is observed that the detection performance of the non-quantized schemes [190, 196] are slightly better than that of the proposed scheme. On the other side, the proposed scheme performs much better than that of the one-bit autocorrelation based schemes, with comparable complexity. While considering the accuracy-complexity

FIGURE 6.6: Probability of detection versus SNR: Effect of filter coefficients bit-width.

FIGURE 6.7: Probability of detection/probability of false alarm (in red color) versus SNR under different uncertainty factors (α) in dB.

FIGURE 6.8: Probability of detection curves for the proposed one-bit quantization scheme versus the ED [91], multiplier-less correlator [Chapter 4], and one-bit autocorrelation [195] based scheme.

trade-off, the proposed scheme is much efficient than that of conventional multi-bit schemes.

TABLE 6.1: Resource consumption of proposed design on Zynq XC7Z045, compared to the multiplierless correlator-based spectrum sensing (Mless sensing).

Design	FFs	LUTs	Slices	DSPs	% Util.
Proposed design (for 10 narrowbands)	65732	57755	–	20	26.4 (LUTs)
Mless correlator (for one narrowband)	24,000	29,895	7,806	0	13.67 (LUTs)

6.5.2 Implementation Results

To evaluate the resource overheads of the proposed sensing scheme and to estimate its power consumption, the design is implemented on a Xilinx Zynq XC7Z045 FPGA board that forms the processing logic for the radio platform. The detailed resource consumption of the design is shown in Table 6.1. The design achieves an operating frequency of 125 MHz on the device, and the complete design consumes only 26.4% of the resources on the Zynq design even with all 10 channels implemented in parallel, allowing the entire processing chain to be implemented on the same design without the need for advanced techniques like partial reconfiguration. For comparison, we also implemented the multiplier-less correlator (Mless correlator) scheme on the same device, and observe that the multiplier-less design consumes almost the half the resources (LUTs) for sensing one narrowband. The results of the comparison also given in Table 5.1. The power consumption on the device also evaluated using the power analyser tool integrated into Xilinx's Vivado toolflow; to provide an accurate estimate, the post routed design is simulated feeding actual LDACS frames as inputs at a clock frequency of 100 MHz (LDACS frames generated from the code released by DLR). The tools estimates that the design consumes a mere 408 mW in operation with a static power consumption of 203 mW, which is significantly lower than the 1038 mW consumed by the multiplier-less correlator based spectrum sensing scheme in Chapter 4. The lower power consumption, combined with the overall resource efficiency in performing parallel sensing across all channels makes this design an ideal choice for deployment in power constrained scenarios like an aircraft on-board system.

FIGURE 6.9: The overview and contributions of Chapter 6.

6.6 Summary

In this chapter, a power-efficient scheme for wideband sensing in CR networks is explored using a one-bit quantized computational pipeline. The proposed scheme uses a modified FIR pipeline aiming to reduce the computational complexity by replacing the multiplier at each tap with a multiplexer that uses the one-bit quantized signal to select between two possible filter coefficient values. The proposed architecture is implemented in hardware and evaluated the system using a simulated LDACS scenario, using the signals generated through the LDACS communication model, mimicking

an actual LDACS transmission system. A detection algorithm is also proposed to utilize the output of this architecture for efficient sensing by reducing the effect of power leakage from occupied subbands. The results show that the extreme quantized signal (one-bit) can be effectively deployed to detect spectral holes in a wideband sensing scheme, and the architecture combined with the detection scheme provides a good accuracy-complexity trade-off among competing wideband sensing schemes. The significant contributions of Chapter 6 are summarized in Fig. [6.9](#).

Chapter 7

Conclusions and Future Research

Air traffic management (ATM) systems are currently approaching operating limits, especially in high-density areas, and in the current form, ATMs will not be capable of handling the projected growth in future air traffic. LDACS is identified as the appropriate candidate to support the future needs of air-to-ground communications. In this thesis, the use of CR concepts in LDACS communications has been proposed. Similar to the conventional terrestrial CR, LDACS-CR also uses the spectrum sensing techniques to identify the vacant bands and use that spectrum holes for transmission. This thesis has proposed spectrum sensing techniques and their low complexity architectures to find the spectrum holes in the LDACS-Band. We have shown that enhanced spectrum sensing techniques offer improved detection accuracy without incurring the computational complexity. Moreover, we have implemented the proposed algorithms in FPGA platforms to estimate the computational resources and power usage. The practicality of the proposed scheme was also shown in this thesis by integrating the proposed scheme into the LDACS radio platform. We also showed that the decision threshold could be calculated on the fly with the aid of unbiased noise estimation, which implicates the practicality of the proposed techniques. The major issues associated with the spectrum sensing such as low SNR wall, noise uncertainty issues, reconfigurability among others are addressed in this thesis with the intelligent use of the known features of the LDACS signals. This chapter concludes the different contributions described in this thesis and sketches areas for future research.

7.1 Accuracy-complexity trade-off of the proposed schemes

Table 7.1 provides an overview of the minimum required SNR and the power consumption of the proposed narrowband schemes. The performance is analyzed using the LDACS signals generated according to the specifications. As shown in the table, the multiplier-less correlator provides the best detection accuracy with more power consumption. Whereas, the CFD scheme archives reliable detection accuracy with less power consumption. The power consumption of the CFD scheme was reduced by the optimized design of the hardware architecture. Results showed that the effect of uncertainty is higher in the case of ED-based schemes, controlled in CFD schemes

TABLE 7.1: Summary of the detection accuracy and power consumption of the proposed narrowband sensing schemes.

Scheme	Minimum SNR for desired detection accuracy (in dB)	Power Consumption
Adaptive ED (Chapter 3)	-10 (with 5% NU)	411 mW
Mless sensing (Chapter 4)	-14	1160 mW
Simplified CFD (Chapter 5)	-12	312 mW

FIGURE 7.1: The accuracy-complexity comparison of the proposed narrowband sensing schemes

FIGURE 7.2: Overview of the proposed schemes of this thesis.

and negligible for correlator detection. The accuracy-complexity comparison of the proposed schemes is schematically represented in Fig.7.1.

7.2 Summary of Contributions

We have proposed enhancements to the conventional spectrum sensing techniques to cater to the diverse channel conditions of aeronautical communications. Various sensing techniques based on energy detection, cross-correlation, and cyclostationary feature detection have been used to improve the detection accuracy. In addition, their low complexity implementation of the proposed methods are performed. The analytical formulas for the decision thresholds for the proposed schemes have been appropriately defined for the smoother reproduction of the proposed schemes. Various spectrum sensing scheme proposed in this thesis and the major contributions of these schemes are summarized in Figure. 7.2

7.2.1 Energy detection based schemes

Existing energy detection schemes have the drawbacks such as higher SNRs for accurate decision making, noise uncertainty issues, and inability to distinguish primary users and noise. In chapter 3, two modified energy detection based sensing techniques have been proposed to cater to the SNR wall and noise uncertainty issues.

- The first one is an energy-difference detection scheme in which the spectrum energy irregularities of the neighboring LDACS and DME channels were exploited for the detection process. We have shown that the energy-difference algorithm considerably improves the detection accuracy compared to the conventional ED schemes. We also have shown that FFB assisted sensing reduces the computational complexity of the scheme compared to the conventional per-channel approach.
- The second approach was an adaptive weighted ED scheme with real-time noise variance estimation. The results showed that the schemes outperform conventional ED and energy-difference detection schemes without many additional resources. The scheme introduced a novel noise variance estimation technique in which the noise variance is estimated on the fly with the knowledge of the features of the received LDACS signals. The simulation results also indicate that the technique is immune to noise uncertainty issues as the noise variance is estimated from the same frequency channel. The proposed scheme is termed as a hybrid scheme as it uses two features of the received signal: energy and autocorrelation during the detection process. We have also implemented the proposed technique in FPGA, and it is integrated into the LDACS radio platform.

7.2.2 Low-power correlator detection

In Chapter 4, a multiplier-less correlator based spectrum sensing scheme is proposed in which the known preamble signals of the LDACS frames were used to find the spectrum occupancy. Cross-correlator based schemes provide better accuracy than autocorrelation based schemes. We have shown that the novel multiplier-less correlator architecture reduces the implementation complexity of the cross-correlator detector. The proposed architecture replaces the multiplication operations by shift add and

bank of multiplexers, which considerably reduced the resource overheads. A detailed analysis of the detection performance for different quantization levels was conducted and observed that there is no appreciable gain beyond 6-bit quantization. The detection performances were analyzed for varying SNR ranging from -20dB to 0dB, and 100% accuracy was achieved for even -12 dB SNR. Moreover, it is observed that the noise uncertainty was not affected the detection performance as the chosen decision threshold is independent of noise variance. Apart from the mentioned contributions, the proposed scheme was integrated into the LDACS processing chain, and thus re-configurability of the proposed architecture as synchronizer also enabled. The major attractions of the scheme are summarized below.

- Modified matched-filtering without employing multiplications.
- The same hardware can be used for synchronization at LDACS receiver.
- Improved detection accuracy.
- Reduced complexity (compared to the conventional correlators)

7.2.3 Low-complexity cyclostationary feature detection

In Chapter 5, a low-complexity cyclostationary feature detection scheme is proposed in which the known cyclic properties of the received signals were used to detect the spectrum holes. CFDs can distinguish the primary signals from the noise and interference even at low SNR states. However, the high computational complexity of conventional CFDs makes it not appropriate for the real-time implementation on power-constrained systems like aeronautical communications. The proposed sliding correlator based CFD scheme is a low complexity scheme as only one cyclic frequency is required to be analyzed for the detection process. The proposed detector achieves dominating detection performance by the intelligent estimation of the autocorrelation coefficient and the real-time noise variance estimation. The noise uncertainty issues were addressed by the on the fly estimation of the noise variance from the same frequency channel. Moreover, the proposed scheme was implemented in FPGA to show its practical applicability. The FPGA implementation shows that the design consumes only a fraction of the resources (DSPs 7.3%, LUTs 4.7%, and FFs 4.9%) on a small FPGA device, making it ideally befitted for deployment in power-constrained

aeronautical communication systems. The significant contributions of the scheme are summarized below.

- The modified test statistic with the introduction of real-time noise variance estimation improves the detection accuracy and the stability against noise uncertainty.
- The noise variance estimation is done parallelly while processing the detection algorithm, which improves the throughput of the scheme.
- Efficient hardware implementation of the proposed algorithm demonstrates the practical applicability of the proposed scheme.

7.2.4 Power-efficient Wideband Spectrum Sensing Scheme

A power-efficient one-bit wideband spectrum sensing scheme was proposed in Chapter 6 to reduce the power consumption of the detector considerably. In this scheme, FIR filter assisted channelization and detection is used to split the wideband into several narrow bands of particular bandwidths and central frequencies. The novelty of the proposed scheme was the one-bit quantization of the input signal and the assisted filter design. Results show that the multiplier-less filter architecture considerably reduces power consumption, which is an ideal choice for power-constrained systems such as aeronautical communication. The proposed scheme provides the best accuracy-throughput-complexity trade-off among all the proposed spectrum sensing schemes in this thesis.

7.3 Future research directions

Different approaches to find the spectrum holes of the LDACS spectrum are discussed in this thesis. The first four techniques are suitable for narrowband sensing, and the last one deals with wideband sensing. However, the wideband spectrum sensing techniques are more sensitive to the received signal SNR. Next-generation aeronautical systems are expected to operate at low-SNR regimes where ED techniques are inaccurate. Minimal research has been investigated in the area of wideband spectrum

sensing performance at very low SNR, although aforementioned is an encouraging area of research that ought to be considered as a potential future direction.

Once the spectrum holes are detected, the CR required to determine a suitable channel for transmission among the detected spectrum holes. A spectrum management unit necessitates being included in the CR system to select the most suitable channel for transmission. Unlike the terrestrial communication system, the spectrum allocation should be prioritized based on the safety of aircraft. In addition to the safety concerns, the responsibilities of the spectrum management unit in an aeronautical CR systems include spectrum decision, spectrum sharing, and access, and spectrum mobility. The application of machine learning techniques for spectrum management is a potential research candidate in this direction. Usage of different learning techniques enables proper selection and switching of the channel, which improves the throughput of the CR by utilizing the resources effectively.

The spectrum sensing performance and the spectrum access schemes are highly depended on the PU traffic and interference. Different approaches to mitigate the interference from legacy systems on LDACS are discussed in the literature [197–199]. However, none of the methods deals with the analysis of the effect of interference on the throughput of SUs. In this context, the analysis of the impact of primary user traffic and interference from DME and other legacy systems has potential research significance. The abovementioned issues in the context of aeronautical CR are not available in the literature (to the best of our knowledge). Detailed analysis of the combined effect of PU traffic and PU interference on the throughput of secondary users in the aeronautical domain has a potential impact. In another direction, more analysis of the impact of interference on aeronautical PUs due to DSA also has a significant research value to ensure the safety of aircraft.

Appendix A

Derivation of Noise variance estimation

Let the received signal be $x(n)$ with $n = 0, 1, \dots, N$, and $N = K(N_{CP} + N_D)$. $x(n)$ can be arranged as a column vector $X = [x(0)x(1)x(2)\dots x(N-1)]^T$. The joint probability density function (PDF) of X under $\mathcal{H}_0$ and $\mathcal{H}_1$ is given by [117]

$$f(x|\sigma_w^2, \gamma) = \frac{(1-\gamma)^{K(N_{CP}+N_D)}}{(\pi\sigma_w^2)^{K(N_{CP}+N_D)}(1-\gamma^2)^{KN_{CP}}} \times \exp\left(-\frac{A_x - \gamma B_x - \gamma^2 C_x}{\sigma_w^2(1+\gamma)}\right), \quad (\text{A.1})$$

where $\gamma = 0$ for $\mathcal{H}_0$ and $\frac{\sigma_x^2}{\sigma_s^2 + \sigma_w^2}$ for $\mathcal{H}_1$, σ_w^2 is the noise variance and σ_s^2 is the signal variance. The terms A_x , B_x and C_x are given as [117]

$$A_x = \frac{1}{K(N_{CP} + N_D)} \sum_{n=0}^{K(N_{CP}+N_D)} |x(n)|^2, \quad (\text{A.2})$$

$$B_x = 2 \sum_{n \in S} \text{Re}[x(n)x(n+N_D)], \quad (\text{A.3})$$

$$C_x = A_x - \sum_{n \in S} (|x(n)|^2 + |x(n+N_D)|^2), \quad (\text{A.4})$$

with $S = k(N_{CP} + N_D), \dots, k(N_{CP} + N_D) + N_{CP} - 1, k \in \mathbb{Z}$.

The natural logarithm of (A.1) gives

$$\begin{aligned} \log(f(x|\sigma_w^2, \gamma)) = & -K(N_{CP} + N_D)\log(\pi) - K(N_{CP} + N_D)\log(\sigma_w^2) + \\ & K(N_{CP} + N_D)\log(1-\gamma) - KN_{CP}\log(1-\gamma^2) - \frac{A_x - \gamma B_x - \gamma^2 C_x}{\sigma_w^2(1+\gamma)} \end{aligned} \quad (\text{A.5})$$

$\log(f(x|\sigma_w^2, \gamma))$ is a concave function at low SNR, the solutions for optimum σ_w^2 and γ is obtained from their first derivaties. The first derivates of $\log(f(x|\sigma_w^2, \gamma))$ with respect to σ_w^2 and γ are given in (A.6) and (A.7) respectively.

$$\frac{\partial[\log(f(x|\sigma_w^2, \gamma))]}{\partial\sigma_w^2} = -\frac{K(N_{CP} + N_D)}{\sigma_w^2} + \frac{A_x - \gamma B_x - \gamma^2 C_x}{\sigma_w^4(1 + \gamma)} \quad (\text{A.6})$$

$$\frac{\partial[\log(f(x|\sigma_w^2, \gamma))]}{\partial\gamma} = -\frac{K(N_{CP} + N_D)}{1 - \gamma} + \frac{2KN_{CP}\gamma}{1 - \gamma^2} + \frac{A_x + \gamma B_x + 2\gamma C_x + \gamma^2 C_x}{\sigma_w^2(1 + \gamma)^2} \quad (\text{A.7})$$

$$\frac{\partial[\log(f(x|\sigma_w^2, \gamma))]}{\partial\sigma_w^2} = 0 \Rightarrow \hat{\sigma}_w^2 = \frac{A_x - \gamma B_x - \gamma^2 C_x}{K(N_{CP} + N_D)(1 + \gamma)} \quad (\text{A.8})$$

Substituting (A.8) to (A.6)

$$\frac{\partial[\log(f(x|\sigma_w^2, \gamma))]}{\partial\gamma} = \frac{K(N_{CP} + N_D)(B_x + 2\gamma C_x)}{A_x - \gamma B_x - \gamma^2 C_x} - \frac{2KN_D\gamma}{1 - \gamma^2} \quad (\text{A.9})$$

Also, note that for a sufficiently large number of samples, $C_x = \frac{N_D - N_{CP}}{N_D + N_{CP}} A_x$.

Solving $\frac{\partial[\log(f(x|\sigma_w^2, \gamma))]}{\partial\gamma} = 0$ gives

$$\hat{\gamma} = \frac{K(N_D + N_{CP})B_x}{2KN_{CP}A_x} \quad (\text{A.10})$$

substituting (A.10) in (A.8) gives,

$$\hat{\sigma}_w^2 = \frac{A_x}{K(N_D + N_{CP})} - \frac{B_x}{2KN_{CP}} = E_x - \rho_x \quad (\text{A.11})$$

In the manuscript, the terms A_x and B_x are represnted in a more simplified form,

$$E_x = \frac{A_x}{K(N_D + N_{CP})} \quad (\text{A.12})$$

$$\rho_x = \frac{B_x}{2KN_{CP}} \quad (\text{A.13})$$

The term ρ_x is estimated in a simplified form of B_x . i.e, to estimate the term B_x we can use the equation $B_x = 2\sum_{n=0}^{K(N_{CP}+N_D)} \text{Re}[x(n)x(n+N_D)]$ instead of $B_x = 2\sum_{n \in S} \text{Re}[x(n)x(n+N_D)]$ because $E[\sum_{n \notin S} \text{Re}[x(n)x(n+N_D)]] = 0$.

The distribution of the estimator $\hat{\sigma}_w^2$ for $\mathcal{H}_0$ and $\mathcal{H}_1$ are given as,

$$\hat{\sigma}_{w_i}^2 \sim \begin{cases} \mathcal{N}\left(\sigma_w^2, \frac{2\sigma_w^4}{K(N_{CP}+N_D)} + \frac{\sigma_w^4(N_{CP}+N_D)}{2KN_{CP}^2}\right), & \mathcal{H}_0 \\ \mathcal{N}\left(\sigma_w^2, \frac{2(\sigma_s^2+\sigma_w^2)^2}{K(N_{CP}+N_D)} + \frac{(\sigma_s^2+\sigma_w^2)^2(N_{CP}+N_D)+\sigma_s^4N_{CP}}{2KN_{CP}^2}\right), & \mathcal{H}_1 \end{cases} \quad (\text{A.14})$$

From (A.14), it is clear that the variance of the proposed estimator asymptotically diminishes to zero for both the hypotheses.

Publications

Journal Articles

Accepted

1. Mathew, L. K., Shanker, S., Vinod, A. P., and Madhukumar, A. S. (2019). An Adaptive Energy Detection Scheme with Real-Time Noise Variance Estimation. *Circuits, Systems, and Signal Processing*, 1-25, doi:10.1007/s00034-019-01281-0.
2. Shreejith, S., Mathew, L. K., Prasad, V. A., and Fahmy, S. A. (2018). Efficient spectrum sensing for aeronautical radars using low-power correlators. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, 26(6), pp.1183-1191.

Under Revision

3. Mathew, L. K., Shanker, S., Vinod, A. P., and Madhukumar, A. S., Design and Implementation of a Simplified Cyclostationary based Spectrum Sensing System. in *Circuits, Systems, and Signal Processing*.
- 4 Mathew, L. K., Shanker, S., Vinod, A. P., and Madhukumar, A. S, Power-efficient wideband sensing using one-bit quantization and modified filter bank architecture. in *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*,

Conference Proceedings

5. Mathew, L. K., and Vinod, A. P. (2016, September). An energy-difference detection based spectrum sensing technique for improving the spectral efficiency

of LDACS1 in aeronautical communications. In 2016 IEEE/AIAA 35th Digital Avionics Systems Conference (DASC) (pp. 1-5).

6. Mathew, L. K., Vinod, A. P., and Madhukumar, A. S. (2019, May). A Cyclic Prefix Assisted Spectrum Sensing Method for Aeronautical Communication Systems. In 2019 IEEE International Symposium on Circuits and Systems (ISCAS) (pp. 1-5). IEEE.

Bibliography

- [1] N Fistas and B Phillips. Action plan 17-future communications study-final conclusions and recommendations report. In *in Proc. IEEE. Dig. Avion Syst. Conf*, page 12, 2007.
- [2] M. Schnell, U. Epple, D. Shutin, and N. Schneckenburger. LDACS: future aeronautical communications for air-traffic management. *IEEE Commun. Mag.*, 52(5):104–110, May 2014.
- [3] M Sajatovic, B Haindl, U Epple, T Gräupl, C Rihacek, M Schnell, N Fistas, JU Koch, HW Kim, and E Le-Ho. Updated ldacs1 system specification. *SESAR P15*, 2, 2011.
- [4] Miodrag Sajatovic, B Haindl, M Ehammer, Th Gräupl, M Schnell, U Epple, and S Brandes. L-DACS1 system definition proposal: Deliverable D2. *Eurocontrol Study Report*, 2009.
- [5] Melvin J Zeltser, Frederick R Morser, Philip Long, and Frank Box. White paper: Spectrum depletion analysis. *The MITRE Corp. MITRE MP 03W0000068*, 2003.
- [6] Frank Schreckenbach, Katia Leconte, Cedric Baudoin, Christian Kissling, Christian Bauer, and Serkan Ayaz. Functional building blocks for an integrated aeronautical ip-network. In *2008 Integrated Communications, Navigation and Surveillance Conference*, pages 1–9. IEEE, 2008.
- [7] J. Mitola and G. Q. Maguire. Cognitive radio: making software radios more personal. *IEEE Pers. Commun.*, 6(4):13–18, Aug 1999.
- [8] C. Zhang, Y. Zhang, J. Xiao, and J. Yu. Aeronautical central cognitive broadband air-to-ground communications. *IEEE J. Sel. Areas Commun.*, 33(5):946–957, May 2015.

- [9] Yang Wang. Cognitive radio for aeronautical air-ground communications. *IEEE Aerosp. Electron. Syst. Mag.*, 25(5):18–23, May 2010.
- [10] R. Fantacci and A. Tani. Performance evaluation of a spectrum-sensing technique for cognitive radio applications in b-vhf communication systems. *IEEE Trans. Veh. Technol.*, 58(4):1722–1730, May 2009.
- [11] Ponnu Jacob, AS Madhukumar, and AP Vinod. Efficient aviation spectrum management through dynamic frequency allocation. In *Integrated Communication, Navigation, and Surveillance Conference (ICNS), 2015*, pages L3–1. IEEE, 2015.
- [12] Ponnu Jacob, Rajendra Prasad Sirigina, AS Madhukumar, and Vinod Achutavarrier Prasad. Cognitive radio for aeronautical communications: A survey. *IEEE Access*, 4:3417–3443, 2016.
- [13] Tevfik Yucek and Huseyin Arslan. A survey of spectrum sensing algorithms for cognitive radio applications. *IEEE Commun. Surveys Tuts.*, 11(1):116–130, 2009.
- [14] H. Pradhan, S. S. Kalamkar, and A. Banerjee. Sensing-throughput tradeoff in cognitive radio with random arrivals and departures of multiple primary users. *IEEE Communications Letters*, 19(3):415–418, March 2015. doi: 10.1109/LCOMM.2015.2393305.
- [15] Harry Urkowitz. Energy detection of unknown deterministic signals. *Proceedings of the IEEE*, 55(4):523–531, 1967.
- [16] H-S Chen, Wen Gao, and David G Daut. Signature based spectrum sensing algorithms for ieee 802.22 wran. In *2007 IEEE International Conference on Communications*, pages 6487–6492. IEEE, 2007.
- [17] M. Derakhshani, T. Le-Ngoc, and M. Nasiri-Kenari. Efficient cooperative cyclostationary spectrum sensing in cognitive radios at low snr regimes. *IEEE Trans. Wireless Commun.*, 10(11):3754–3764, November 2011.
- [18] Andrea Mariani, Andrea Giorgetti, and Marco Chiani. Snr wall for energy detection with noise power estimation. In *Communications (ICC), 2011 IEEE International Conference on*, pages 1–6. IEEE, 2011.
- [19] Danijela Cabric, Shridhar Mubaraq Mishra, and Robert W Brodersen. Implementation issues in spectrum sensing for cognitive radios. In *Signals, systems*

- and computers, 2004. Conference record of the thirty-eighth Asilomar conference on*, volume 1, pages 772–776. Ieee, 2004.
- [20] M. Derakhshani, M. Nasiri-Kenari, and T. Le-Ngoc. Cooperative cyclostationary spectrum sensing in cognitive radios at low snr regimes. In *2010 IEEE International Conference on Communications*, pages 1–5, May 2010.
- [21] William A Gardner. Signal interception: A unifying theoretical framework for feature detection. *IEEE Trans. Commun.*, 36(8):897–906, 1988.
- [22] Yonghong Zeng and Y-C Liang. Eigenvalue-based spectrum sensing algorithms for cognitive radio. *IEEE Trans. Commun.*, 57(6), 2009.
- [23] A. Kortun, T. Ratnarajah, M. Sellathurai, C. Zhong, and C. B. Papadias. On the performance of eigenvalue-based cooperative spectrum sensing for cognitive radio. *IEEE J. Sel. Topics Signal Process*, 5(1):49–55, Feb 2011.
- [24] Shanker Shreejith, Abhishek Ambede, AP Vinod, and Suhaib A Fahmy. A power and time efficient radio architecture for LDACS1 air-to-ground communication. In *in Proc. IEEE. Dig. Avion Syst. Conf.*, pages 1–6. IEEE, 2016.
- [25] URL <https://www.faa.gov/nextgen/>.
- [26] SESAR Joint Undertaking. European ATM master plan, 2 eds. october 2012. *SESAR Joint Undertaking*, 2012.
- [27] R. J. Kerczewski, J. M. Budinger, and T. J. Gilbert. Technology assessment results of the eurocontrol/faa future communications study. In *2008 IEEE Aerospace Conference*, pages 1–13, March 2008.
- [28] R. J. Kerczewski and G. Dyer. Eurocontrol/faa future communications study - phase ii technology assessments. In *2007 IEEE Aerospace Conference*, pages 1–8, March 2007.
- [29] T. Gilbert, J. Jin, J. Berger, S. Henriksen, and J. Budinger. Future communication study technology investigation conclusions and recommendations. In *2008 Integrated Communications, Navigation and Surveillance Conference*, pages 1–13, May 2008.
- [30] B. Kamali. *Airport Communications from Analog AM to AeroMACS*, pages 1–40. IEEE, 2018. ISBN 9781119281139. URL <https://ieeexplore.ieee.org/document/8538823>.

- [31] Yiping Chen. A survey of aeromacs: Next generation airport surface mobile communication systems. In *IET International Communication Conference on Wireless Mobile and Computing (CCWMC 2011)*, pages 513–516, Nov 2011.
- [32] C. Morlet, N. Ricard, and S. F. Rodriguez. Options for the iris satellite-based datalink. In *2011 Integrated Communications, Navigation, and Surveillance Conference Proceedings*, pages B5–1–B5–11, May 2011.
- [33] Ulrich Epple and Michael Schnell. Overview of legacy systems in l-band and its influence on the future aeronautical communication system ldacs1. *IEEE Aerospace and Electronic Systems Magazine*, 29(2):31–37, 2014.
- [34] Najett Neji, Raul De Lacerda, Alain Azoulay, Thierry Letertre, and Olivier Outtier. Survey on the future aeronautical communication system and its development for continental communications. *IEEE Trans. on Veh. Tech.*, 62(1):182–191, 2012.
- [35] Thomas Gräupl. L-dacs1: Analysis, design and evaluation of the quality-of-service protocols of the future aeronautical communication system. 2012.
- [36] Snjezana Gligorevic, Michael Schnell, and Ulrich Epple. *The LDACS1 physical layer design*. INTECH Open Access Publisher, 2011.
- [37] T Graupl, M Ehammer, and C-H Rokitansky. L-dacs 1 data link layer design and performance. In *2009 Integrated Communications, Navigation and Surveillance Conference*, pages 1–12. IEEE, 2009.
- [38] Sinja Brandes, U Epple, Snjezana Gligorevic, Michael Schnell, Bernhard Haindl, and Miodrag Sajatovic. Physical layer specification of the l-band digital aeronautical communications system (l-dacs1). In *2009 Integrated Communications, Navigation and Surveillance Conference*, pages 1–12. IEEE, 2009.
- [39] Simon Haykin. Cognitive radio: brain-empowered wireless communications. *IEEE journal on selected areas in communications*, 23(2):201–220, 2005.
- [40] Ian F Akyildiz, Won-Yeol Lee, Mehmet C Vuran, and Shantidev Mohanty. Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey. *Computer networks*, 50(13):2127–2159, 2006.
- [41] Khaled Ben Letaief and Wei Zhang. Cooperative communications for cognitive radio networks. *Proceedings of the IEEE*, 97(5):878–893, 2009.

- [42] Sudhir Srinivasa and Syed Ali Jafar. Cognitive radios for dynamic spectrum access-the throughput potential of cognitive radio: A theoretical perspective. *IEEE Commun. Mag.*, 45(5):73–79, 2007.
- [43] Ekram Hossain, Dusit Niyato, and Zhu Han. *Dynamic spectrum access and management in cognitive radio networks*. Cambridge university press, 2009.
- [44] B. Wang and K. J. R. Liu. Advances in cognitive radio networks: A survey. *IEEE J. Sel. Topics Signal Process.*, 5(1):5–23, 2011.
- [45] Ankit Kaushik, Shree Krishna Sharma, Symeon Chatzinotas, Björn Ottersten, and Friedrich K Jondral. Sensing-throughput tradeoff for interweave cognitive radio system: A deployment-centric viewpoint. *IEEE Trans. Wireless Commun.*, 15(5):3690–3702, 2016.
- [46] Aaqib Patel, Mohammed Zafar Ali Khan, Shabbir N Merchant, Uday B Desai, and Lajos Hanzo. The achievable rate of interweave cognitive radio in the face of sensing errors. *IEEE Access*, 5:8579–8605, 2016.
- [47] Miltiades C Filippou, David Gesbert, and George A Ropokis. A comparative performance analysis of interweave and underlay multi-antenna cognitive radio networks. *IEEE Trans. Wireless Commun.*, 14(5):2911–2925, 2015.
- [48] Fidan Mehmeti and Thrasyvoulos Spyropoulos. Performance analysis, comparison, and optimization of interweave and underlay spectrum access in cognitive radio networks. *IEEE Trans. Veh. Technol.*, 67(8):7143–7157, 2018.
- [49] Fidan Mehmeti and Thrasyvoulos Spyropoulos. Stay or switch?: Analysis and comparison of delays in cognitive radio networks with interweave and underlay spectrum access. In *Proceedings of the 14th ACM International Symposium on Mobility Management and Wireless Access*, pages 9–18. ACM, 2016.
- [50] Rekha Menon, R Michael Buehrer, and Jeffrey H Reed. Outage probability based comparison of underlay and overlay spectrum sharing techniques. In *Proc. IEEE DySPAN*, volume 5, pages 101–109, 2005.
- [51] Nurul H Mahmood, Ferkan Yilmaz, Geir E Oien, and Mohamed-Slim Alouini. On hybrid cooperation in underlay cognitive radio networks. *IEEE Trans. Wireless Commun.*, 12(9):4422–4433, 2013.

- [52] Lokman Sboui, Zouheir Rezki, and Mohamed-Slim Alouini. Energy-efficient power allocation for underlay cognitive radio systems. *IEEE Trans. Cog. Commun. and Netw.*, 1(3):273–283, 2015.
- [53] Chaoqing Tang, Gaofeng Pan, and Tingting Li. Secrecy outage analysis of underlay cognitive radio unit over nakagami- m fading channels. *IEEE Wireless Commun. Lett.*, 3(6):609–612, 2014.
- [54] Sachitha Kusaladharma and Chintha Tellambura. Aggregate interference analysis for underlay cognitive radio networks. *IEEE Wireless Commun. Lett.*, 1(6):641–644, 2012.
- [55] Mohammad Shaqfeh, Ammar Zafar, Hussein Alnuweiri, and Mohamed-Slim Alouini. Overlay cognitive radios with channel-aware adaptive link selection and buffer-aided relaying. *IEEE Trans. Commun.*, 63(8):2810–2822, 2015.
- [56] Fahimeh Jasbi and Daniel KC So. Hybrid overlay/underlay cognitive radio network with mc-cdma. *IEEE Trans. Veh. Technol.*, 65(4):2038–2047, 2015.
- [57] Wei Liang, Soon Xin Ng, and Lajos Hanzo. Cooperative overlay spectrum access in cognitive radio networks. *IEEE Communications Surveys & Tutorials*, 19(3):1924–1944, 2017.
- [58] Vasu Chakravarthy, Xue Li, Zhiqiang Wu, Michael A Temple, Fred Garber, Rajgopal Kannan, and Athanasios Vasilakos. Novel overlay/underlay cognitive radio waveforms using sd-smse framework to enhance spectrum efficiency-part i: theoretical framework and analysis in awgn channel. *IEEE Trans. Commun.*, 57(12):3794–3804, 2009.
- [59] Matteo Gandetto and Carlo Regazzoni. Spectrum sensing: A distributed approach for cognitive terminals. *IEEE J. Sel. Areas Commun.*, 25(3):546–557, 2007.
- [60] Ghurumuruhan Ganesan, Ye Geoffrey Li, Benny Bing, and Shaoqian Li. Spatiotemporal sensing in cognitive radio networks. *IEEE J. Sel. Areas Commun.*, 26(1):5–12, 2008.
- [61] Parthaprathim De and Ying-Chang Liang. Blind spectrum sensing algorithms for cognitive radio networks. *IEEE Trans. Veh. Technol.*, 57(5):2834–2842, 2008.

- [62] Abdelmohsen Ali and Walaa Hamouda. Advances on spectrum sensing for cognitive radio networks: Theory and applications. *IEEE communications surveys & tutorials*, 19(2):1277–1304, 2016.
- [63] Dinesh Datla, Alexander M Wyglinski, and Gary J Minden. A spectrum surveying framework for dynamic spectrum access networks. *IEEE Trans. Veh. Technol.*, 58(8):4158–4168, 2009.
- [64] Beibei Wang and KJ Ray Liu. Advances in cognitive radio networks: A survey. *IEEE Journal of selected topics in signal processing*, 5(1):5–23, 2010.
- [65] Beibei Wang and KJ Ray Liu. Advances in cognitive radio networks: A survey. *IEEE Journal of selected topics in signal processing*, 5(1):5–23, 2010.
- [66] Krzysztof Cichoń, Adrian Kliks, and Hanna Bogucka. Energy-efficient cooperative spectrum sensing: A survey. *IEEE Communications Surveys & Tutorials*, 18(3):1861–1886, 2016.
- [67] Shree Krishna Sharma, Eva Lagunas, Symeon Chatzinotas, and Björn Ottersten. Application of compressive sensing in cognitive radio communications: A survey. *IEEE communications surveys & tutorials*, 18(3):1838–1860, 2016.
- [68] Yunxia Chen, Qing Zhao, and Ananthram Swami. Distributed spectrum sensing and access in cognitive radio networks with energy constraint. *IEEE Trans. Signal Process*, 57(2):783–797, 2008.
- [69] Majed Haddad, Salah Eddine Elayoubi, Eitan Altman, and Zwi Altman. A hybrid approach for radio resource management in heterogeneous cognitive networks. *IEEE J. Sel. Areas Commun.*, 29(4):831–842, 2011.
- [70] Mikio Hasegawa, Hiroshi Hirai, Kiyohito Nagano, Hiroshi Harada, and Kazuyuki Aihara. Optimization for centralized and decentralized cognitive radio networks. *Proceedings of the IEEE*, 102(4):574–584, 2014.
- [71] Woongsup Lee. Resource allocation for multi-channel underlay cognitive radio network based on deep neural network. *IEEE Communications Letters*, 22(9):1942–1945, 2018.
- [72] Rui Zhang, Ying-Chang Liang, and Shuguang Cui. Dynamic resource allocation in cognitive radio networks. *IEEE Sig. Process. Mag.*, 27(3):102–114, 2010.

- [73] Georgios I Tsiropoulos, Octavia A Dobre, Mohamed Hossam Ahmed, and Kareem E Baddour. Radio resource allocation techniques for efficient spectrum access in cognitive radio networks. *IEEE Communications Surveys & Tutorials*, 18(1):824–847, 2014.
- [74] Dileep M Kalathil and Rahul Jain. Spectrum sharing through contracts for cognitive radios. *IEEE Trans. Mob. Comput.*, 12(10):1999–2011, 2012.
- [75] Seunghyun Lee and Rui Zhang. Cognitive wireless powered network: Spectrum sharing models and throughput maximization. *IEEE Trans. Cogn. Commun. and Netw.*, 1(3):335–346, 2015.
- [76] Xinbing Wang, Zheng Li, Pengchao Xu, Youyun Xu, Xinbo Gao, and Hsiao-Hwa Chen. Spectrum sharing in cognitive radio networks—an auction-based approach. *IEEE Trans. on Syst., Man, Cybernet., Part B (Cybernetics)*, 40(3):587–596, 2009.
- [77] Julie Thomas and Prasanth P Menon. A survey on spectrum handoff in cognitive radio networks. In *2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*, pages 1–4. IEEE, 2017.
- [78] Won-Yeol Lee and Ian F Akyildiz. Spectrum-aware mobility management in cognitive radio cellular networks. *IEEE Trans. Mob. Comp.*, 11(4):529–542, 2011.
- [79] Yiming Zhou, Zheng Zhou, and Shibo Zhang. An improved spectrum sensing method: energy-autocorrelation-based detection technology. *Circuits, Systems, and Signal Processing*, 32(1):273–282, 2013.
- [80] Jwo-Yuh Wu, Chih-Hsiang Wang, and Tsang-Yi Wang. Performance analysis of energy detection based spectrum sensing with unknown primary signal arrival time. *IEEE Trans. Commun.*, 59(7):1779–1784, 2011.
- [81] Yonghong Zeng, Ying-Chang Liang, and Rui Zhang. Blindly combined energy detection for spectrum sensing in cognitive radio. *IEEE Signal Processing Letters*, 15:649–652, 2008.
- [82] Wei Zhang, Ranjan K Mallik, and Khaled Ben Letaief. Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks. *IEEE Trans. Wireless Commun.*, 8(12):5761–5766, 2009.

- [83] Yunfei Chen. Analytical performance of collaborative spectrum sensing using censored energy detection. *IEEE Trans. Wireless Commun.*, 9(12):3856–3865, 2010.
- [84] Hano Wang, Gosan Noh, Dongkyu Kim, Sungtae Kim, and Daesik Hong. Advanced sensing techniques of energy detection in cognitive radios. *Journal of communications and networks*, 12(1):19–29, 2010.
- [85] Saman Atapattu, Chintla Tellambura, and Hai Jiang. Energy detection based cooperative spectrum sensing in cognitive radio networks. *IEEE Trans. Wireless Commun.*, 10(4):1232–1241, 2011.
- [86] Warit Prawatmuang, Daniel KC So, and Emad Alsusa. Sequential cooperative spectrum sensing technique in time varying channel. *IEEE Trans. Wireless Commun.*, 13(6):3394–3405, 2014.
- [87] Y-C Liang, Yonghong Zeng, Edward Peh, and Anh Tuan Hoang. Sensing-throughput tradeoff for cognitive radio networks. In *2007 IEEE International Conference on Communications*, pages 5330–5335. IEEE, 2007.
- [88] William A Gardner. Cyclostationarity in communications and signal processing. Technical report, STATISTICAL SIGNAL PROCESSING INC YOUNTVILLE CA, 1994.
- [89] John G Proakis. Digital communications fifth edition, 2001, 2001.
- [90] Ana I Pérez-Neira, Miguel Angel Lagunas, Miguel Angel Rojas, and Petre Stoica. Correlation matching approach for spectrum sensing in open spectrum communications. *IEEE Trans. Signal Process*, 57(12):4823–4836, 2009.
- [91] Miguel López-Benítez and Fernando Casadevall. Improved energy detection spectrum sensing for cognitive radio. *IET communications*, 6(8):785–796, 2012.
- [92] I. Sobron, P. S. R. Diniz, W. A. Martins, and M. Velez. Energy detection technique for adaptive spectrum sensing. *IEEE Trans. Commun.*, 63(3):617–627, March 2015.
- [93] L. Rugini, P. Banelli, and G. Leus. Small sample size performance of the energy detector. *IEEE Communications Letters*, 17(9):1814–1817, Sep. 2013.

- [94] S. Ciftci and M. Torlak. A comparison of energy detectability models for spectrum sensing. In *IEEE GLOBECOM 2008 - 2008 IEEE Global Telecommunications Conference*, pages 1–5, Nov 2008.
- [95] John D Edell. Wideband, noncoherent, frequency-hopped waveforms and their hybrids in low-probability-of-intercept communications. Technical report, Naval Research Lab Washington DC, 1976.
- [96] J. M. Bruno and B. L. Mark. A recursive algorithm for wideband temporal spectrum sensing. *IEEE Trans. Commun.*, 66(1):26–38, Jan 2018.
- [97] Don J Torrieri. *Principles of secure communication systems*. Artech House, INC., 1985.
- [98] Jinbo Wu, Tao Luo, and Guangxin Yue. An energy detection algorithm based on double-threshold in cognitive radio systems. In *2009 First International Conference on Information Science and Engineering*, pages 493–496. IEEE, 2009.
- [99] L. K. Mathew and P. Verma. Double threshold energy detection using sequential cooperative spectrum sensing in rayleigh fading. In *2015 International Conference on Signal Processing and Communication (ICSC)*, pages 83–87, March 2015. doi: 10.1109/ICSPCom.2015.7150625.
- [100] Shi-Qi Liu, Bin-Jie Hu, and Xian-Yi Wang. Hierarchical cooperative spectrum sensing based on double thresholds energy detection. *IEEE Communications Letters*, 16(7):1096–1099, 2012.
- [101] Ashish Bagwari, Geetam Singh Tomar, and Shekhar Verma. Cooperative spectrum sensing based on two-stage detectors with multiple energy detectors and adaptive double threshold in cognitive radio networks. *Canadian Journal of Electrical and Computer Engineering*, 36(4):172–180, 2013.
- [102] Quoc-Tuan Vien, Huan X Nguyen, Ramona Trestian, Purav Shah, and Orhan Gemikonakli. A hybrid double-threshold based cooperative spectrum sensing over fading channels. *IEEE Trans. Wireless Commun.*, 15(3):1821–1834, 2015.
- [103] Abhijit Bhowmick, Aniruddha Chandra, Sanjay Dhar Roy, and Sumit Kundu. Double threshold-based cooperative spectrum sensing for a cognitive radio network with improved energy detectors. *IET Communications*, 9(18):2216–2226, 2015.

- [104] Prashob R Nair, A Prasad Vinod, Kavallur Gopi Smitha, and Anoop Kumar Krishna. Fast two-stage spectrum detector for cognitive radios in uncertain noise channels. *IET communications*, 6(11):1341–1348, 2012.
- [105] Xiang Ling, Bin Wu, Hong Wen, Pin-Han Ho, Zhiqiang Bao, and Lili Pan. Adaptive threshold control for energy detection based spectrum sensing in cognitive radios. *IEEE Wireless Commun. Lett.*, 1(5):448–451, 2012.
- [106] Libin K Mathew, Shruti Sharma, and Pankaj Verma. An adaptive algorithm for energy detection in cognitive radio networks. In *Advances in Computing and Communication Engineering (ICACCE), 2015 Second International Conference on*, pages 104–107. IEEE, 2015.
- [107] Shibing Zhang and Zhihua Bao. An adaptive spectrum sensing algorithm under noise uncertainty. In *2011 IEEE International Conference on Communications (ICC)*, pages 1–5. IEEE, 2011.
- [108] Daniela Mercedes Martínez Plata and Ángel Gabriel Andrade Reátiga. Evaluation of energy detection for spectrum sensing based on the dynamic selection of detection-threshold. *Procedia Engineering*, 35:135–143, 2012.
- [109] Deepak R Joshi, Dimitrie C Popescu, and Octavia A Dobre. Adaptive spectrum sensing with noise variance estimation for dynamic cognitive radio systems. In *2010 44th Annual Conference on Information Sciences and Systems (CISS)*, pages 1–5. IEEE, 2010.
- [110] Ashish Muralidharan, Prajwal Venkateswaran, SG Ajay, D Arun Prakash, Mohandeep Arora, and S Kirthiga. An adaptive threshold method for energy based spectrum sensing in cognitive radio networks. In *2015 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT)*, pages 8–11. IEEE, 2015.
- [111] Priyanka Rawat, Kamal Deep Singh, and Jean Marie Bonnin. Cognitive radio for m2m and internet of things: A survey. *Computer Communications*, 94:1–29, 2016.
- [112] G. Yang, J. Wang, J. Luo, O. Y. Wen, H. Li, Q. Li, and S. Li. Cooperative spectrum sensing in heterogeneous cognitive radio networks based on normalized energy detection. *IEEE Trans. Veh. Technol.*, 65(3):1452–1463, March 2016.

- [113] E. Chatziantoniou, B. Allen, and V. Velisavljevic. Threshold optimization for energy detection-based spectrum sensing over hyper-rayleigh fading channels. *IEEE Commun. Lett.*, 19(6):1077–1080, June 2015.
- [114] C. Liu, M. Li, and M. Jin. Blind energy-based detection for spatial spectrum sensing. *IEEE Wireless Commun. Lett.*, 4(1):98–101, Feb 2015.
- [115] T. S. Syed and G. A. Safdar. History-assisted energy-efficient spectrum sensing for infrastructure-based cognitive radio networks. *IEEE Trans. Veh. Technol.*, 66(3):2462–2473, March 2017.
- [116] Joseph M Bruno and Brian L Mark. A recursive algorithm for wideband temporal spectrum sensing. *IEEE Trans. Commun.*, 66(1):26–38, 2017.
- [117] M. Jin, Q. Guo, J. Xi, Y. Li, and Y. Li. On spectrum sensing of ofdm signals at low snr: New detectors and asymptotic performance. *IEEE Trans. Signal Process*, 65(12):3218–3233, June 2017.
- [118] William A Gardner. Exploitation of spectral redundancy in cyclostationary signals. *IEEE Sig. process. mag.*, 8(2):14–36, 1991.
- [119] G. Huang and J. K. Tugnait. On cyclostationarity based spectrum sensing under uncertain gaussian noise. *IEEE Trans. Signal Process*, 61(8):2042–2054, April 2013.
- [120] K. W. Choi, W. S. Jeon, and D. G. Jeong. Sequential detection of cyclostationary signal for cognitive radio systems. *IEEE Trans. Wireless Comm.*, 8(9):4480–4485, Sep. 2009.
- [121] J. Shen and E. Alsusa. Joint cycle frequencies and lags utilization in cyclostationary feature spectrum sensing. *IEEE Trans. Signal Proces.*, 61(21):5337–5346, Nov 2013.
- [122] A. Zahedi-Ghasabeh, A. Tarighat, and B. Daneshrad. Spectrum sensing of ofdm waveforms using embedded pilots in the presence of impairments. *IEEE Trans. Veh. Tech.*, 61(3):1208–1221, March 2012.
- [123] Y. Zeng, Y. Liang, and T. Pham. Spectrum sensing for ofdm signals using pilot induced auto-correlations. *IEEE J. Sel. Areas Commun*, 31(3):353–363, March 2013.

- [124] Andrea Tani and Romano Fantacci. A low-complexity cyclostationary-based spectrum sensing for uwb and wimax coexistence with noise uncertainty. *IEEE Trans. Veh. Technol.*, 59(6):2940–2950, 2010.
- [125] Sayak Bose and Balasubramaniam Natarajan. Reliable spectrum sensing for resource allocation of cognitive radio based wimax femtocells. In *In Proc. IEEE Consumer Comm. and Net. Conf. (CCNC)*, pages 889–893. IEEE, 2012.
- [126] A. Tani, R. Fantacci, and D. Marabissi. A low-complexity cyclostationary spectrum sensing for interference avoidance in femtocell lte-a-based networks. *IEEE Trans. Veh. Technol.*, 65(4):2747–2753, April 2016.
- [127] Yonghong Zeng and Ying-Chang Liang. Covariance based signal detections for cognitive radio. In *2007 2nd IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pages 202–207. IEEE, 2007.
- [128] Yonghong Zeng and Ying-Chang Liang. Spectrum-sensing algorithms for cognitive radio based on statistical covariances. *IEEE Trans. Veh. Technol.*, 58(4):1804–1815, 2008.
- [129] Yonghong Zeng, Choo Leng Koh, and Y-C Liang. Maximum eigenvalue detection: Theory and application. In *2008 IEEE International Conference on Communications*, pages 4160–4164. IEEE, 2008.
- [130] Ahmed Mohammed Mikaeil, Bin Guo, and Zhijun Wang. Machine learning to data fusion approach for cooperative spectrum sensing. In *2014 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery*, pages 429–434. IEEE, 2014.
- [131] Yingqi Lu, Pai Zhu, Donglin Wang, and Michel Fattouche. Machine learning techniques with probability vector for cooperative spectrum sensing in cognitive radio networks. In *2016 IEEE Wireless Communications and Networking Conference*, pages 1–6. IEEE, 2016.
- [132] Haleh Hosseini, Sharifah Kamilah Bte Syed-Yusof, Norsheila Fisal, and Ali Farzamnia. Compressed wavelet packet-based spectrum sensing with adaptive thresholding for cognitive radio. *Canadian Journal of Electrical and Computer Engineering*, 38(1):31–36, 2015.

- [133] Nam-Seog Kim and Jan M Rabaey. A dual-resolution wavelet-based energy detection spectrum sensing for uwb-based cognitive radios. *IEEE Trans. Circuits Syst. I.: Regular Papers*, 65(7):2279–2292, 2017.
- [134] CK Tan and WK Lim. Reliable and low-complexity wavelet-based spectrum sensing for cognitive radio systems at low snr regimes. *Electronics Letters*, 48(24):1565–1567, 2012.
- [135] Haleh Hosseini, Alagan Anpalagan, Kaamran Raahemifar, Serhat Erkucuk, and Salman Habib. Joint wavelet-based spectrum sensing and fbmc modulation for cognitive mmwave small cell networks. *IET Communications*, 10(14):1803–1809, 2016.
- [136] Mengda Lin, A Prasad Vinod, and Chong Meng Samson See. A new flexible filter bank for low complexity spectrum sensing in cognitive radios. *Journal of Signal Processing Systems*, 62(2):205–215, 2011.
- [137] R Mahesh and A Prasad Vinod. A low-complexity flexible spectrum-sensing scheme for mobile cognitive radio terminals. *IEEE Trans. Circuits Syst. II: Express Briefs*, 58(6):371–375, 2011.
- [138] Kavallur Gopi Smitha and A Prasad Vinod. A multi-resolution fast filter bank for spectrum sensing in military radio receivers. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, 20(7):1323–1327, 2011.
- [139] Behrouz Farhang-Boroujeny. Filter bank spectrum sensing for cognitive radios. *IEEE Trans. Signal Process*, 56(5):1801–1811, 2008.
- [140] Yong Ching Lim and Ya Jun Yu. Synthesis of very sharp hilbert transformer using the frequency-response masking technique. *IEEE Trans. Signal Process*, 53(7):2595–2597, 2005.
- [141] Yong Lim. Frequency-response masking approach for the synthesis of sharp linear phase digital filters. *IEEE transactions on circuits and systems*, 33(4):357–364, 1986.
- [142] R Mahesh and A Prasad Vinod. Reconfigurable low area complexity filter bank architecture based on frequency response masking for nonuniform channelization in software radio receivers. *IEEE Transactions on Aerospace and Electronic Systems*, 47(2):1241–1255, 2011.

- [143] R Mahesh and A Prasad Vinod. Low complexity flexible filter banks for uniform and non-uniform channelisation in software radios using coefficient decimation. *IET Circuits, Devices & Systems*, 5(3):232–242, 2011.
- [144] Y. C. Lim and B. Farhang-Boroujeny. Fast filter bank (FFB). *IEEE Trans. Circuits Syst. II, Analog Digit. Signal Process.*, 39(5):316–318, May 1992.
- [145] Tim Hentschel. Channelization for software defined base-stations. In *Annales des Telecommunications*, volume 57, page 386. Springer, 2002.
- [146] Lee Pucker. Channelization techniques for software defined radio. In *Proceedings of SDR Forum Conference*, pages 1–6, 2003.
- [147] S. Dhabu, A. P. Vinod, and A. S. Madhukumar. Low complexity fast filter bank-based channelization in L-DACS1 for aeronautical communications. In *2015 IEEE 13th International New Circuits and Systems Conference (NEWCAS)*, pages 1–4, June 2015.
- [148] Abhishek Ambede, Shanker Shreejith, A Prasad Vinod, and Suhaib A Fahmy. Design and realization of variable digital filters for software-defined radio channelizers using an improved coefficient decimation method. *IEEE Trans. Circuits Syst. I: EXPRESS BRIEFS*, 63(1):59–63, 2015.
- [149] Abhishek Ambede, Kavallur Gopi Smitha, and A Prasad Vinod. A modified coefficient decimation method to realize low complexity fir filters with enhanced frequency response flexibility and passband resolution. In *2012 35th International Conference on Telecommunications and Signal Processing (TSP)*, pages 658–661. IEEE, 2012.
- [150] Abhishek Ambede, Kavallur Gopi Smitha, and A Prasad Vinod. A low-complexity uniform and non-uniform digital filter bank based on an improved coefficient decimation method for multi-standard communication channelizers. *Circuits, Systems, and Signal Processing*, 32(6):2543–2557, 2013.
- [151] Abhishek Ambede, Shanker Shreejith, A Prasad Vinod, and Suhaib A Fahmy. Design and realization of variable digital filters for software-defined radio channelizers using an improved coefficient decimation method. *IEEE Trans. Circuits Syst. I: EXPRESS BRIEFS*, 63(1):59–63, 2015.

- [152] Zhi Quan, Shuguang Cui, Ali H Sayed, and H Vincent Poor. Optimal multiband joint detection for spectrum sensing in cognitive radio networks. *IEEE Trans. Signal Process*, 57(3):1128–1140, 2008.
- [153] RG Baraniuk. A lecture on compressive sensing [j]. *IEEE Signal Processing Magazine*, 24(4):118–121, 2007.
- [154] Shree Krishna Sharma, Eva Lagunas, Symeon Chatzinotas, and Björn Ottersten. Application of compressive sensing in cognitive radio communications: A survey. *IEEE communications surveys & tutorials*, 18(3):1838–1860, 2016.
- [155] Fatima Salahdine, Naima Kaabouch, and Hassan El Ghazi. Bayesian compressive sensing with circulant matrix for spectrum sensing in cognitive radio networks. In *2016 IEEE 7th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, pages 1–6. IEEE, 2016.
- [156] Taha A Khalaf, Mohammed Y Abdelsadek, and Mohammed Farrag. Compressed measurements based spectrum sensing for wideband cognitive radio systems. *International Journal of Antennas and Propagation*, 2015, 2015.
- [157] Hongjian Sun, Wei-Yu Chiu, and Arumugam Nallanathan. Adaptive compressive spectrum sensing for wideband cognitive radios. *IEEE Communications Letters*, 16(11):1812–1815, 2012.
- [158] Yulin Wang and Gengxin Zhang. Compressed wideband spectrum sensing based on discrete cosine transform. *The Scientific World Journal*, 2014, 2014.
- [159] Xiaoming Chen, Hsiao-Hwa Chen, and Weixiao Meng. Cooperative communications for cognitive radio networks—from theory to applications. *IEEE Communications surveys & tutorials*, 16(3):1180–1192, 2014.
- [160] Tao Cui, Feifei Gao, and Arumugam Nallanathan. Optimization of cooperative spectrum sensing in cognitive radio. *IEEE Trans. Veh. Technol.*, 60(4):1578–1589, 2011.
- [161] Ghurumuruhan Ganesan and Ye Li. Cooperative spectrum sensing in cognitive radio, part ii: multiuser networks. *IEEE Trans. Wireless Commun.*, 6(6):2214–2222, 2007.

- [162] Marko Kosunen, Vesa Turunen, Kari Kokkinen, and Jussi Rynänen. Survey and analysis of cyclostationary signal detector implementations on fpga. *IEEE journal on emerging and selected topics in circuits and systems*, 3(4):541–551, 2013.
- [163] S. Chaudhari, V. Koivunen, and H. V. Poor. Autocorrelation-based decentralized sequential detection of ofdm signals in cognitive radios. *IEEE Trans. Signal Process*, 57(7):2690–2700, July 2009.
- [164] GNU Radio. URL <http://www.gnuradio.org/>.
- [165] Paul D Sutton, Jorg Lotze, Hicham Lahlou, Suhaib A Fahmy, Keith E Nolan, Baris Ozgul, Thomas W Rondeau, Juanjo Noguera, and Linda E Doyle. Iris: an architecture for cognitive radio networking testbeds. *IEEE communications magazine*, 48(9):114–122, 2010.
- [166] George Eichinger, Kaushik Chowdhury, and Miriam Leeser. Crush: Cognitive radio universal software hardware. In *Proceedings of the International Conference on Field Programmable Logic and Applications (FPL)*, pages 26–32, 2012.
- [167] Khanh Le, Prasanthi Maddala, Craig Gutterman, Kyle Soska, Aveek Dutta, Dola Saha, Peter Wolniansky, Dirk Grunwald, and Ivan Seskar. Cognitive radio kit framework: experimental platform for dynamic spectrum research. *ACM SIGMOBILE Mobile Computing and Communications Review*, 17(1):30–39, Jan 2013.
- [168] Kiarash Amiri, Yang Sun, Patrick Murphy, Chris Hunter, Joseph R Cavallaro, and Ashutosh Sabharwal. WARP, a unified wireless network testbed for education and research. In *Proceedings of the IEEE International Conference on Microelectronic Systems Education*, pages 53–54, 2007.
- [169] Jorg Lotze, Suhaib A. Fahmy, Juanjo Noguera, B. Ozgul, Linda E. Doyle, and Robert Esser. Development framework for implementing FPGA-based cognitive network nodes. In *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM)*, pages 1–7, 2009.
- [170] Shanker Shreejith, Bhaskar Banarjee, Kizheppatt Vipin, and Suhaib A Fahmy. Dynamic Cognitive Radios on the Xilinx Zynq Hybrid FPGA. In *Proceedings of the International Conference on Cognitive Radio Oriented Wireless Networks (CROWNCOM)*, pages 427—437, 2015.

- [171] S. Shreejith, A. Ambede, A. P. Vinod, and S. A. Fahmy. A Power and Time Efficient Radio Architecture for LDACS1 Air-to-Ground Communication. In *in Proc. IEEE Dig. Avion Syst. Conf*, pages 1–6, 2016.
- [172] Sinja Brandes and Michael Schnell. Mitigation of pulsed interference in ofdm based systems. In *Proc. 13th Int. OFDM Workshop*, pages 193–197, 2008.
- [173] Ulrich Epple and Michael Schnell. Overview of interference situation and mitigation techniques for ldacs1. In *in Proc. IEEE. Dig. Avion Syst. Conf.*, pages 4C5–1. IEEE, 2011.
- [174] Morris H DeGroot and Mark J Schervish. *Probability and statistics*. Pearson Education, 2012.
- [175] W. L. Chin, J. M. Li, and H. H. Chen. Low-complexity energy detection for spectrum sensing with random arrivals of primary users. *IEEE Trans. Veh. Technol.*, 65(2):947–952, Feb 2016.
- [176] J. Wang, Z. Chen, Y. Xu, Z. Song, and R. Chen. Spectrum sensing with random arrivals of primary users by using multiple antennas. In *2017 International Conference on Computer, Information and Telecommunication Systems (CITS)*, pages 190–194, July 2017.
- [177] . URL <https://www.ldacs.com/software/>.
- [178] S. Das and S. Mukhopadhyay. Soc fpga implementation of energy based co-operative spectrum sensing algorithm for cognitive radio. In *2015 6th International Conference on Computers and Devices for Communication (CODEC)*, pages 1–4, Dec 2015.
- [179] Thinh H Pham, Suhaib A. Fahmy, and Ian Vince McLoughlin. Low-Power Correlation for IEEE 802.16 OFDM Synchronization on FPGA. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, 21(8):1549–1553, 2013.
- [180] Kun-Wah Yip, Yik-Chung Wu, and Tung-Sang Ng. Design of multiplierless correlators for timing synchronization in IEEE 802.11 a wireless LANs. *IEEE Transactions on Consumer Electronics*, 49(1):107–114, 2003.
- [181] B. Ronak and S. A. Fahmy. Multi-pumping flexible DSP blocks for resource reduction on Xilinx FPGAs. *IEEE Transactions on Computer Aided Design of Integrated Circuits and Systems*, 36, 2017.

- [182] A. Ambede, A. P. Vinod, and A. S. Madhukumar. Design of a low complexity channel filter satisfying LDACS1 spectral mask specifications for air-to-ground communication. In *Proceedings of the Integrated Communications Navigation and Surveillance (ICNS) Conference*, pages 7E3:1–7, April 2016.
- [183] H. Jamal and D. W. Matolak. FBMC and L-DACS performance for future air-to-ground communication systems. *IEEE Trans. Veh. Technol.*, 66(6):5043–5055, June 2017.
- [184] D. W. Matolak and R. Sun. Air-ground channel characterization for unmanned aircraft systems—part i: Methods, measurements, and models for over-water settings. *IEEE Trans. Veh. Technol.*, 66(1):26–44, Jan 2017.
- [185] R. Sun and D. W. Matolak. Air-ground channel characterization for unmanned aircraft systems part ii: Hilly and mountainous settings. *IEEE Trans. Veh. Technol.*, 66(3):1913–1925, March 2017.
- [186] D. W. Matolak and R. Sun. Air-ground channel characterization for unmanned aircraft systems—part iii: The suburban and near-urban environments. *IEEE Trans. Veh. Technol.*, 66(8):6607–6618, Aug 2017.
- [187] R. Sun, D. W. Matolak, and W. Rayess. Air-ground channel characterization for unmanned aircraft systems—part iv: Airframe shadowing. *IEEE Trans. Veh. Technol.*, 66(9):7643–7652, Sep. 2017.
- [188] P Mohana Shankar. *Fading and shadowing in wireless systems*. Springer, 2017.
- [189] . URL <http://www.ldacs.com/software/>.
- [190] Libin K Mathew and AP Vinod. An energy-difference detection based spectrum sensing technique for improving the spectral efficiency of LDACS1 in aeronautical communications. In *in Proc. IEEE. Dig. Avion Syst. Conf*, pages 1–5. IEEE, 2016.
- [191] Seyede Mahya Safavi and Mahdi Shabany. A real-time, low-power implementation for high-resolution eigenvalue-based spectrum sensing. *Analog Integr. Circuits Signal Process.*, 77(3):437–447, 2013.
- [192] Rohit B Chaurasiya and Rahul Shrestha. Hardware-efficient and fast sensing-time maximum-minimum-eigenvalue-based spectrum sensor for cognitive radio network. *IEEE Trans. Circuits Syst. I, Reg. Papers*, 2019.

- [193] J. N. Laska, Z. Wen, W. Yin, and R. G. Baraniuk. Trust, but verify: Fast and accurate signal recovery from 1-bit compressive measurements. *IEEE Trans. Signal Process.*, 59(11):5289–5301, Nov 2011.
- [194] A. Ali and W. Hamouda. Low power wideband sensing for one-bit quantized cognitive radio systems. *IEEE Wireless Commun. Lett.*, 5(1):16–19, Feb 2016.
- [195] A. Ali and W. Hamouda. Power-efficient wideband spectrum sensing for cognitive radio systems. *IEEE Trans. Veh. Technol.*, 67(4):3269–3283, 2018.
- [196] S. Shreejith, L. K. Mathew, V. A. Prasad, and S. A. Fahmy. Efficient spectrum sensing for aeronautical Idacs using low-power correlators. *IEEE Trans. Very Large Scale Integr. (VLSI) Syst.*, 26(6):1183–1191, June 2018.
- [197] Ulrich Epple and Michael Schnell. Advanced blanking nonlinearity for mitigating impulsive interference in ofdm systems. *IEEE Trans. Veh. Technol.*, 66(1):146–158, 2016.
- [198] Giulio Bartoli, Romano Fantacci, Dania Marabissi, Luigia Micciullo, Claudio Armani, and Roberto Merlo. A novel mitigation scheme for jtids impulsive interference on Idacs system based on sensing and symbol retransmission. *Journal of Signal Processing Systems*, 73(3):255–266, 2013.
- [199] Ulrich Epple, Dmitriy Shutin, and Michael Schnell. Mitigation of impulsive frequency-selective interference in ofdm based systems. *IEEE Wirless Commun. Lett.*, 1(5):484–487, 2012.