ENERGY BASED SPECTRUM SENSING FOR ENABLING DYNAMIC SPECTRUM ACCESS IN COGNITIVE RADIOS

BY SAMSON SEQUEIRA

A thesis submitted to the
Graduate School—New Brunswick
Rutgers, The State University of New Jersey
in partial fulfillment of the requirements
for the degree of
Master of Science
Graduate Program in Electrical and Computer Engineering

Written under the direction of
Prof. Predrag Spasojevic

and approved by

New Brunswick, New Jersey
May, 2011
ABSTRACT OF THE THESIS

ENERGY BASED SPECTRUM SENSING FOR
ENABLING DYNAMIC SPECTRUM ACCESS IN
COGNITIVE RADIOS

by Samson Sequeira
Thesis Director: Prof. Predrag Spasojevic

Spectrum scarcity is increasingly becoming an obstacle for the implementation of new wireless technologies. On the contrary, recent studies have discovered considerable under-utilization of the allocated spectrum by the licensed users. This suggests that the solution to the problem is a transition from static spectrum allocation policies to dynamic spectrum access methodologies. This can be accomplished through the use of Cognitive Radio technology. Cognitive Radio is considered as an intelligent radio which is capable of altering its transmission or reception parameters in accordance to the radio environment and the network state to use the available spectrum optimally. Significant research efforts have furthered Cognitive Radios since the idea was first conceived by Joseph Mitola in 1998.

Cognitive Radio technology allows for the licensed spectrum of the primary users to be used on an opportunistic basis by unlicensed secondary users. A vital requirement of such an opportunistic scheme is that the licensed primary users be protected from detrimental interference from the secondary users while at the same time optimizing the performance for the secondary users. Thus the reliable detection of primary users offers better secondary system throughput via increased spectral efficiency in addition
to safeguarding the primary system.

Spectrum sensing is a technique used to detect the presence of primary users in the licensed spectrum. It is the estimation of the instantaneous occupancy of the frequency spectrum and is a key enabling factor for Cognitive Radios. Various techniques exist for performing spectrum sensing. In addition to primary user detection, spectrum sensing can also be employed for secondary detection and co-existence, interference analysis in multi-radio environments etc.

In this thesis we study adaptive spectrum sensing based on energy detection with a purpose of demonstrating Dynamic Spectrum Access. The major focus has been to evaluate algorithms that can allow for estimation of noise in the presence of the signal which is essential for energy detection based schemes. We also present the system level implementation and evaluation of a Dynamic Spectrum Access setup developed using the USRP2/GNU Radio platform on the ORBIT Wireless Testbed at WINLAB as part of the WINLAB-NEC Collaborative Cognitive Radio Project.
Acknowledgements

I would like to thank first and foremost my family for their unwavering support and encouragement throughout my graduate study. I would like to thank my advisor Prof. Predrag Spasojevic for his invaluable guidance and inspiration in my research. His advice as well as the numerous discussions we had, have helped me understand a lot of various topics and greatly benefitted my research. I would like to thank Prof. Dipankar Raychaudhuri and Prof. David Daut for being on my thesis committee.

I am grateful to all my friends here at WINLAB, without whom this experience would not have been the same. In particular I would like to thank Srinivas Pinagapany, Ashwin Revo and Abhishek Bindiganavile who were part of this research project. I would also like to thank the WINLAB staff for all the facilities and help in academic matters.

I would like to thank Masayuki Ariyoshi and Yasunori Futatsugi of System Platforms Research Labs, NEC Corporation, Japan for funding this project and providing valuable suggestions and guidance throughout the project.
# Table of Contents

Abstract ................................................................. ii

Acknowledgements ....................................................... iv

List of Tables ........................................................... viii

List of Figures ............................................................ ix

1. Introduction .......................................................... 1
   1.1. Background Overview ............................................. 1
   1.2. Cognitive Radio Technology ..................................... 2
   1.3. Software-Defined Radio ......................................... 3
       1.3.1. Functions of an SDR ....................................... 3
   1.4. Spectrum Sensing ................................................ 4
   1.5. Thesis Organization .............................................. 5

2. Signal Model and Energy Detection ................................. 6
   2.1. Signal Model .................................................... 6
       2.1.1. Wireless Microphone ..................................... 6
       Baseband Representation of the WM signal .................. 7
   2.2. Energy Detection ................................................ 7
       2.2.1. Fourier Analysis .......................................... 9
       2.2.2. Estimating the Power Spectral Density .................. 10
       Periodogram .................................................... 10
       Averaged Periodogram .......................................... 11
       2.2.3. Periodogram statistics evaluation ....................... 12
3. Noise Floor Estimation ........................................ 14
   3.1. Estimating the noise in the presence of the signal .......... 14
   3.2. Rank-Order Filtering ........................................ 15
      3.2.1. Rank-Order Filter .................................... 15
      3.2.2. ERODE and DILATE ................................. 16
      3.2.3. Algorithm ........................................... 16
   3.3. Akaike Information Criterion & Minimum Description Length .... 19
      3.3.1. Akaike Information Criteria (AIC) .................. 19
      3.3.2. Minimum Description Length (MDL) .................. 20
      3.3.3. Application of AIC and MDL for eigenvalue selection .... 20

4. Energy Based Spectrum Sensing .................................. 23
   4.1. Problem Formulation ....................................... 23
   4.2. Neyman-Pearson Criteria .................................. 24
   4.3. Results .................................................. 24

5. Dynamic Spectrum Access and GNU Radio Implementation ....... 27
   5.1. DSA Techniques .......................................... 27
   5.2. System Model ............................................ 28
      5.2.1. Top-level System Setup ............................. 28
      5.2.2. Functional Overview ................................ 29
   5.3. Experimentation Platform .................................. 31
      5.3.1. USRP .............................................. 31
      Features of USRP2 ....................................... 32
      5.3.2. GNU Radio ......................................... 32
      5.3.3. Orbit Wireless Testbed ............................. 33
   5.4. Spectrum Sensing Setup .................................... 33
   5.5. Interference Suppression ................................... 34
      Time Windowing ........................................... 35
      Carrier Cancellation ...................................... 36
5.6. GNU Radio/ USRP2 DSA setup ........................................... 37
5.7. Results ............................................................................. 38

6. Conclusions ......................................................................... 42
References ................................................................................ 43
List of Tables

2.1. Parameter values to simulate wireless microphone signal . . . . . . . . . 8
2.2. Parameter values for noise periodogram simulation . . . . . . . . . . . . 12
2.3. Mean and the Variance of the averaged periodogram of $w[n]$ . . . . . . 13
4.1. Simulation Setup for Sensing . . . . . . . . . . . . . . . . . . . . . . . 24
5.1. Secondary system setup . . . . . . . . . . . . . . . . . . . . . . . . . . . 37
List of Figures

1.1. Co-existing Primary and Secondary users ............................. 1
2.1. Signal Representation .................................................. 6
2.2. Block diagram of an energy detector ................................. 8
2.3. Averaged Periodogram of white noise $w[n]$ ......................... 13
3.1. Rank-order filter ...................................................... 15
3.2. Rank-order filtering Algorithm Implementation ..................... 16
3.3. PSD vector and kernel ............................................... 17
3.4. Example illustrating the ROF algorithm ............................. 17
3.5. Noise Floor Estimate using Rank-Order Filtering .................. 18
3.6. Rank-Order Filtering complexity .................................... 19
3.7. ROF performance as a function of iterations ....................... 20
3.8. Sorted PSD for AIC and MDL ....................................... 22
3.9. Choosing the eigenvalues for AIC and MDL ......................... 22
4.1. Performance of noise power estimation schemes .................... 25
4.2. MSE of the noise estimation schemes ............................... 25
5.1. Dynamic Spectrum Access Spectrogram (a) DSA using OFDM Secondary Transceiver. (b) DSA using NC-OFDM Secondary Transceiver. (c) DSA using Interference-Suppressed NC-OFDM Secondary Transceiver. .... 28
5.2. System Setup .......................................................... 29
5.3. Functional Overview .................................................. 30
5.4. USRP2 ............................................................... 32
5.5. Spectrum as observed on a USRP2 .................................. 34
5.6. GNU Radio flowgraph ................................................ 34
5.7. GNU Radio flowgraph ................................................ 35
5.8. Block diagram of IA-PFT based NC-OFDM transmitter ................. 35
5.9. TW operation on NC-OFDM symbols .................................. 36
5.10. Pulse shaped TW symbols .............................................. 36
5.11. CC symbols in frequency .............................................. 37
5.12. IA-PFT processed NC-OFDM symbol ............................... 37
5.13. Different Modes of the wireless microphone ......................... 38
5.14. Secondary system setup ............................................... 39
5.15. Spectrogram snapshot .................................................. 39
5.16. Spectrum shoing suppression in leakage ............................ 40
5.17. Suppression gain as a function of the secondary transmit power .... 40
5.18. BER vs. primary transmit power ...................................... 41
5.19. BER vs. secondary transmit power .................................... 41
Chapter 1
Introduction

1.1 Background Overview

Radio frequency spectrum is a valuable resource which is becoming scarce day by day. This scarcity can hinder the development of new and better wireless technologies. The spectrum allocation policies now existent, have led to an under-utilization of the available spectrum [1], [2]. Opportunistic access of the licensed spectrum by unlicensed devices is being considered as a potential solution to the spectrum scarcity problem. In this approach the secondary users will actively monitor the usage of the licensed spectrum and will occupy this spectrum as and when it becomes available. A key and stringent requirement in this is that the licensed users be protected from detrimental interference due to the unlicensed secondary users. The performance of the secondary users should also be optimized, since they do not have a dedicated time or frequency slot for spectrum access. They also have to overcome any interference that might be coming from the primary users. This scenario is highlighted in Figure 1.1.

Figure 1.1: Co-existing Primary and Secondary users
Spectrum sensing is a technique that is used to detect the presence of primary users in the licensed spectrum. It is one of the key enabling factors in Cognitive Radios. Various techniques like energy detection, matched filter detection, cyclostationary feature detection etc, have been considered in enabling secondary spectrum access.

In this thesis, we have considered power spectral density (PSD) based energy detection as the technique to perform spectrum sensing. Energy detection requires the knowledge of the noise power in the frequency band of interest. The actual noise power at any given time is not known and an estimate of the noise power has to be used. We have studied some algorithms that can be used in estimating the noise floor and have evaluated their performance. The performance of energy detection based on these noise floor estimates is also evaluated.

We have also developed a Dynamic Spectrum Access system as part of the WINLAB-NEC Collaborative Cognitive Radio Project. This implementation consists of adaptive spectrum sensing mechanism followed by dynamic secondary access realized using Non-Contiguous Orthogonal Frequency Division Multiplexing (NC-OFDM) [3]. Also we have implemented an interference suppression technique to protect the primary users as proposed in [20]. The system has been developed using the USRP2/GNU Radio platform [30], [29] on the Orbit wireless testbed at WINLAB, Rutgers University [31], [32]. We have evaluated the system to study the performance of the primary and secondary systems.

1.2 Cognitive Radio Technology

Cognitive Radio (CR) is defined as “a paradigm for wireless communication in which either the network or the wireless node itself changes particular transmission or reception parameters to execute its tasks efficiently without interfering with licensed users” [4]. This means that the cognitive radio must be able to sense the Radio Frequency (RF) spectrum as well as determine the state of the network so as to operate in an optimal way. Because of its capability to perform opportunistic spectrum access it is
proposed as the solution to the spectral scarcity problem. The concept of cognitive radios was first conceived by Joseph Mitola in 1998 [5], ever since significant research has been going on in making cognitive radios a practicality. The Software Defined Radio (SDR) is the core of cognitive radios and this is explained in the following section. The cognitive radio can be thought of as a ‘smart’ software defined radio.

1.3 Software-Defined Radio

A Software-Defined Radio is a communication device where components that are typically implemented using hardware are defined in software and realized via programmable hardware [6]. The implementation can be performed on general purpose computers or dedicated embedded systems. Some of the key characteristics of a SDR are multi-band antennas, wide-band RF converters, Digital-to-Analog Converters (DAC), Analog-to-Digital Converters (ADC) and a general purpose processor to manage signal processing. This makes a software defined radio ideal in implementing dynamic spectrum access since it can operate in a wide range of frequencies, realize various modulation and coding schemes. Software defined radios allow us to vary the transmission characteristics on-the-fly based on the current RF occupancy and the state of the network.

1.3.1 Functions of an SDR

The key functions of an ideal SDR can be classified as follows [7]:

- **Transmitting functions**
  - determining channel availability
  - evaluating the channel characteristics
  - adaptive channel modulation
  - dynamic setting of transmit frequency and power

- **Receiving functions**
  - diagnose the corresponding channel and adjacent channels
– identify the channel modulation
– adaptively estimate and equalize the channel impairments
– agile error detection and correction

1.4 Spectrum Sensing

Spectrum sensing is defined as “the art of performing measurements on a part of the spectrum and forming a decision related to spectrum usage based upon the measured data [11].” Spectrum sensing gives us the instantaneous occupancy of the spectrum. By knowing which part of the spectrum is unoccupied, we can use it to realize opportunistic spectrum, access while avoiding the occupied spectrum to prevent interfering with the primary users. Since the radio environment can change at any time it is required that the spectrum be sensed periodically so that the secondary users can back off from using the frequencies occupied by the primary users. Spectrum sensing increases spectral efficiency thereby increasing system throughput.

Spectrum sensing has been studied by the IEEE 802.22 working group for Wireless Regional Area Network (WRAN) [21]. While FCC in its most recent ruling has removed the mandatory sensing requirement for unlicensed devices in TV whitespaces, it mentions that spectrum sensing still remains a crucial factor in enabling efficient secondary access and would be considered for future unlicensed spectrum releases [13].

The methods to perform spectrum sensing are:

• **Energy Detection**

  Energy detection is the simplest of the methods since it does not require any prior information about the signal to be detected. Therefore it is independent of the signal and can be used to detect any signal. On the other hand energy detection cannot differentiate between signals. It senses the occupancy of a particular band of frequencies by comparing the energy in that band to a detection threshold. To set the detection threshold, energy detection requires the knowledge of the noise power in the band to be sensed.
• **Matched Filter Detection**

Matched filter detection is the most optimal detection technique. The filter is matched to the signal being detected, which means that prior knowledge of the signal is required. This technique can be applied only when we choose to detect specific signals, but is very accurate since it maximizes the $SNR$ for the signal.

• **Cyclostationary Feature Detection**

Cyclostationary feature detection also requires some knowledge of the type of signal to be detected. Modulated signals exhibit cyclostationary property. If the modulation of the signal is known beforehand this can be used in detecting the presence of the signal.

Spectrum sensing enabled Dynamic Spectrum Access can be used to realize newer wireless applications like emergency networks, high-powered wireless LANs, internet and TV backhaul etc.

### 1.5 Thesis Organization

Chapter 2 describes the signal model and introduces the type of signal to be detected. It explains energy detection and mentions its key characteristics. It also presents the methods used in estimating the Power Spectral Density(PSD) and gives a Fourier analysis on the periodogram.

In chapter 3 the need for estimating noise in the presence of the signal is explained. It presents the various algorithms that were used to estimate noise floor and provides evaluation results.

In chapter 4 the overall problem of spectrum sensing is formulated and evaluation results on this are provided.

In chapter 5 the functional description and system level implementation of the Dynamic Spectrum Access system developed are provided. The platform used for experimentation is also explained here.

Chapter 6 summarizes the results and provides some conclusions based on these results.
Chapter 2
Signal Model and Energy Detection

2.1 Signal Model

The received signal \( y(t) \), it is the sum of the transmitted signal \( x(t) \) and the Additive White Gaussian Noise (AWGN) \( w(t) \). Let \( N \) be the number of complex samples collected at the receiver. Then the received sampled signal can be represented as:

\[
    y[n] = x[n] + w[n]
\]  

(2.1)

This is illustrated in Figure 2.1.

![Signal Representation](image)

Figure 2.1: Signal Representation

2.1.1 Wireless Microphone

We consider the primary signal to be a Wireless Microphone (WM) signal. Wireless microphones typically use Frequency Modulation (FM) and have most of their power limited to a small portion of the bandwidth. The maximum bandwidth of the wireless microphone is 200 kHz as specified by the FCC in Part 74 of the Code of Federal Regulations [26]. In [25] various modes for simulating the wireless microphone are provided. The spectral plots for the various modes of the WM signal are given in
Chapter 5.

The different modes of the Wireless Microphone are:

- Loud Speaker mode
- Soft Speaker mode
- Silent mode

**Baseband Representation of the WM signal**

$x(t)$ is the wireless microphone signal, which is a frequency modulated signal.

The complex baseband representation of $x(t)$ is expressed as

$$\bar{g}(t) = g_I(t) + jg_Q(t)$$  

(2.2)

The real-valued signal $g(t)$ is given by:

$$g(t) = g_I(t)\cos(2\pi f_c t) - g_Q(t)\sin(2\pi f_c t)$$  

(2.3)

where $f_c$ is the frequency of the carrier signal, $g_I(t)$ and $g_Q(t)$ are the in-phase component and quadrature component of the signal respectively and are defined as:

$$g_I(t) = \cos(\beta \sin(\pi f_m t))g_Q(t) = \sin(\beta \sin(2\pi f_m t))$$  

(2.4)

where $\beta$ is the modulation index of the FM signal and is defined as:

$$\beta = \frac{\Delta f}{f_m}$$  

(2.5)

The parameters for the various modes of the wireless microphone are tabulated on Table 2.1.

### 2.2 Energy Detection

Energy detection is a technique used to detect the presence of unknown signals [16]. Therefore it is used in spectrum sensing to detect the occupancy of the Radio Frequency
Table 2.1: Parameter values to simulate wireless microphone signal

<table>
<thead>
<tr>
<th>Mode</th>
<th>Tone ($f_m$)</th>
<th>Frequency deviation ($\Delta f$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loud Speaker</td>
<td>13.4 kHz</td>
<td>+/- 5kHz</td>
</tr>
<tr>
<td>Soft Speaker</td>
<td>3.9 kHz</td>
<td>+/- 15kHz</td>
</tr>
<tr>
<td>Silent Speaker</td>
<td>32 kHz</td>
<td>+/- 32.6 kHz</td>
</tr>
</tbody>
</table>

spectrum. This technique is independent of the signals to be detected, therefore does not require prior knowledge of these signals. The energy in the band of interest is compared to a detection threshold to determine if this band is occupied or not. This requires the knowledge of the noise energy in the band to be sensed; based on this the detection threshold is calculated using Neyman-Pearson criteria.

Energy detection can be performed in time domain or frequency domain. In the time domain we calculate the energy directly from the samples obtained. Performing energy detection in the time domain would require channelizing the spectrum into frequency bands using filter-banks to identify which bands are occupied. Energy detection can similarly performed in the frequency domain by taking an FFT of the samples in time. The energy in both the domains is the same as proven by Parseval’s theorem. The FFT operation readily does channelizing by dividing the spectrum into subcarriers. Energy detection is performed in the frequency domain by taking the FFT of the samples and obtaining the power spectral density (PSD) of the signal. This average periodogram is used as the PSD estimate[14]. The block diagram of a frequency domain energy detector is shown in Figure 2.2.

The $N$ complex samples received are divided into $K$ segments, each of size $L$ which is the FFT length. An FFT operation is performed on each of the segments followed by a magnitude squaring operation. This output is averaged over all the $K$ segments to obtain the periodogram. Further analysis on this is given in Section 2.2.2.

![Figure 2.2: Block diagram of an energy detector](image)
2.2.1 Fourier Analysis

In this section we provide a Fourier analysis using complex representation. The noise is characterized as Additive White Gaussian (AWGN) and is represented as $w[n]$ of length $N$ complex samples.

\[ w[n] = w_R[n] + iw_I[n] \]  
(2.6)

It is zero-mean ($\mu_w = 0$) and has a variance $\sigma_w^2$. The probability distribution of $w[n]$ is expressed as:

\[ w_R[n] \sim N(0, \sigma_w^2/2) \]  
(2.7)

\[ w_I[n] \sim N(0, \sigma_w^2/2) \]  
(2.8)

\[ w[n] \sim N(0, \sigma_w^2) \]  
(2.9)

The Discrete Fourier Transform (DFT) of $w[n]$ is:

\[ W[k] = \sum_{n=0}^{N-1} w[n] e^{-\frac{2\pi}{N}kn} \quad k = 0, ..., N - 1 \]  
(2.10)

$W[k]$ is complex-valued and can be written as:

\[ W[k] = W_R[k] + iW_I[k] \]  
(2.11)

The mean and the variance are given by:

\[ \mu_{W_R} = \mu_{W_I} = 0 \]  
(2.12)

\[ \sigma_{W_R}^2 = \sigma_{W_I}^2 = \frac{N}{2} \sigma_w^2 \]  
(2.13)

The probability distribution of $W[k]$ can be expressed as:
\[ W_R[k] \sim N(0, \frac{N}{2} \sigma_w^2) \] (2.14)

\[ W_I[k] \sim N(0, \frac{N}{2} \sigma_w^2) \] (2.15)

\[ W[k] \sim N(0, N \sigma_w^2) \] (2.16)

The magnitude of \( W[k] \) is given by:

\[ |W[k]| = \sqrt{W_R^2[k] + W_I^2[k]} \] (2.17)

### 2.2.2 Estimating the Power Spectral Density

Power Spectral Density (PSD) is the power per unit of frequency as a function of the frequency [15]. Its unit is \( W/Hz \). Various methods exist for the estimation of the PSD. Here we consider the periodogram to estimate the PSD.

**Periodogram**

The periodogram of noise \( w[n] \) is:

\[ P_W[k] = \frac{1}{N} |W[k]|^2 \quad k = 0, ..., N - 1 \] (2.18)

The mean of \( P_W[k] \) is:

\[ \mu_{P_W} = \frac{1}{N} \left[ \frac{1}{N} \sum_{k=0}^{N-1} |W[k]|^2 \right] = \frac{1}{N} \left[ \sum_{n=0}^{N-1} |w[n]|^2 \right] = \sigma_w^2 \] (2.19)

The variance of \( P_W[k] \) is:

\[ \sigma_{P_W}^2 = E[P_W^2[k]] - E^2[P_W[k]] = \sigma_w^2 \] (2.20)

\[ \sigma_{P_W}^2 = \mu_{P_W}^2 = \sigma_w^2 E[P_W^2[k]] = E\left[ \frac{1}{N^2} (W_R^4[k] + W_I^4[k]) \right] = \frac{1}{N^2} E[W_R^4[k] + W_I^4[k] + 2W_R^2[k]W_I^2[k]] \] (2.21)
\[
\sigma_{PW}^2 = \frac{1}{N^2} \left[ E[W_R^4[k]] + E[W_I^4[k]] + 2E[W_R^2[k]]E[W_I^2[k]] \right]
\] (2.22)

We have shown that:
\[
E[W_R^2[k]] = \sigma_{W_R}^2 = \frac{N}{2} \sigma_w^2 \quad E[W_I^2[k]] = \sigma_{W_I}^2 = \frac{N}{2} \sigma_w^2
\] (2.23)

The fourth moment of a Gaussian random variable with distribution \(N(0, \sigma^2)\) is \(3\sigma^4\). Therefore we have:
\[
E[W_R^4[k]] = E[W_I^4[k]] = \frac{3N^2 \sigma_w^4}{4}
\] (2.24)

Substituting for each of the terms we obtain:
\[
E[P^2_W[k]] = \frac{1}{N^2} \left[ \frac{3N^2 \sigma_w^4}{4} + \frac{3N^2 \sigma_w^4}{4} + 2 \frac{N}{2} \sigma_w^2 \frac{N}{2} \sigma_w^2 \right] = \frac{8N^2 \sigma_w^4}{4N^2} = 2\sigma_w^4
\] (2.25)

Therefore we obtain the variance as:
\[
\sigma_{PW}^2 = 2\sigma_w^4 - \sigma_w^4 = \sigma_w^4
\] (2.26)

**Averaged Periodogram**

Averaged periodogram is obtained by averaging \(L\)-point DFT over \(K\) segments of data such that \(L \times K = N\). The averaged periodogram of noise is:
\[
PA_W[k] = \frac{1}{K} \sum_{m=0}^{K-1} P_{W_m}[k] \quad k = 0, \ldots, L - 1
\] (2.27)

\(P_{W_m}[k]\) is the periodogram of \(m^{th}\) segment of length \(L\) taken from \(w[n]\). This is given by:
\[
P_{W_m}[k] = \frac{1}{L} |W_m[k]|^2 \quad k = 0, \ldots, L - 1
\] (2.28)

\(W_m[k]\) is given by:
Table 2.2: Parameter values for noise periodogram simulation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of samples ($N$)</td>
<td>384000</td>
</tr>
<tr>
<td>FFT size ($N_{FFT}$)</td>
<td>256</td>
</tr>
<tr>
<td>Noise Power ($\sigma_w^2$)</td>
<td>1.5873W</td>
</tr>
<tr>
<td>Variance of $W[k]$ ($\sigma_W^2$)</td>
<td>6.0951e+005</td>
</tr>
</tbody>
</table>

\[ W_m[k] = \sum_{n=mL}^{(m+1)L-1} w[n] e^{-\frac{2\pi i}{L} kn} \quad k = 0, ..., L - 1 \quad (2.29) \]

The mean of $PA_W[k]$ is:

\[ \mu_{PA_W} = \frac{1}{L} \sum_{k=0}^{L-1} PA_W[k] = \frac{1}{L} \sum_{k=0}^{L-1} \frac{1}{K} \sum_{m=0}^{K-1} \frac{1}{L} |W_m[k]|^2 = \frac{1}{LK} \sum_{m=0}^{K-1} \frac{1}{L} \sum_{k=0}^{L-1} |W_m[k]|^2 \quad (2.30) \]

From Parseval’s theorem we obtain:

\[ \frac{1}{L} \sum_{k=0}^{L-1} |W_m[k]|^2 = \sum_{n=0}^{N-1} |w[n]|^2 = L\sigma_w^2 \quad (2.31) \]

Substituting this we get:

\[ \mu_{PA_W} = \frac{LK}{LK} \sum_{m=0}^{K-1} L\sigma_w^2 = \frac{LK}{LK} \frac{LK}{LK} \sigma_w^2 = \sigma_w^2 \quad (2.32) \]

The variance of $PA_W[k]$ is:

\[ \sigma_{PA_W}^2 = Var(PA_W[k]) = Var\left(\frac{1}{K} \sum_{m=0}^{K-1} P_W[k]\right) = \frac{1}{K^2} Var\left(\sum_{m=0}^{K-1} P_W[k]\right) = \frac{1}{K^2} \sum_{m=0}^{K-1} \sum_{w=0}^{4} \sigma_w^4 \quad (2.33) \]

2.2.3 Periodogram statistics evaluation

The periodogram estimate of the PSD was evaluated using MATLAB. The parameters used for simulation are given in Table 2.2.

Figure 2.3 shows the averaged periodogram of noise. From the averaged periodogram we estimate the mean and the variance of noise. The estimates are a close match to the actual values as shown in Table 2.2.3.
Figure 2.3: Averaged Periodogram of white noise $w[n]$

Table 2.3: Mean and the Variance of the averaged periodogram of $w[n]$

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Expression</th>
<th>Theoretical</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of the averaged periodogram ($\mu_{P_W}$)</td>
<td>$\sigma^2_w$</td>
<td>1.5873</td>
<td>1.5873</td>
</tr>
<tr>
<td>Variance of the averaged periodogram ($\sigma^2_{P_W}$)</td>
<td>$\frac{\sigma^4_w}{K}$</td>
<td>0.0015</td>
<td>0.0017</td>
</tr>
</tbody>
</table>

Once we have calculated the estimate of the Power Spectral Density we can carry out detection to identify the presence or absence of signals in the band of interest. This is explained in the Chapters 3 and 4.
Chapter 3

Noise Floor Estimation

Energy detection requires the knowledge of the noise power in the band of interest. The actual noise power at any given time is not known therefore an estimate of the noise has to be used. The performance of the energy detector depends on the estimate of the noise. In [19], the authors provide an analysis of how the performance of an energy detector reduces when an estimate of the noise power is used instead of the actual value. They also suggest techniques to improve performance in the case when the estimate is used.

3.1 Estimating the noise in the presence of the signal

Some papers have suggested the estimation of the noise power from some other reference band which is more likely to be vacant [19]. Other papers suggest that the noise power can be measured before the experiment by RF shielding the receiver and then the threshold of the radio be calibrated accordingly [22].

Reasons to estimate the noise in the presence of the signal

- Calibrating the device based on the noise power is an tedious process.

- In addition to this, it also requires taking the system offline which makes if infeasible in realistic scenarios.

- The noise floor of the receivers also drift with time due to thermal variations as well as aging of components.

- The noise floor at the receiver may not be flat across the whole spectrum due to filtering irregularities.
Therefore there is a need for real-time noise estimation schemes, that can assist in setting the detection threshold in practical scenarios. The estimation of the noise floor has to be performed in the presence of the signal. We consider techniques for noise estimation that do not assume downtime or vacant frequency bands.

The three techniques that we have considered are:

1. Rank-Order Filtering (ROF)
2. Akaike Information Criteria (AIC)
3. Minimum Description Length (MDL)

3.2 Rank-Order Filtering

The rank-order filtering technique uses an implementation based on rank-order filters. This approach is based on the method suggested in [12] which is influenced by morphological image processing. The authors use binary processing and suggest rank-order filtering as an alternative. It is motivated by the fact that we can “eyeball” a spectral plot and estimate the noise floor. This algorithm does that for us automatically.

3.2.1 Rank-Order Filter

A rank-order filter of rank \( m \) takes a vector of length \( N \) as the input and outputs the \( m^{th} \) smallest value in the vector and is denoted by \( R(N, m) \). This is illustrated in Figure 3.1 with an example.

![Figure 3.1: Rank-order filter](image-url)
3.2.2 ERODE and DILATE

The two fundamental operations to the rank-order filtering technique are ERODE and DILATE. The combination of first eroding a vector followed by dilating it, is called opening. The terms open, erode and dilate are obtained from the use of this technique for images known as morphological image processing. To erode a vector we pass it through a rank-order filter of rank 1 i.e. \( R(K,1) \), where \( K \) is the kernel size. Kernel is the segment of the PSD vector that is being operated by the rank-order filter at any given time. To dilate a vector we pass it through a rank-order filter of rank \( K \) i.e. \( R(K,K) \). The opening operation eliminates the spectral peaks in the PSD vector corresponding to the signals. Doing this iteratively transforms the original PSD vector into the desired noise floor vector.

3.2.3 Algorithm

Estimating the noise floor is done by processing the PSD vector using the rank-order filtering approach as illustrated in Figure 3.2. We start with an initial kernel size \( K = 2 \).

![Figure 3.2: Rank-order filtering Algorithm Implementation](image)

Each iteration consists of the following two procedures:

1. ERODE:

   (a) Place the kernel at the first frequency bin in the PSD vector as shown in
Figure 3.3: PSD vector and kernel

(b) Rank-order filter the bins corresponding to the kernel in the PSD vector with rank 1, i.e. $R(K, 1)$.

(c) Move the kernel by one bin position to the right.

(d) Repeat steps b) and c) until the kernel reaches the last bin in the vector.

2. DILATE:

(a) Place the kernel at the last frequency bin in the PSD vector.

(b) Rank-order filter the bins corresponding to the kernel in the PSD vector with rank $K$, $R(K, K)$.

(c) Move the kernel by one bin position to the left.

(d) Repeat steps b) and c) until the kernel reaches the first bin in the vector.

The algorithm execution has been illustrated in the example given in Figure 3.4.

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20</td>
<td>34</td>
<td>93</td>
<td>40</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>34</td>
<td>93</td>
<td>40</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>34</td>
<td>93</td>
<td>40</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>34</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>5</td>
<td>20</td>
<td>34</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>6</td>
<td>20</td>
<td>34</td>
<td>40</td>
<td>40</td>
</tr>
</tbody>
</table>

Figure 3.4: Example illustrating the ROF algorithm
At the end of the iteration the total power contained in the spectrum i.e. sum of powers in all bins, is compared to the total power contained at the end of the earlier iteration. If the percentage change in the total power is less than \( \epsilon \) we increment the value of \( K \) by 1 and repeat the procedures, else the algorithm is terminated and the PSD vector now reflects the noise floor.

The estimation of the noise floor from the power spectral density is shown in Figure 3.5. We can see that the Rank-order filtering algorithm is tracking the lower edge of the PSD. From simulations we have found that the noise floor estimate obtained from this algorithm is approximately \( \alpha \sigma_{PSD} \) less than the expected, where \( \sigma_{PSD} \) is the standard deviation of the PSD. The parameter \( \alpha \) has found to be approximately equal to 1.42.

![Power Spectral Density](image)

**Figure 3.5:** Noise Floor Estimate using Rank-Order Filtering

We have evaluated the complexity of the algorithm in terms of number of iterations required to estimate the noise floor for the three different modes of the wireless microphone. This is shown in Figure 3.6.

The output of the algorithm as a function of the number of iterations is illustrated in Figure 3.7.
3.3 Akaike Information Criterion & Minimum Description Length

Information theoretic criteria based methods are used in model selection problems. A well known application in the field of signal processing, where such techniques are used is, to detect the number of significant eigenvalues is a signal representation. We study two such techniques and apply it to the problem of detecting spectral occupancy. These techniques allow us to automatically estimate the spectrum since they do not require any subjective approach [18].

3.3.1 Akaike Information Criteria (AIC)

The Akaike Information Criteria (AIC) is a model selection technique proposed by Hirotugu Akaike [8]. From a set of possible models it tries to find the model that best fits the data. The AIC method chooses the model that gives the minimum value for $AIC$, defined by:

$$AIC = -2\log(f(X|\hat{\Theta})) + 2k$$

where $X = x(1), ..., x(N)$ is a set of $N$ observations, $f(X|\hat{\Theta})$ is a set of probability densities that parameterize a family of models, and $k$ is the number of free adjusted parameters.
Figure 3.7: ROF performance as a function of iterations

3.3.2 Minimum Description Length (MDL)

The Minimum Description Length (MDL) also is a model selection technique. It was proposed by Schwartz and Rissanen [9], [10]. It selects the best model based on the criteria of minimum code length. It chooses the model that gives the least value for $MDL$ as defined by:

$$MDL = -\log(f(X|\hat{\Theta})) + \frac{1}{2}k\log N$$ (3.2)

where $X = x(1),...,x(N)$ is a set of $N$ observations, $f(X|\hat{\Theta})$ is a set of probability densities that parameterize a family of models, and $k$ is the number of free adjusted parameters.

3.3.3 Application of AIC and MDL for eigenvalue selection

The application of AIC and MDL techniques to select the most relevant eigenvalues from a set of eigenvalues is given in [17],[18]. The expressions for computing AIC and MDL, derived from their respective criteria will be:

$$AIC(k) = (N - k)L \log(\alpha(k)) + k(2N - k)$$ (3.3)
\[ MDL(k) = (N - k)L \log(\alpha(k)) + k/2(2N - k) \log(L) \quad (3.4) \]

\( N \) is the total number of eigenvalues; \( k \) is the number of eigenvalues which are assumed to correspond to the signal in the \( k^{th} \) model; \( L \) is the number of data samples used in estimating the eigenvalues. \( \alpha(k) \) is defined as:

\[ \alpha(k) = \frac{\left( \frac{\sum_{i=k+1}^{N} \lambda_i}{N-k} \right)^{1/N}}{\left( \frac{\prod_{i=k+1}^{N} \lambda_i}{N-k} \right)^{1/N}} \quad (3.5) \]

We consider the power values corresponding to the frequency bins in the periodogram to be the eigenvalues. The eigenvectors in this case form the FFT matrix which corresponds to sinusoidal basis functions. Each data sample is a realization of the periodogram which are averaged to obtain the averaged periodogram. Therefore the model now corresponds to:

- \( N \) - FFT size; the total number of frequency bins
- \( k \) - number of frequency bins assumed to correspond to the signal in the \( k^{th} \) model
- \( L \) - number of segments over which the periodogram is averaged
- \( P_y[k] \) - periodogram sorted in the descending order, where \( k = 0, 1, \ldots, N - 1 \)

The frequency bins in the sorted periodogram up to the bin that corresponds to the minimum value of either AIC or MDL are considered to be containing the signal. We take the mean of the remaining frequency bins to obtain the estimate of the noise power. This is illustrated in Figures 3.8 and 3.9.

In chapter 4 we use the noise floor estimates given by these algorithms to set the detection threshold for energy detection. The performance of these techniques in terms of probability of detection is provided.
Figure 3.8: Sorted PSD for AIC and MDL

Figure 3.9: Choosing the eigenvalues for AIC and MDL
Chapter 4
Energy Based Spectrum Sensing

4.1 Problem Formulation

The problem of energy detection can be formulated as a hypothesis testing problem[22],[16].
The aim is to detect the presence or absence of a signal in low SNR regimes.

\[ H_0 : y[n] = w[n] \]  
(4.1)

\[ H_1 : y[n] = x[n] + w[n] \]  
(4.2)

\( H_0 \) corresponds to the case where only noise (AWGN is present) and \( H_1 \) corresponds to the case where the signal is present along with noise. We can define the \( SNR \) as follows:

\[ SNR = \frac{\sigma_x^2}{\sigma_w^2} \]  
(4.3)

\( \sigma_x^2 \) is the signal power and \( \sigma_w^2 \) is the noise power.

Periodogram

The averaged periodogram of the signal \( y[n] \) is:

\[ PA[k] = \frac{1}{K} \sum_{m=0}^{K-1} \frac{1}{L} \sum_{n=0}^{L-1} y_m[n] e^{-2\pi i kn} |^2 \quad k = 0, ..., L - 1 \]  
(4.4)

For hypothesis \( H_0 \), we know that the mean of the periodogram is \( \sigma_w^2 \) and the variance is \( \frac{\sigma^4}{K} \). Invoking the Central Limit Theorem (CLT) we assume power of each frequency bin to be \( N \sim (\sigma_x^2, \frac{\sigma^4}{K}) \).

Test Statistic
The test statistic for each frequency bin \(k\) is:

\[
T(k) = \frac{1}{K} \sum_{m=0}^{K-1} \frac{1}{L} |Y_m[k]|^2 \quad k = 0, ..., L - 1
\]  

(4.5)

### 4.2 Neyman-Pearson Criteria

The detection is performed on the basis of a Constant False Alarm Rate (CFAR). The Neyman-Pearson technique provides a threshold for detection subject to a constant probability of false alarm \(p_{fa}\).

\(\gamma\) is the detection threshold which is defined as:

\[
\gamma = Q\left(\frac{T - \sigma_y^2}{\sqrt{\frac{\sigma_y^4}{K}}}ight)
\]

(4.6)

The detection rule now becomes:

\[
T < \gamma \quad H_0 : \text{Frequency bin vacant}
\]  

(4.7)

\[
T > \gamma \quad H_1 : \text{Frequency bin occupied}
\]  

(4.8)

### 4.3 Results

The performance of the energy detection scheme is evaluated. We perform detection on a per Resource Block (RB) basis. A resource block is defined as a set of frequency bins allocated to a user for a fixed duration. The primary signal detected here is a wireless microphone signal in the loud mode. The simulation setup is given in Table 4.3:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth scanned</td>
<td>3.84 MHz</td>
</tr>
<tr>
<td>FFT size</td>
<td>256</td>
</tr>
<tr>
<td>Resource Block (RB) bandwidth</td>
<td>240 kHz</td>
</tr>
<tr>
<td>No. of RBs sensed</td>
<td>16</td>
</tr>
<tr>
<td>No. of frequency bins in each RB</td>
<td>16</td>
</tr>
<tr>
<td>Bin resolution</td>
<td>15 kHz</td>
</tr>
</tbody>
</table>
Figure 4.1: Performance of noise power estimation schemes

Figure 4.1 shows the probability of miss as a function of the SNR for the 3 noise floor estimation schemes. This is compared to that of an ideal energy detection scheme i.e. assuming that the true noise power at the receiver is known. The AIC and the MDL perform close to the theoretical energy detection, while the ROF scheme’s performance is slightly off. This is due to the fact the ROF scheme tracks the lower edge of the noise floor and this has to adjusted.

Figure 4.2: MSE of the noise estimation schemes

The accuracy of the estimate is also a function of the bandwidth. The Mean Square Error (MSE) of the estimates is shown in Figure 4.2.
We see that the noise floor estimation techniques considered give a fairly good estimated of the noise power and can be used to perform energy based spectrum sensing in realistic scenarios.
Dynamic Spectrum Access (DSA) involves the opportunistic access of the spectrum based on the current occupancy of the RF spectrum. This approach requires that the incumbent primary users be protected from detrimental interference from the opportunistic secondary users. A parallel problem in this scenario is that the secondary users must also be assured of some quality of service since they do not have a dedicated bandwidth and have to overcome the interference from the primary users. To address this issue we have developed an adaptive sense-and-carefully-transmit system∗ that detects the presence of primary users and provides opportunistic access to secondary users in the vacant frequencies. An adaptive spectrum sensing scheme which uses a frequency dependent detection threshold is used to detect the primary users. The result of sensing is provided to the secondary transmission scheme. The secondary system is a NC-OFDM transceiver that dynamically adapts its transmission characteristics to reflect the most recently sensed result thereby avoiding interference to the primary users.

5.1 DSA Techniques

Our objective here was to experimentally evaluate various types of DSA techniques as illustrated in Figure 5.1 to achieve better spectral utilization.

The most basic approach is to have no secondary transmission when a primary user is detected and transmit using OFDM when the primary user is not detected. This

∗This implementation was performed as part of the WINLAB-NEC COllaborative Cognitive Radio project and is joint work with Srinivas Pinagapany
would cause minimal interference to the primary user. In some cases the primary user is narrow-band, and avoiding secondary transmission completely would lead to inefficient use of spectrum and poor secondary performance. These issues can be overcome by employing NC-OFDM transmission. When primary users are detected in the bandwidth of interest, the NC-OFDM sub-carriers corresponding to the frequencies of the primary users as well as few adjacent ones are deactivated i.e. turned OFF for transmission. This approach while increasing the efficiency of secondary spectrum access would cause interference to the primary users due to spectral leakage. For the third technique in addition to the non-contiguous secondary operation we employ advanced interference avoidance. The problem of spectral leakage is diminished by the use of time windowing and cancelation carrier schemes which result in maximum side-lobe suppression.

5.2 System Model

5.2.1 Top-level System Setup

The system has the following three main functional units as shown in Figure 5.2:
1. Primary transmitter

The primary transmitter in our system is a wireless microphone signal which has been emulated using a Vector Signal Generator (VSG).

2. Secondary Transmitter

   (a) Spectrum Sensing Module

       The spectrum sensing technique used is energy detection based on ROF noise floor estimation.

   (b) NC-OFDM Transmitter with interference avoidance capability

       Non-Contiguous OFDM (NC-OFDM) is used to realize the secondary system.

3. Monitoring Node

   This is used to observe the RF spectrum of the primary and the secondary systems.

5.2.2 Functional Overview

Figure 5.3(a) illustrates the functional aspect of our experimental system. The process begins with sensing the desired spectrum to determine if the primary transmitter is ON and its spectrum information i.e. carrier frequency and bandwidth. Spectrum sensing is done using a power spectral density based detector that operates using an adaptive threshold. This adaptive threshold is calculated based on the automatic estimation
of the instantaneous noise floor achieved by means of rank-order filtering algorithm. During this period of sensing the secondary does not employ any transmissions since it is in reception mode and hence it is referred to as the quiet period. The quiet period involves time taken to collect samples and process these samples to arrive at a decision regarding the presence of the primary transmitter. If the primary transmitter is not detected, we proceed with OFDM transmission which occupies the entire bandwidth of interest. If a primary transmitter is detected we employ NC-OFDM transmission which has subcarriers deactivated at those frequencies occupied by the primary transmitter as illustrated in Figure 5.3(b). In both these cases the secondary system transmits for a predetermined period of time, after which it again enters the quiet period. This cyclic operation continues for the whole duration of time that the secondary system is
in operation.

Choosing the duration of the secondary transmission is a key design issue. It should depend on the type of primary transmission. The primary transmission could be continuous or intermittent depending on the type of application. If the secondary transmission duration chosen is too long then there are chances that the primary transmitter might come ON during this period. On the other hand if this duration is too short the secondary system would spend a larger fraction of time in the sensing operation thereby not achieving maximum efficiency possible.

5.3 Experimentation Platform

This section describes the platform used in the implementation of the project.

5.3.1 USRP

The Universal Software Radio Peripheral (USRP) is a low cost software radio device developed by Ettus Research [30]. It is a open-source hardware unit which allows for flexible and easy implementation of most communication systems.

The USRP can be controlled via a personal computer which acts as the host machine using GNU Radio which is a open-source software. More details about the GNU Radio software are given in section 5.3.2. High sample rate processing, like digital up- and down conversion is performed in the FPGA while rest of signal processing is implemented in C++/Python on the host machine.

The first version of the USRP (called USRP1) connects to the host computer via a USB interface and can handle up to 16MHz of bandwidth. The USRP2 (shown in Figure 5.4) is an improved version which uses a Gigabit Ethernet interface to communicate with the host computer and can handle a maximum bandwidth of 50MHz.

The USRP devices can be used with interchangeable daughterboards. The different daughterboards operate in different frequency bands and provide the RF front-end for communication in the desired part of the spectrum. In our experiments we have used the XCVR2450 which operates in the 2.4GHz and 5GHz ISM bands.
Features of USRP2

The key features of USRP2 are [30]:

- Two 100 MS/s 14-bit analog to digital converters
- Two 400 MS/s 16-bit digital to analog converters
- Digital downconverters with programmable decimation rates
- Digital upconverters with programmable interpolation rates
- Gigabit Ethernet Interface
- 2 Gbps high-speed serial interface for expansion
- Capable of processing signals up to 100 MHz wide
- Modular architecture supports a wide variety of RF daughterboards
- Auxiliary analog and digital I/O support complex radio controls such as RSSI and AGC

5.3.2 GNU Radio

GNU Radio is an open-source software that allows for the implementation of SDRs using low-cost RF hardware like the USRP [29]. GNU Radio provides the signal processing framework which allows for the creation of reconfigurable radios.
GNU Radio applications are written using Python and C++. The performance critical signal processing blocks are implemented in C++. Python is used to "glue" i.e. connect the signal processing blocks together depending on the target application. This interconnection of signal processing blocks constitutes a Python flowgraph.

GNU Radio along with USRP provides a easy-to-use platform on which real-time applications can be programmed and tested.

5.3.3 Orbit Wireless Testbed

ORBIT is a wireless testbed at Wireless Information Network Laboratory (WINLAB), Rutgers University used to emulate and evaluate wireless protocols and applications [31],[32]. It primarily consists of 400 nodes with attached with several types of radios to facilitate various wireless experiments. Among these there are a several USRP devices which can be used to perform experiments pertaining to the physical layer.

In this thesis we have used the USRP/GNU radio platform available in ORBIT to demonstrate Dynamic Spectrum Access (DSA) and also to verify real-time performance of the proposed techniques.

5.4 Spectrum Sensing Setup

We have implemented an adaptive sensing scheme based on the ROF technique described earlier. This method can adapt to changes over time as well as frequency dependent noise floor. The noise floor as perceived by the receiver is usually non-flat with tapering at the edges, due to filtering irregularities. As as example the spectrum as observed from the samples collected on the USRP2 is shown is figure 5.5.

The GNU Radio flowgraph of the spectrum sensing module is shown in figure 5.6.

An example snapshot of the noise floor estimate as given by the ROF technique implemented in GNU Radio is shown in figure 5.7.
5.5 Interference Suppression

NC-OFDM is used for the secondary system to provide dynamic spectrum access. The subcarriers corresponding to the primary’s frequencies are deactivated to create a notch around the primary’s transmission. In spite of this there is spectral leakage into the notch. The Interference Avoidance by Partitioned Frequency Time (IA-PFT) technique provides additional suppression in the spectral notch.

In the IA-PFT technique process the information symbols in two streams namely, TW and CC as shown in Figure 5.8. These two streams are generated by TW mapper and CC mapper blocks which use the carrier-mask to determine the position of the notch. Once the notch is determined, the TW mapper deactivates 10 sub-carriers on either side of the notch and sends the symbols with remaining sub-carriers for TW processing. The CC mapper generates a symbol stream with complementary sub-carrier map having only the 10 sub-carriers on the edges of the notch. These two streams are then processed separately as explained in the following subsections:
Time Windowing

Time windowing involves pulse shaping the NC-OFDM symbols with a raised cosine filter. Before shaping, an IFFT operation is performed on the modulated symbols. A cyclic prefix and a tail are added to the symbols as shown in Figure . The cyclic prefix is generated from the trailing part of the NC-OFDM symbols whereas the tail is generated by copying the symbols from the leading part of the NC-OFDM symbols.

The symbols are shaped with a raised cosine type filter and the tail from the current symbol is added to cyclic prefix of the next symbol as shown in Figure 5.10(a).

The tail of the current OFDM symbol is then discarded to generate the time window processed symbol stream as shown in Figure 5.10(b).
Figure 5.9: TW operation on NC-OFDM symbols

![TW operation on NC-OFDM symbols diagram](image)

Figure 5.10: Pulse shaped TW symbols

![Pulse shaped TW symbols diagram](image)

**Carrier Cancelation**

Two CC tones are added at the extreme ends of the notch, as shown in Figure 5.11, to cancel the interference due to the 10 active sub-carriers next to the edges of the notch. To calculate the strength of the CC tones we first generate the Inter-Carrier Interference matrix $\mathbf{W}$. The matrix $\mathbf{W}$ is pre-calculated using the size of the NC-OFDM symbols ($N_{FFT}$). Depending on the position of notched sub-carriers, we select a sub-matrix of $\mathbf{W}$ called $\tilde{\mathbf{W}}$ to calculate the CC tones to be inserted. The CC tone vector $\mathbf{h}'$ is given by,

$$
\mathbf{h}' = \tilde{\mathbf{W}}' \mathbf{X}
$$

where,

- $\tilde{\mathbf{W}}' = $ Sub-matrix of $\mathbf{W}'$
- $\mathbf{X} = $ Input symbol vector used for calculating CC tones

IFFT is performed over the CC symbols to generate the lower NC-OFDM symbol stream in Figure 5.11. In this stream, only the CC tones and the sub-carriers needed to calculate CC are active. As a result, the TW and CC streams are complementary in nature. The CC processed NC-OFDM symbols are zero padded to match the length of the TW processed symbols.

The subcarriers from TW and CC are combined together to obtain the IA-PFT processed NC-OFDM symbols. This is highlighted in figure 5.12.
5.6 GNU Radio/ USRP2 DSA setup

The primary signal is a wireless microphone signal transmitted via a Vector Signal Generator (VSG). Various modes of the wireless microphone (refer chapter 2) were simulated in MATLAB and the baseband samples were transmitted using the VSG at the desired transmit power and frequency. The spectra of these modes as observed on a spectrum analyzer are shown in Figure 5.13.

We have also evaluated the performance of the primary system in the presence of regular OFDM and IA-PFT enabled NC-OFDM. For this we considered a packet based system, with GMSK modulation and bandwidth of 180kHz.

The secondary system setup was based on the LTE [28] specifications. This is tabulated in the table 5.1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Bandwidth</td>
<td>3.84 MHz</td>
</tr>
<tr>
<td>FFT size</td>
<td>256</td>
</tr>
<tr>
<td>RB size</td>
<td>12</td>
</tr>
<tr>
<td>Number of RBs</td>
<td>12</td>
</tr>
<tr>
<td>Occupied Bandwidth</td>
<td>2.16 MHz</td>
</tr>
</tbody>
</table>

This is illustrated in figure 5.14. An example snapshot of the spectrogram is given in figure 5.15. Here RB3 is occupied by the primary signal. In addition to this RB RB2 and RB4 are also notched out.
5.7 Results

The secondary spectrum was measured through over-the-air experiments using GNU Radio / USRP2. Figure 5.16 shows the spectrum of the regular NC-OFDM and IA-PFT based NC-OFDM as compared to the AWGN noise floor. The IA-PFT technique achieves about 10 dB additional suppression in the notch when compared to regular NC-OFDM.

Figure 5.17 shows the suppression in a RB(180 kHz) as a function of the secondary transmit power. At higher secondary powers we cannot see gain through suppression due to the saturation of the amplifier.

Figure 5.18 shows the BER performance of the regular NC-OFDM and IA-PFT based NC-OFDM with varying primary transmit power. We can see there is about 10 dB performance gain for the IA-PFT as a direct consequence of the additional suppression.

Figure 5.18 shows the BER performance of the regular NC-OFDM and IA-PFT
based NC-OFDM with varying secondary transmit power. We can see there is about 10 dB performance gain for the IA-PFT as a direct consequence of the additional suppression.
Figure 5.16: Spectrum showing suppression in leakage

Figure 5.17: Suppression gain as a function of the secondary transmit power
Figure 5.18: BER vs. primary transmit power

Figure 5.19: BER vs. secondary transmit power
Chapter 6
Conclusions

• The thesis explores the topic of Spectrum Sensing for Cognitive Radios and also discusses Dynamic Spectrum Access.

• The energy detection technique for spectrum sensing has been studied.

• The following algorithms have been applied for noise floor estimation and their performance is evaluated.
  – Rank-Order Filtering
  – Akaike Information Criteria
  – Minimum Description Length

• Energy detection based on the estimates of the noise floor is analyzed and its performance is found to be close to that of theoretical energy detection.

• Spectrum sensing based on Rank-order filtering technique is implemented on the GNU Radio/ USRP2 platform. This has been integrated with the DSA setup

• IA-PFT technique for interference suppression has been implemented on the GNU Radio/ USRP2 platform. Its performance has been evaluated through over-the-air experiments, and this is found to be in close match to the simulation results given in the literature

• The performance of a primary system is evaluated in the presence of a secondary system with both interference suppression technique enabled and disabled. The performance gain with interference suppression is characterized.
References


[26] FCC 47 CFR, Part 74, Subpart H  *Low Power Auxiliary Stations*

[27] 3GPP, TS 36.211 (V9.1.0)  *Physical channels and modulation*  March 2010

[28] Dr. Wes McCoy  *Overview of the 3GPP Long Term Evolution Physical Layer*


[31] *ORBIT, Wireless Testbed*  http://www.orbit-lab.org

[32] *WINLAB, Rutgers University, NJ*  http://www.winlab.rutgers.edu