IMPROVING THE PERFORMANCE OF COGNITIVE RADIO USING THE CONCEPT OF WAVELETS

Akshay Dhawan, 071032
Ravi Anand, 071125
Shefali Arora, 071109

under the Supervision of

Dr. Ghanshyam Singh, ECE

May-2011

Project Report submitted in partial fulfillment of the requirement
for the degree of
Bachelor of Technology

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY, WAKNAGHAT

"The only way of finding the limits of the possible is by going beyond them into the impossible."

-Arthur C. Clarke

"To climb steep hills requires a slow pace at first."

Contents

Certificate from Supervisor

This is to certify that project report entitled as **"Improving the performance of Cognitive Radio using the concept of Wavelets"**, submitted by *Akshay Dhawan (071032)*, *Ravi Anand (071125)* and *Shefali Arora (071109)* in partial fulfillment for the award of degree of Bachelor of Technology in Electronics and Communication Engineering to **Jaypee University of Information Technology, Waknaghat** has been carried out under my supervision. This work has not been submitted partially or fully to any other University or Institute for the award of this or any other degree or diploma.

Dr. Ghanshyam Singh
Associate Professor
Deptt. of ECE

It is certified that this work has not been submitted partially or fully to any other University or Institute for the award of this or any other degree or diploma.

Akshay Dhawan (071032)
Ravi Anand (071125)
Shefali Arora (071109)

Acknowledgement

First and foremost, we thank the Lord by whose grace we have been able to conclude the project. We look back to express our immense sense of gratitude; for all the help, guidance and support they lent us, throughout the course of our endeavor. We thank laudable Dr. Ghanshyam Singh, our advisor, who has always encouraged us to put in our best efforts and deliver a quality and professional output. His methodology of working over the basics and laying a strong foundation has taught us that output is not the END of project. We really thank him for his time and efforts.

Secondly, we thank our panel Dr. D.S. Saini, Vipin Balyan and Md. Wajid for their patient hearing of our ideas and opening up our minds to newer horizons by pointing out our flaws, providing critical comments and suggestions to improve the quality of our work and appreciating our efforts.
It is a pleasure to Mr. Kamlesh Shrivastava for guiding us throughout our lab work and providing us an immense support.

Finally, and most importantly, we thank our families. They have been present through every step of our life, providing support in difficult times. They have been a constant source of inspiration, and this thesis is dedicated to them.

(Akshay Dhawan) (Ravi Anand) (Shefali Arora)

List of Figures

List of Acronyms

AI- Artificial Intelligence
CPU- Central Processing Unit
CR - Cognitive Radio
CWT- Continuous Wavelet Transform
DWT- Discrete Wavelet Transform
FCC- Federal Communications Commission
FFT- Fast Fourier Transform
FT- Fourier Transform
MAC- Media Access Control
MF- Matched Filter
NTIA- National Telecommunications and Information Administration
PSD- Power Spectral Density
PU- Primary User
QoS- Quality of Service
RF- Radio Frequency
SDR- Software Defined Radio
SNR- Signal to Noise Ratio
STFT- Short Term Fourier Transform
SU- Secondary User
WRAN- Wireless Regional Area Networks

Abstract

Wavelets and *cognitive radio* are two of the most important approaches that are shaping the future of wireless communication systems. At a first glance, wavelets and cognitive radio do not seem to be overlapping significantly; however, there is a strong synergy between the capabilities of wavelets and the goals of cognitive radio. One of the objectives of this thesis is to shed light on the significance of merger of these two important concepts. Cognitive radio is a software radio aware of its operational environment (radio spectrum) and capabilities. It has been widely recognized that utilization of radio spectrum by licensed wireless systems, e.g. TV broadcasting, aeronautical and military purposes is quite low. In particular, at any given time and spatial region, there are frequency bands where there is no signal occupancy. There has been recent interest in improving spectrum utilization by permitting secondary usage using cognitive radios. Wavelets are relatively recent development in applied mathematics. In the last ten years, interest in them has grown explosively. Wavelets are simple mathematical tool with a great variety of applications. Cognitive radios use spectrum sensing to determine frequency bands that are vacant of licensed signal transmissions and transmit on such portions to meet regulatory constraints of avoiding harmful interference to licensed systems. Future cognitive radios will be capable of scanning a wide band of frequencies, of the order in GHz, and employ adaptive waveforms for transmission depending on the estimated spectrum of licensed systems. They would also be able to decide the various parameters that are required for transmission of a signal such as maximum output power, type of waveform, modulation type and frequency range; while at the receiver denoise the signal. In this thesis, the implementation of cognitive radio has been ignited. It is aimed to emphasize that rigid, coarse spectrum allocation would be history for cognitive radio, wavelets when combined with cognitive radio would increase spectral efficiency and move to a demand based approach in order to maximize the performance of unlicensed communications.

Chapter 1

Introduction

In this thesis, we consider the problem of signal denoising using various methods and spectrum sensing for cognitive radio applications and present a new approach based on wavelets for spectrum sensing. The purpose of this chapter is to introduce the problem addressed in the thesis, motivate the need for a new approach, and describe the relationship of wavelets with cognitive radio and how it acts as a powerful tool in increasing its performance.

1.1 Motivation

The development of wireless technologies has rapidly increased the demand for spectrum resources. However, most of the spectrum has already been allocated to licensed users or primary users(PU), especially in the frequency below a few GHz. The *National Telecommunications and Information Administration's* (NTIA) frequency allocation chart in the United States indicates overlapping allocations over all of the frequency bands [1], which reinforces the scarcity mindset. Under this static frequency allocation for wireless systems are regulated through spectrum assignments, operating frequencies and bandwidths, with constraints on power emission that limits their range. Due to these constraints, most communications systems are designed so that they achieve the best possible spectrum efficiency within the assigned bandwidth using sophisticated modulation, coding, multiple antennas and other techniques. While the current spectrum allocation leaves no available bandwidth for future wireless systems, actual measurements of spectrum utilization shows that many assigned bands are not being used at every location and time. A greater percentage of the spectrum is available at higher frequencies.
Studies carried out by the *Federal Communications Commission*(FCC) Spec-

trum Policy Task Force reported the vast temporal and geographic variations in the usage of allocated spectrum with utilization ranging from 15% to 85% [2]. A recent study conducted by *Shared Spectrum* [3] shows that the average spectrum occupancy in the frequency band from 30 MHz to 3000 MHz over multiple locations is merely 5.2%. The maximum occupancy is about 13% in New York city. These measurements seriously question the suitability of the current regulatory regime and possibly provide the opportunity to solve the spectrum bottleneck. Unfortunately, creating a new spectrum allocation chart based on the usage distribution is not only impractical but also inefficient, because it is not possible to predict and optimize an allocation that would suit all current and future wireless systems. Furthermore, any change in the spectrum allocation could create an opposition from the current users/owners of the spectrum. Therefore, the solution to this problem should preserve rights and access priorities of primary users. In order to solve the conflicts between spectrum scarcity and spectrum under utilization, cognitive radio (CR) technology was recently proposed [4]. In IEEE 802.22, the CR technique is introduced for the standardization of *wireless regional area networks* (WRAN) to use frequency resources, which were originally allocated for broadcasting (54 - 862 MHz). In [5] a CR is designed as an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environmental 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 type) in real-time, with two primary objectives in mind:

(i) highly reliable communications whenever and wherever needed.

(ii) efficient utilization of the radio spectrum.

Six keywords stand out from this definition: *awareness, intelligence, learning, adaptivity, reliability* and *efficiency.* This has been represented in hexagon as shown in the figure1.1. on page 3.

Consequently, the CR will play the leading role in the transition from coarse spectrum allocation to dynamic spectrum allocation. In order to protect the PUs from unlicensed users or secondary users (SU), spectrum sensing is a key function to decide whether a frequency band is empty or not. As explained before, a cognitive radio is designed to be aware of and sensitive to the changes in its surroundings. Therefore, the SUs should monitor licensed bands, and opportunistically transmit whenever no primary signal is detected. Consequently, spectrum sensing may be identified as a key enabling functionality to ensure that a CR would not interfere with primary users. In

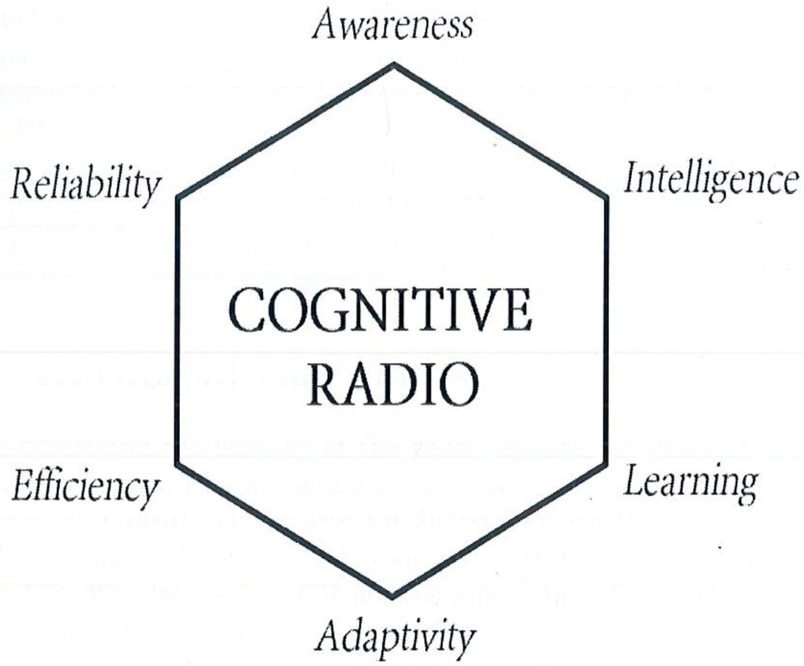


Figure 1.1: Keywords that represent the definition of CR.

the thesis, we would address this problem and look into the "intelligence developing" of cognitive radio. This is a very dynamic and creative concept since it is still into fabrication process and has no boundaries.

1.2 Spectrum Sensing Challenges

SU bands have to dynamically sense the radio spectrum environment and rapidly tune their transmitter parameters to effectively utilize the available spectrum that is not being utilized by the PU. The critical problem is the need to process multi-gigahertz wide bandwidth and reliably detect presence of primary users and that too, in time of the order of microseconds to allocate it as soon as possible so that a primary user does not start to use it again and kick out the SU or SU pose harmful interference to the PU. The example of harmful interference is when a CR may not be able to reliably detect a PU signal and therefore may start sending although the PU is using that frequency band[6]. This is the classic problem in wireless networks where a receiver is unable to the transmitter and starts its own transmission, thereby interfering with the intended receiver of the transmission. The probability that such an incident would happen is known as *probability of false alarm* [7]. Another example is when a cognitive radio is using a frequency band that was deemed free by the sensing process but may not be able to reliably detect that a PU has reappeared. Therefore, it may not vacate the frequency band quickly enough and therefore continue to send creating harmful interference to the primary user's transmission. From these two examples, we can see that there are clearly two requirements on a CR sensing receiver that influence the amount of harmful interference.

1.3 Outline of the Thesis

Before describing the content of the thesis chapter by chapter, we give you an idea of the topics we are going to discuss.
Chapter 2: Cognitive Radio:An Introduction:We show how an evolution of Software Defined Radio is required with new *traits* of Intelligence to give us CR. We also see hoe CR acts as a paradigm for wireless communication in which either a network or wireless node changes its transmission or reception parameters to communicate efficiently.
Chapter 3: Wavelets:We look into the concept of wavelets, how and why they are advantageous and where it surpasses other transforms such as *Fourier transform*.
Chapter 4: Denoising:Here, we will discuss DWT and the general algorithm for any basic denoising scheme.We would also see soft and hard thresholding and analyse the difference by simulating the same for an audio signal.
Chapter 5: Cycle Spinning:Denoising Technique:It is a new denoising technique and hence its recursion i.e. Recursive Cycle Spinning will be studied in this chapter.
Chapter 6: Spectrum Sensing: Discussion of the sensing problem statement and proposed solution to sensing spectrum holes for utilization of the spectrum efficiently. We will simulate edge detection wavelet approach for SS (spectrum sensing) in this chapter.
Chapter 7: Simulating Basic CR Functionality: We would look into the basic simulation of CR and realise allocation,deallocation and minor changes in the transmitted signal at run-time.
Chapter 8: Conclusions and Future Direction: Under this chapter, we have mentioned the possibilities in the field of CR.

Chapter 2

Cognitive Radio: An Introduction

Radio communications are becoming increasingly complex as more devices including laptops, cellular phones, and even sensors compete for limited bandwidth in various frequency ranges. In addition, devices must conform in a growing number of ways to user needs, corporate policies, and government regulations. Also, users often want to utilize their devices with more than one wireless technology, such as for both cellular and Wi-Fi communications. Cognitive radio is an emerging radio approach in which transceivers are combined with sensors, intelligence, and adaptability. *"A cognitive radio is an adaptive, multi-dimensionally aware, autonomous radio system that learns from its experiences to reason, plan, and decide future actions to meet user needs."*

Conventional Radio	*Software Radio*	*Cognitive Radio*
supports only fixed no. of funtionalities	more functionalities, software control	creates new waveforms on its own
not reconfigrable	software can be updated	highly configrable
less services	limited services	any no. of services can be added

Figure 2.1: The difference between a conventional radio,software radio and CR.The evolution has been from left to right.

The term "cognitive radio" was coined in a 1999 technical paper by Joseph Mitola, now vice president for the research enterprise at the Stevens Institute of Technology. At the time, he was researching communications for the US Department of Defense. His pioneering research was designed to help the

military enable communications among its 297 families of radios and 42 air interfaces. CR is an evolution of the software-defined radio (SDR), a term that Mitola also coined. SDRs use software in place of individual components traditionally implemented in hardware, such as amplifiers, modulators, and demodulators. That way, instead of having to use separate radios for different standards, spectrum ranges, and capabilities, users could work with a single radio that supports multiple parameters.
However, SDR allows only for adaptability. It doesn't sense what other users are doing in a spectrum range or include the ability to make link-optimization decisions. According to Mitola, CRs add cognition and the ability to make adjustments to the radio based on algorithms in a cognition engine. CRs can function without SDRs. However, SDRs give CRs more flexibility in choosing communications options.

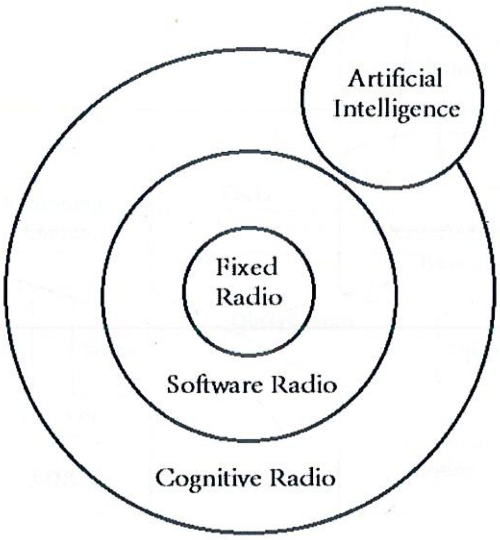


Figure 2.2: Venn Diagram to show the evolution of CR.Clearly, SDR when combined with intelligence results in concept of CR.

2.1 Cognitive Radio: Need for Development

Some wireless-service providers set up policies, such as the maximum power level that devices could use, that customers must follow. Government regulations also limit the frequency bands and communications technologies that radios can use, and other aspects of wireless transmissions.Instead of micromanaging every antenna and power level,policies are required at a macro scale i.e. such an infrastucture has to be developed that resolves such problems itself. Using one device rather than multiple ones to meet all these needs is more economical. Moreover, it is highly efficient to use a single device that can adapt in the middle of a communications session or work with radios that use different technologies when necessary. This would help military and emergency-services agencies, which don't all use the same wireless technology.

2.2 Cognitive Radio: Introduction

A transmitter or a receiver designed intelligently to detect whether particular segment of radio spectrum is currently in use or unused and to jump in and out very rapidly without interfering transmission of other users.

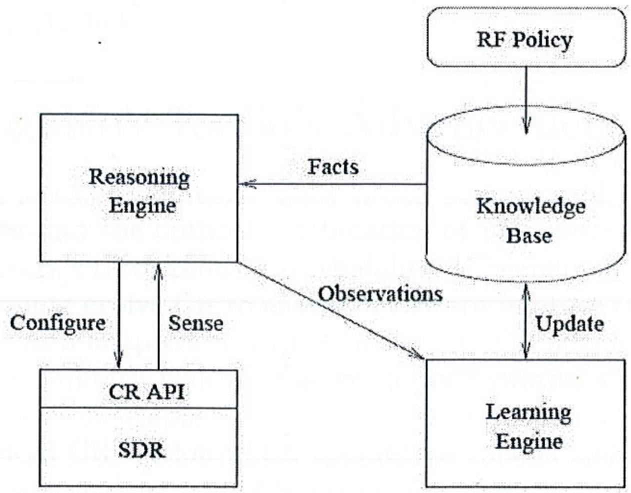


Figure 2.3: Functional portion of a CR, representing reasoning and learning capabilities.

To improve a link, CR systems must understand user needs, such as quality of service requirements for various types of transmissions, whether battery life is more important than high throughput, and what protocol and frequency the intended recipient is using. The systems also must recognize the RF environment's physical properties such as signal interference and attenuation. CR uses these capabilities to adjust factors such as signal power, communications protocol and spectrum. The enhanced version of fig. 1.1 has been shown in fig. 2.3. It covers the flow diagram of those functionalities.

2.3 Main Functions

The main functions of Cognitive Radios are:
(i) Spectrum Sensing: Detecting the unused spectrum and sharing it without harmful interference with other users, it is an important requirement of the Cognitive Radio network to sense spectrum holes, detecting primary users is the most efficient way to detect spectrum holes.
(ii) Channel Estimation: In order to set up the link, channel sounding is used to estimate the quality of sub-channels between SUs that want to communicate. The transmission parameters (transmit power, bit rate, coding, etc.) are determined based on the channel sounding results.
(iii) Medium Access Control: As long as it can be assured that all Sub-Channels are used exclusively, i.e. all Sub-Channels used by one SU Link cannot be used by any other SU Link this problem comes down to a simple token-passing algorithm ensuring that only one of the two communication peers is using the link.

2.4 Cognitive Radio's Advancements

Current CR research addresses many areas, including SDR and the use of AI to quickly find the optimal combination of parameters for increasing a link's or network's throughput and reliability. Research into intelligent-radio technology would evolve CR to enable devices to improve their performance by learning which adaptive strategies work best. CR advances will probably come from the military, which has access to wide swaths of spectrum and the funds to invest in new approaches. Some industry observers expect users to adopt a reduced CR version which operates in smaller spectrum ranges and has less decision making ability in noncritical applications such as Internet access.

Chapter 3

Wavelets

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Interchanges between these fields during the last ten years have led to many new wavelet applications such as image compression, turbulence, human vision, radar, and earthquake prediction [8].

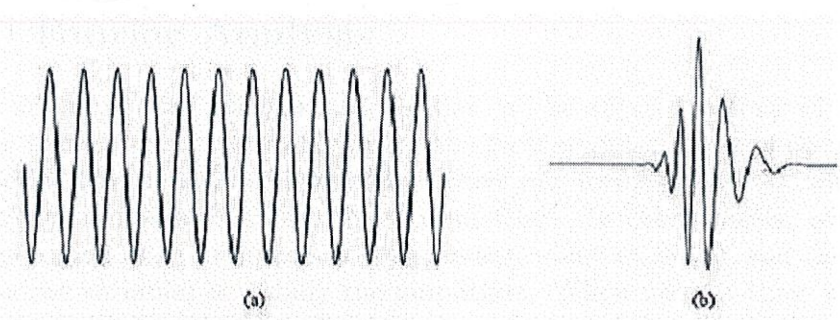


Figure 3.1: Figure to show (a)wave and (b)wavelet.

3.1 Overview

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. This idea is not new.

Approximation using superposition of functions has existed since the early 1800's, when Joseph Fourier discovered that he could superpose sines and cosines to represent other functions. However, in wavelet analysis, the scale that we use to look at data plays a special role[9]. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large "window", we would notice gross features. Similarly, if we look at a signal with a small "window", we would notice small features. The result in wavelet analysis is to see both the forest and the trees, so to speak. The wavelet analysis procedure is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet. Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. Because the original signal or function can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet functions), data operations can be performed using just the corresponding wavelet coefficients. And if you further choose the best wavelets adapted to your data, or truncate the coefficients below a threshold, your data is sparsely represented. This sparse coding makes wavelets an excellent tool in the field of data compression.

3.2 Fourier Analysis

There are number of transformations that can be applied, among which the Fourier transforms are probably by far the most popular. Most of the signals in practice, are time domain signals in their raw format. That is, whatever that signal is measuring, is a function of time. In other words, when we plot the signal one of the axes is time (independent variable), and the other (dependent variable) is usually the amplitude. When we plot time- domain signals, we obtain a time-amplitude representation of the signal. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal. The frequency spectrum of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal.

Intuitively, we all know that the frequency is something to do with the change in rate of something. If something (a mathematical or physical variable, would be the technically correct term) changes rapidly, we say that it is of high frequency, where as if this variable does not change rapidly, i.e., it changes smoothly, we say that it is of low frequency. If this variable does not change at all, then we say it has zero frequency, or no frequency. If the FT of a signal in time domain is taken, the frequency-amplitude representation of that signal is obtained. In other words, we now have a plot with one axis being the frequency and the other being the amplitude. This plot tells us how much of each frequency exists in our signal. Often times, the information that cannot be readily seen in the time-domain can be seen in the frequency domain.

FT gives the frequency information of the signal, which means that it tells us how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist. FT decomposes a signal to complex exponential functions of different frequencies. The way it does this, is defined by the following two equations:[10]

$$X(f) = \int_{-\infty}^{\infty} x(t).e^{-j2\pi ft}dt \tag{3.1}$$

This information is not required when the signal is so-called stationary . Let's take a closer look at this stationarity concept more closely, since it is of paramount importance in signal analysis. Signals whose frequency content do not change in time are called stationary signals . In other words, the frequency content of stationary signals do not change in time. In this case, one does not need to know at what times frequency components exist , since all frequency components exist at all times. If a signal is of frequency 50 Hz for the first 5 seconds and after that it changes to 100 Hz and again after next 5 seconds it changes to 200 Hz. In this case the fourier transform will show only the frequencies available in the signal not the time at which those frequencies existed.

3.3 Wavelet Transform

The Wavelet transform provides the time-frequency representation. Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. We used Short Term Fourier Transform for non-stationary signals having stationary in small parts. There is only a minor difference between STFT and FT. In STFT, the signal is divided into small enough segments, where these segments (portions) of the signal can be assumed to be stationary. For this

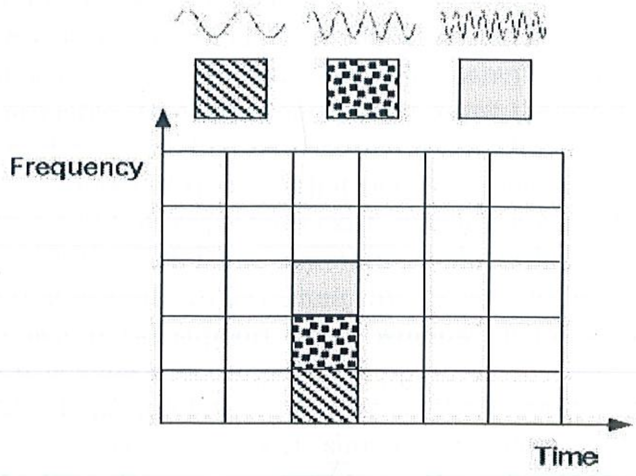


Figure 3.2: Fourier basis functions, time-frequency tiles, and coverage of time-frequency plane.

purpose, a window function "w" is chosen. The width of this window must be equal to the segment of the signal where its stationarity is valid.[11]

$$STFT_x^{\omega}(t,f) = \int_t [x(t).\omega(t-t')].e^{-j2\pi ft}dt \tag{3.2}$$

This window function is first located to the very beginning of the signal. That is, the window function is located at t=0. Let's suppose that the width of the window is "T" s. At this time instant (t=0), the window function will overlap with the first T/2 seconds. The window function and the signal are then multiplied. By doing this, only the first T/2 seconds of the signal is being chosen, with the appropriate weighting of the window (if the window is a rectangle, with amplitude "1", then the product will be equal to the signal). Then this product is assumed to be just another signal, whose FT is to be taken. In other words, FT of this product is taken, just as taking the FT of any signal.
The result of this transformation is the FT of the first T/2 seconds of the signal. If this portion of the signal is stationary, as it is assumed, then there will be no problem and the obtained result will be a true frequency representation of the first T/2 seconds of the signal.
The next step, would be shifting this window (for some t1 seconds) to a new location, multiplying with the signal, and taking the FT of the product. This procedure is followed, until the end of the signal is reached by shifting the window with "t1" seconds intervals. The problem with STFT is the

fact whose roots go back to what is known as the *Heisenberg Uncertainty Principle.* This principle originally applied to the momentum and location of moving particles, can be applied to time-frequency information of a signal. Simply, this principle states that one cannot know the exact time-frequency representation of a signal, i.e., one cannot know what spectral components exist at what instances of times. What one can know are the time intervals in which certain band of frequencies exist, which is a resolution problem.[12]
The problem with the STFT has something to do with the width of the window function that is used. To be technically correct, this width of the window function is known as the support of the window. If the window function is narrow, than it is known as compactly supported .
In the FT there is no resolution problem in the frequency domain, i.e., we know exactly what frequencies exist; similarly we there is no time resolution problem in the time domain, since we know the value of the signal at every instant of time. Conversely, the time resolution in the FT, and the frequency resolution in the time domain are zero, since we have no information about them. What gives the perfect frequency resolution in the FT is the fact that the window used in the FT is its kernel, the exp jwt function, which lasts at all times from minus infinity to plus infinity. Now, in STFT, our window is of finite length, thus it covers only a portion of the signal, which causes the frequency resolution to get poorer. What I mean by getting poorer is that, we no longer know the exact frequency components that exist in the signal, but we only know a band of frequencies that exist.
In FT, the kernel function, allows us to obtain perfect frequency resolution, because the kernel itself is a window of infinite length. In STFT is window is of finite length, and we no longer have perfect frequency resolution. You may ask, why don't we make the length of the window in the STFT infinite, just like as it is in the FT, to get perfect frequency resolution? Well, than you loose all the time information, you basically end up with the FT instead of STFT. To make a long story real short, we are faced with the following dilemma. If we use a window of infinite length, we get the FT, which gives perfect frequency resolution, but no time information. Furthermore, in order to obtain the stationarity, we have to have a short enough window, in which the signal is stationary. The narrower we make the window, the better the time resolution, and better the assumption of stationarity, but poorer the frequency resolution: Narrow window gives good time resolution, poor frequency resolution. Wide window gives good frequency resolution, poor time resolution.
The continuous wavelet transform was developed as an alternative approach to the short time Fourier transform to overcome the resolution problem. The wavelet analysis is done in a similar way to the STFT analysis, in the sense

that the signal is multiplied with a function, the mother wavelet function, similar to the window function in the STFT, and the transform is computed separately for different segments of the time-domain signal. However, there are two main differences between the STFT and the CWT:

1. The Fourier transforms of the windowed signals are not taken, and therefore single peak will be seen corresponding to a sinusoid, i.e., negative frequencies are not computed.

2. The width of the window is changed as the transform is computed for every single spectral component, which is probably the most significant characteristic of the wavelet transform.

The continuous wavelet transform is defined as follows:[13]

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^*(\frac{t-\tau}{s})dt \tag{3.3}$$

As seen in the above equation, the transformed signal is a function of two variables, τ and s , the translation and scale parameters, respectively. ψ(t) is the transforming function, and it is called the mother wavelet. The term wavelet means a small wave. The smallness refers to the condition that this (window) function is of finite length (compactly supported). The wave refers to the condition that this function is oscillatory. The term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. In other words, the mother wavelet is a prototype for generating the other window functions. The term translation is used in the same sense as it was used in the STFT; it is related to the location of the window, as the window is shifted through the signal. This term, obviously, corresponds to time information in the transform domain.
The parameter scale in the wavelet analysis is similar to the scale used in maps. As in the case of maps, high scales correspond to a non-detailed global view (of the signal), and low scales correspond to a detailed view. Similarly, in terms of frequency, low frequencies (high scales) correspond to a global information of a signal (that usually spans the entire signal), whereas high frequencies (low scales) correspond to a detailed information of a hidden pattern in the signal (that usually lasts a relatively short time).

3.4 Wavelet vs Fourier Analysis

3.4.1 Similarity between Wavelet and Fourier analysis

The fast Fourier transform (FFT) and the discrete wavelet transform (DWT) are both linear operations that generate a data structure that contains segments of various lengths, usually filling and transforming it into a different data vector of length. The mathematical properties of the matrices involved in the transforms are similar as well. The inverse transform matrix for both the FFT and the DWT is the transpose of the original. As a result, both transforms can be viewed as a rotation in function space to a different domain. For the FFT, this new domain contains basis functions that are sines and cosines. For the wavelet transform, this new domain contains more complicated basis functions called wavelets, mother wavelets, or analyzing wavelets. Both transforms have another similarity. The basis functions are localized in frequency, making mathematical tools such as power spectra (how much power is contained in a frequency interval) useful at picking out frequencies and calculating power distributions.

3.4.2 Dissimilarities between Fourier and Wavelet Transforms

The most interesting dissimilarity between these two kinds of transforms is that individual wavelet functions are localized in space. Fourier sine and cosine functions are not. This localization feature, along with wavelets' localization of frequency, makes many functions and operators using wavelets "sparse" when transformed into the wavelet domain. This sparseness, in turn, results in a number of useful applications such as data compression, detecting features in images, and removing noise from time series. One way to see the time-frequency resolution differences between the Fourier transform and the wavelet transform is to look at the basis function coverage of the time-frequency plane. The square wave window truncates the sine or cosine function to fit a window of a particular width. Because a single window is used for all frequencies in the WFT, the resolution of the analysis is the same at all locations in the time-frequency plane. An advantage of wavelet transforms is that the windows vary. In order to isolate signal discontinuities, one would like to have some very short basis functions. At the same time, in order to obtain detailed frequency analysis, one would like to have some very long basis functions. A way to achieve this is to have short high-frequency basis functions and long low-frequency ones. This happy medium is exactly what you get with wavelet transforms. One thing to remember is that wavelet transforms do not have a single set of basis functions like the Fourier transform, which utilizes just the sine and cosine functions. Instead, wavelet transforms have an infinite set of possible basis functions. Thus wavelet analysis provides immediate access to information that can be obscured by other time-frequency methods such as Fourier analysis.

Chapter 4

Denoising

In cognitive radio, one major cognitive task is to denoise and extract the original signal transmitted. However, an audio signal is composed of a large number of frequencies. Hence, a static threshold-value algorithm may not be an efficient method to denoise an audio signal. The paper investigates discrete wavelet-based algorithm for denoising of an Audio signal. Based upon the principle that in an audio signal high amplitude coefficients of Discrete Wavelet Transform (DWT) are signal components while low amplitude coefficients are noise. The audio signals were taken and corrupted with noise and DWT was applied to transform this noisy audio signal in wavelet domain. Using certain threshold algorithm and transforming the output back to time domain, we obtain audio signal with lesser noise. Then we altered the parameters like type of wavelet chosen for calculating DWT, threshold values and number of iterations which may results into better denoised audio signal.

4.1 Introduction

Donoho [14] introduced the concept of signal denoising using wavelets. For high frequency components, he used linear denoising while for low frequency, a non-linear denoising (wavelet shrinkage) was proposed. This method was modified in [15] by varying the number of iterations (output signal from wavelet denoiser is used as new input signal and it is denoised again with same threshold value) of the algorithm. The criteria for successful noise removal implies that if difference of original signal and the signal obtained by denoising is complete silence, then signal has been perfectly denoised (which is stated as not possible with reasoning below).However, if the difference feels like music, definitely, signal components have been removed and a new lower threshold value has to be set.

$$ErrorEstimation = \left[\frac{E_0}{E_d}\right]^{0.5} \tag{4.1}$$

Where E_0 = energy of original signal
and E_d = energy of denoised signal

4.2 Reason for using DWT

In wavelet transform, the individual wavelet functions are localized in space [16] while Fourier sine and cosine functions are not. Hence, localization of frequency makes many functions and operators using wavelets sparse when they are transformed into the wavelet domain. Due to sparseness, it finds applications in data compression, detecting features in images, and removing noise from time series. Fourier transform does not give any information about which frequency of the sinusoid was present till what time in the signal; it becomes very difficult to reconstruct the original signal back in time domain using its Fourier representation. However, wavelets have removed this drawback by plotting frequency against time rather than amplitude verses frequency as shown in Fig 4.2 Initially, Donoho [14] proposed Short Term Fourier Transform (STFT) method to denoise an audio signal. However, Denoising with STFT (having a fixed scale) may generate a residual noise artifact (musical noise composed of sinusoidal components with random frequencies) [17]. STFT is only good for stationary part of signals. Direct application of thresholding on audio signal denoising creates non-uniform liquid noise [18, 19] (bird noise). CWT could also have been used but it would create significant computations and is highly redundant.

4.3 Threshold Denoising

DWT works on the same principle as human ear to denoise a music signal. Since DWT coefficients are based on amplitude and location of the signal, most of noise can be eliminated from the signal relatively easily. The high frequency components have good temporal localization but its frequency resolution is poor. This is applicable since high frequency components are generally for short duration. The DWT transforms a signal into a set of coefficients. As discussed, these coefficients will be relatively sparse, containing most of the energy into a few peaks. As noise is introduced into the signal, the noise's wavelet transform will be spread out evenly among the

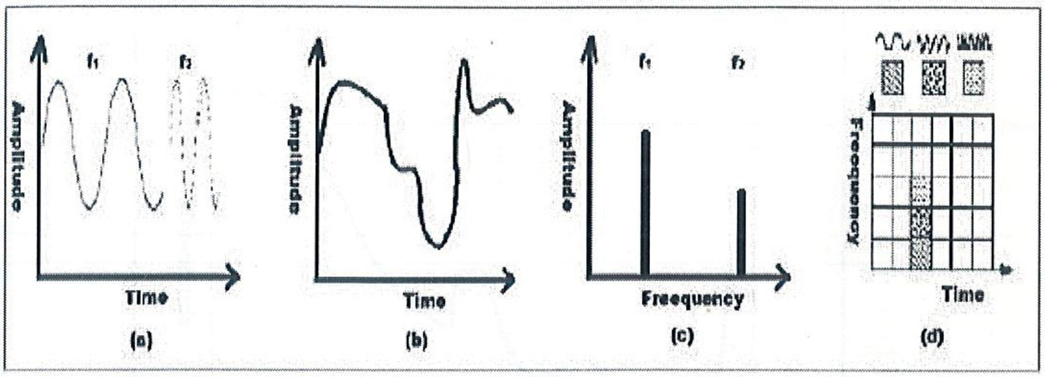


Figure 4.1: (a) represents a non-stationary signal composed of different frequencies at different time,(b) a time domain signal composed of same frequencies but is stationary,(c) Fourier transform of both(a) and (b), (d) represent representation of signal in wavelet domain

coefficients, further, when denoising will be applied, thresholding takes the DWT of the signal plus noise, and eliminates coefficients below the defined threshold, leaving the peaks of the signal plus the noise on the peaks [20]. Thus, this operation is only successful at the places in the signal where only noise exists as shown in Fig 4.3.

4.4 Discrete Wavelet Transform

DWT calculates the wavelet transform of original signal with less no. of computations. The signal is decomposed by passing time domain signal through half band low pass and high pass filters. Filtering the signal is equivalent to convolution of signal with impulse response of filter. Hence, it can be represented as:

$$y_k = x_i \otimes h_i = \sum_{i=-\infty}^{\infty} x_i h_{k-i} \tag{4.2}$$

where x_i is input signal,
h_i is impulse response of filter
and y_i is filter output.
Frequency resolution is doubled because frequency band of the output of filter spans over half the previous frequency band. Thus, every next sample can be eliminated (Nyquist theorem) since maximum frequency has been reduced to

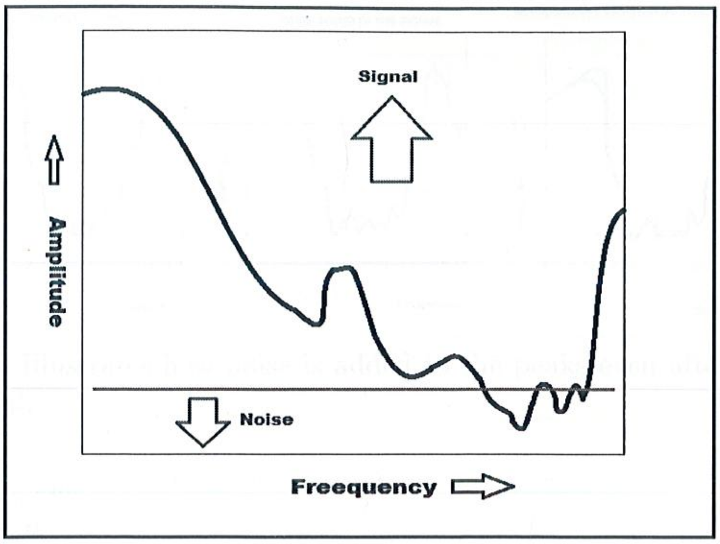


Figure 4.2: This is the way of hard thresholding-above this certain threshold value is taken as signal, rest is considered as noise.

half. Time resolution is half, and above relation changes:

$$y_k = x_i \otimes h_{2k-1} \tag{4.3}$$

Input signal is filtered using high-pass and low-pass filter. Outputs from high-pass filter are called detailed coefficients and outputs from low-pass filter are approximate coefficients which are filtered again.

4.5 Denoising of Audio Signal

Let us assume sampled noisy audio signal y_i

$$y_k = x_i + \sigma_i n_i \tag{4.4}$$

where i=1,2,3 ... N x_i represents original signal,
and σ_n is standard deviation of noise.
The n_i is the array of random numbers generated.
In wavelet domain:

$$w_\psi y_i = (w_\psi)(x_i + \sigma_n n_i) = w_\psi x_i + \sigma_n(w_\psi n_i) \tag{4.5}$$

Solving for x_i gives: $x_i = (w^{-1}{}_\psi)(w_\psi y_i - \sigma_n w_\psi n_i)$ This is soft threshold and is defined as:

$$n_t(z_i) = \begin{Bmatrix} sgn(z_i)(|z_i| - t). & |z_i| > t \\ 0, & else \end{Bmatrix} \tag{4.6}$$

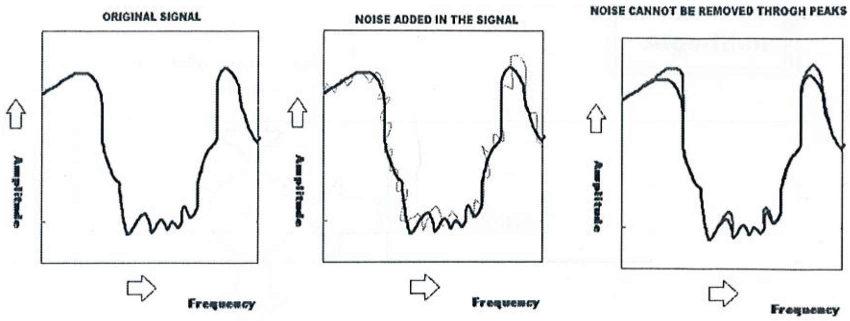


Figure 4.3: Illustrates how noise is added to the peaks even after denoising of the signal.

Where t=$\sigma_n \cdot w_\psi$
and $z_i = w_\psi y_i$
n_t z_i is threshold operator and it's time domain coefficient can be calculated as

$$\overline{x_i} = (w_\varphi)^{-1})(n_t(z_i)) \tag{4.7}$$

The objective is to chose such a threshold value that not only efficiently removes noise (output be close to silence), but also preserve data of the original signal. Choosing a high threshold would deteriorate original signal or might generate noticeable artifacts in the output [17]. On the other hand, a low threshold would not be able to remove noise very well. Thus, all the procedure would turn futile. One of the methods for selection of threshold value 't' was developed by Donoho and Johnstone and it is called VisuShrink [19] (universal threshold). Slightly different universal threshold was proposed in [21, 22] which has the value of t as:

$$t = \sigma_n \sqrt{2log_2(N)} \tag{4.8}$$

Where N denotes number of samples and σ_n is the standard deviation.

4.6 Algorithm

An audio signal (*.wav) is usually too long to be processed entirely in one iteration. Hence, an indispensable step is windowing of time domain signal and choosing the window length [23]. A small window would not be significant enough to treat structures of audio signal well, while a longer window looses significant short transient details in the music.

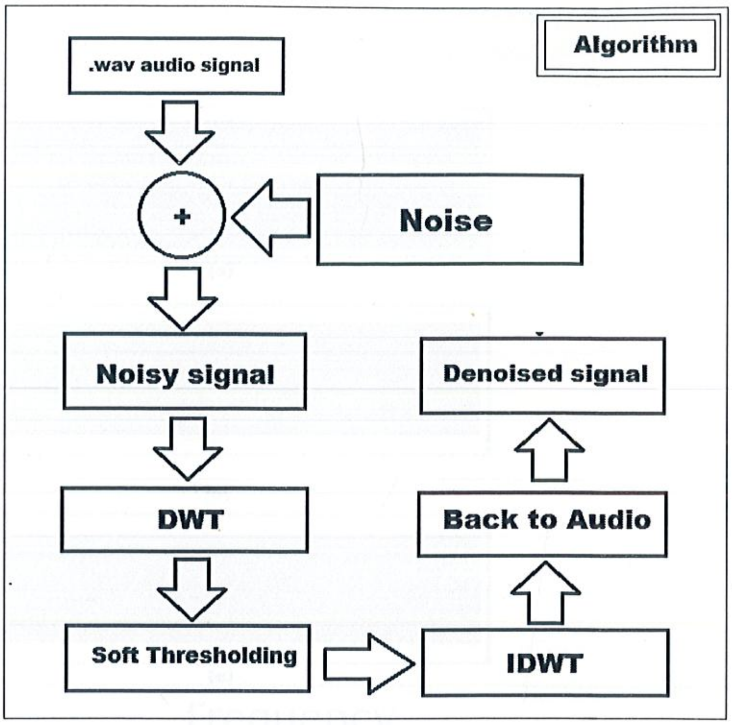


Figure 4.4: Algorithm implemented to denoised the signal

4.7 Simulation and Result

In Matlab, algorithm for soft thresholding including approximation coefficients and detailed coefficients was implemented. Noise was generated using random numbers. These energy of approximate coefficients and approximate coefficients was calculated and used to calculate new coefficients. The vector thus obtained was multiplied with the window and correlated. These correlated values were then thresholded with formula in equation [20]. A higher order filter may increase computational complexity, but improves the denoising result to an observable extent. Wave format audio signals of short duration were chosen to sufficiently see the effects. Variation in threshold values is a mere trade off between signal and noise. Fig 4.5 represents an audio signal taken from a probe into a digital oscilloscope as original signal, noisy signal and denoised signal after the algorithm.

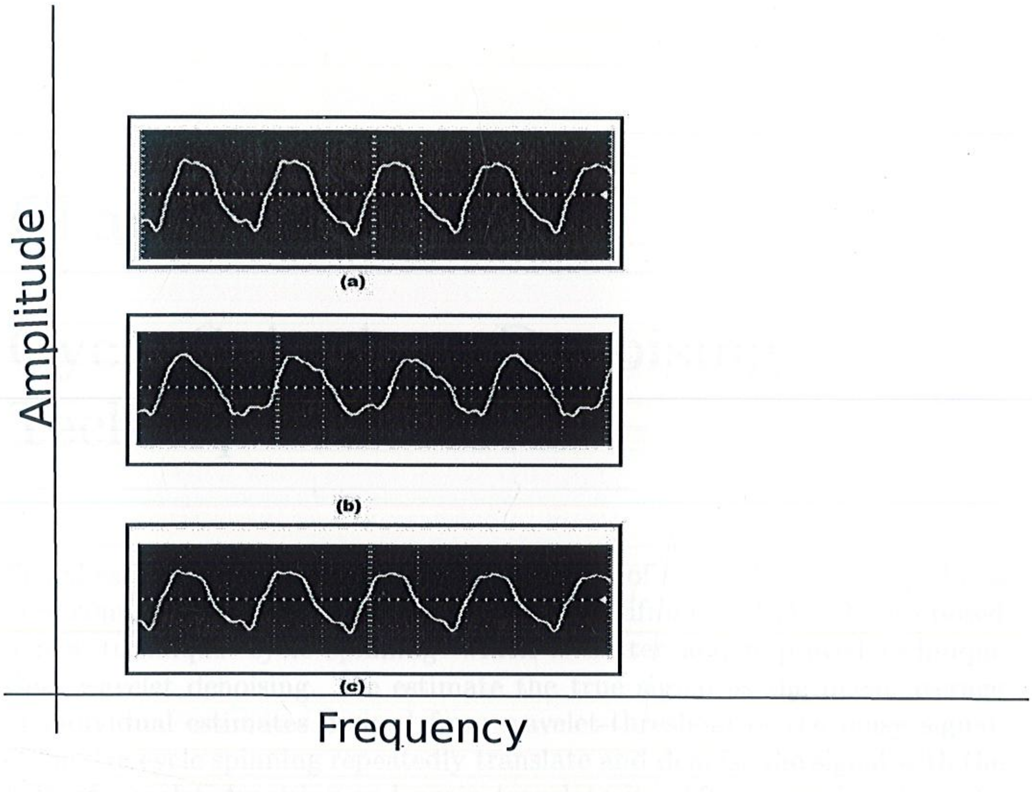


Figure 4.5: The wave signal was observed on Digital CRO and connected to a PC to take the screen shots. (a) is the original input signal (b) is the signal after adding the noise, (c) is the denoised signal waveform

4.8 Conclusion and Future Work

If we set a higher threshold, it removes noise well, but original signal is also lost. The non linear removal of noise [24] makes it quiet suitable for low frequency components. Higher is the order of the filter, better is the denoised signal , more times the algorithm is applied on the signal it produces more or less the same effect. Hard thresholding gives greater noise reduction whereas soft thresholding allows the signal to retain its smoothness. Our objective is to develop a good thresholding algorithm that may have variable threshold values and cognitive radio may be able to decide these values on its own according to the signal for better interpretation of signals at the receiver. We would now set up dynamic threshold values which would first analyse the signal and then denoise it to reconstruct the signal to best possible extent. Also,a procedure has to be developed that may look into the nature of the signal and then decide if hard or soft thresholding would be best suited.

Chapter 5

Cycle Spinning: Denoising Technique

Signal estimation from the various observation of noise corrupted signal is a very common problem in signal processing. Coifman and Donoho proposed a new technique 'cycle spinning' which is better and improved technique than wavelet denoising. We estimate the true signal as the linear average of individual estimates derived from wavelet-threshold of the noisy signal. Recursive cycle spinning repeatedly translate and denoise the signal with the help of wavelet denoising and again translate it. After every iteration the output is used as the input for the next iteration.

5.1 Introduction

Classically it has been assumed that signal is low pass and noise is not low pass. Wavelet denoising is performed by taking the wavelet transform of the noisy signal, and then zeroing out the detail (typically high-pass) coefficients that fall below a certain threshold. An inverse wavelet transform is applied to the threshold value of signal to yield the final estimate [25, 26]. Low-pass filtering, zeroing out detail coefficients removes high-pass noise. In wavelet denoising, if the signal itself has a localized high-pass feature, such as a sharp discontinuity, the corresponding detail coefficients will have significant energy and value below threshold are not made equal to zero. In this way, wavelet denoising can low-pass filter the signal while preserving the high-pass components in selected time intervals. It can be shown that if the wavelet transform used in the denoising has J stages, up to 2^j different estimates can be obtained with different shifts. The cycle spinning estimate is obtained by simply linearly averaging these 2^j estimates. The errors in the 2^j individual estimates will not be dependent, and therefore the averaging will reduce the noise power. The idea is that every shift has different error, which will be reduced by averaging. Wavelet threshold identifies a subspace in which the unknown signal is likely to have most of its energy and projects the noisy signal onto this subspace. Cycle spinning identifies the subspaces; it performs the corresponding denoising projections, and then takes the average of the projections. Output of iteration is input for the next. However, instead of averaging the projections, we can say that it is better to project once onto the intersection of the subspaces. The reason is simple. If the unknown signal has most of its energy in each of the subspaces, it will have most of its energy in their intersection. Since the intersection of subspaces has a much smaller dimension than the subspaces, projecting to the intersection produces an estimate which is much closer to the true signal. To perform the projection onto the intersection of the subspaces, an algorithm called recursive cycle spinning is proposed. It is proved analytically that the estimates from the proposed method globally converge. Recursive cycle spinning outperforms both basic wavelet threshold method and standard cycle spinning.

5.2 Wavelet Denoising

5.2.1 Algorithm

Apply wavelet transform to the noisy signal to produce the noisy wavelet coefficients. Select appropriate threshold limit at each level and threshold method (hard or soft thresholding) to best remove the noises. Inverse wavelet transforms of the thresholded wavelet coefficients to obtain a denoised signal. Consider estimating an unknown discrete-time signal

$$x[n], \qquad n \in 0, 1 \ldots N-1 \tag{5.1}$$

From a noise-corrupted signal,

$$y[n] = x[n] + d[n] \qquad n = 0, \ldots. N-1 \tag{5.2}$$

where d[n] is additive noise. Let

$$Y[n] = W(y[n]) \tag{5.3}$$

Denote a discrete wavelet transform of x[n]. Only orthogonal wavelet transforms are considered here. Basic wavelet denoising is performed by taking the wavelet transform of the noise-corrupted y[n] and then zeroing out the coefficients that fall below a certain threshold. An inverse wavelet transform is applied to the threshold value of signal to get the true signal, as below [27, 28]:

$$X[k] = \left\{ \begin{array}{ll} Y[k], & if Y[k] \geq T(k); \\ 0, & otherwise \end{array} \right\} \tag{5.4}$$

T (k) are certain threshold levels. The final estimate is the inverse wavelet transform of the thresholded coefficients:

$$x = W^{-1}(X) \tag{5.5}$$

5.3 Cycle Spinning

Instead of averaging the 2^j projections, it is better to project directly onto the intersection of the subspaces. So, projecting the noisy signal onto the intersection of the subspaces will remove little of the signal energy. Since the intersection of subspaces typically has a much smaller dimension than the subspaces themselves, projecting onto the intersection of the subspaces will remove much more noise than the projection onto the individual subspaces [25]. To perform the projection an algorithm, cycle spinning is used. The algorithm produces a sequence of estimates. In cycle spinning, the signal is translated by various time shifts. Each time shift is separately transformed and then we denoise, and the estimate is then taken to be the average of these results.

$$x_i = D_i(y[n]) = S_{-i}D(S_i(y[n])) \tag{5.6}$$

where D is a wavelet denoising operator described above and S_i is a left shift by i samples. It can be shown that if a wavelet transform has J stages, one can obtain up to M $=2^j$ different estimates,x_i, i=0 ... M−1. The cycle spinning estimate is simply the linear average of these M estimates [29].

5.4 Recursive Cycle Spinning

Basic algorithm:

1. Use wavelet threshold method of shifted versions of the noisy signal, y to identify M subspaces likely to contain the most of the true signal energy. These spaces were called the denoise spaces of y.

2. Compute the denoise space intersection, the intersection of the M denoise spaces.

3. Project y onto the denoise space intersection to obtain an estimate for the true signal.

Recursive cycle spinning is an approximate method. The algorithm is simple to describe.

Let D_i(x) denote the signal x wavelet denoise using a shift of i. That is,

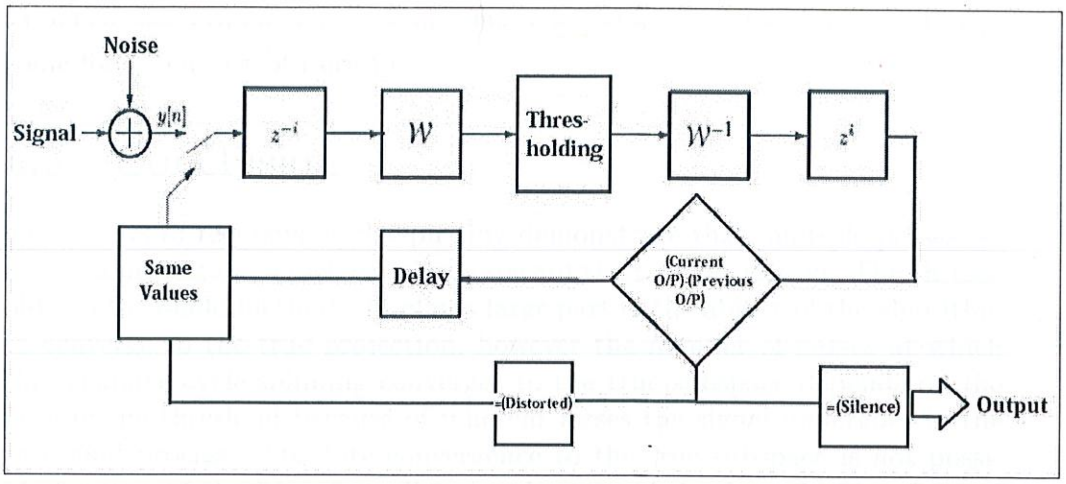


Figure 5.1: A depiction of recursive cycle spinning. The switch is initially in the upper position to draw the noising signal y[n] into the system. Thereafter, the switch is in the lower position to recursively denoise the output of the previous iteration. The shift i is changing from one iteration to the next.

D_i(x) is obtained by shifting x to the left by i samples, wavelet denoising the shifted signal, and then shifting the denoise signal back. Recursive cycle spinning generates sequences of estimates as follows. The initial estimate x_0 is set equal to the original noisy signal: x_0=y.The subsequent estimates are generated from the recursive rule [30]:

$$x_{i+1} = D_i(x_l), \qquad i = lmodM \tag{5.7}$$

That is, the l+ 1^{st} estimate is obtained by denoising the l^{th} estimate with a shift of i, cycling through the shifts i – 0 ... M – 1. The idea of the algorithm is that each iteration projects the estimate to one of the M denoise spaces. Ideally, the algorithm would be performed for an infinite number of iterations, and the estimate sequence would converge to some limit point, say x_∞. This limit point should be affixed point of the recursion updates, so that

$$x_\infty = D_i(X_\infty), \qquad \forall i = 0, ...M - 1 \tag{5.8}$$

This fixed point condition means that x_∞ would be in the range space of projections D_i for all i. That is, x_∞ would be in the denoise space intersection.

The denoise space intersection should be a space of small dimension containing the true signal, and consequently, the final limit point should be close to the true signal. Of course, the convergence of the algorithm is far from obvious. It is possible, that the estimated sequence could bounce between the M subspaces without converging. The algorithm must be terminated after some finite number of iterations.

5.5 Conclusion

The results of recursive cycle-spinning demonstrate that multiple passes result in a projection, which converges toward the true projection. The threshold and threshold method will play a large part in the ability of the algorithm to converge to the true projection, however the number of passes at which the recursive cycle-spinning converges to the true subspace depends on the level of the threshold because of inherent losses the signal undergoes in the threshold process. Absolute convergence to the true subspace is not possible because of the loss of smaller signal components through the course of threshold operation. For a properly chosen threshold, every iteration retains relatively large signal energy; and a large portion of noise is removed. Once we are done with iteration, we come closer to the signal. A point will come where we will have optimum signal.

5.6 Future work

The convergence ability of the algorithm is pointed out by comparing two possible recursive cycle-spinning arrangements to the noiseless and noisy projection. One would expect that as long as there is no overshoot, the coefficients in the case where the most iterations are performed will more closely represent the noiseless coefficients which represents denoising using two iterations of hard threshold method followed by one iteration of soft threshold with the threshold appears to be further from the true projection than our recursive. Notice that the lowest decomposition level detail coefficients are most similar to their counter parts. The convergence of the upper level coefficients therefore appears to lag the lower coefficients in the convergence process. Hence convergence overshoot may occur first at the lowest level of decomposition and produce signal degradation of low frequency signal components. We leave this determination for future study.

Chapter 6

Sensing

For cognitive radio the main issue is to sense and identify all spectrum holes present in the environment. In this paper we are proposing a wavelet approach for spectrum sensing and spectrum hole identification. We will apply wavelet transform on the sub-divided signal to detect the edges and holes over a wide frequency band. The proposed sensing techniques provide an effective radio sensing architecture to identify and locate spectrum holes in the signal spectrum.

6.1 Introduction

Cognitive radio is gaining popularity these days. The main reason of this is the lack of availability of spectrum. For industrial and economic development, the need of spectrum is very crucial and necessary. Cognitive radio helps in efficient utilization of any spectrum available. It removes the problem of spectrum scarcity. Terminals are assumed to be capable of making intelligent decisions i.e., the devices will be capable of optimizing the resource usage for their individual need [31, 32, 33]. Hence, the first and very important task in a cognitive radio is the spectrum sensing, where bandwidth is suppressed. The energy detection techniques can be broadly classified as "Transmitter Detection" and "Receiver Detection". In the first category, the PU is assumed to be transmitting and in the latter, the PU is receiving. In this paper we will mainly focus on transmitter detection. There exist several different approaches for transmitter detection which may be used in different sensing scenarios. The most well-known methods are perhaps energy detection, cyclostationary detection and matched filter (MF) detection, and these will be briefly described below. Furthermore, spectrum sensing can be performed by a single unit or it can be collaborative in which case measurements from several sensors are combined in a fusion center to obtain a more reliable decision. In this manner cooperative spectrum sensing [34] offers increased detection performance by spatial diversity of the sensors. The least demanding approach is energy detection. An energy detector measures the energy in a radio resource and compares the value against a threshold. Generally, if and only if the measured energy is below the threshold, the radio resource is declared as not occupied, i.e., it is available for opportunistic use. Energy detection is a non-specific detection method in the sense that no particular knowledge of the signal properties is used. In this sense, energy detection can be used for declaring whether a resource is occupied or not, but it cannot be used to identify the type of system or user (e.g., primary or secondary) that is occupying the channel. Also, an energy detector needs to have an idea of the noise level to adjust the detection threshold [35]. There are various kinds of spectrum sensing techniques [36]: transmitter detection, cooperative detection and interference-based detection [33]. There are three different energy detection techniques: energy detection [37, 38, 39], matched filter detection and cyclostationary feature detection [40].Transmitter detection observes the signal from primary transmitter. It is a non cooperative spectrum sensing technique; hence it is less complex and is known for its simplicity. The cooperative detection requires additional overhead traffic i.e. information from multiple cognitive radios is provided for reliable primary user detection. The system is undertaken by a number of cognitive radios [41] and adjust overall cognitive radio network to suit our needs. The advantage of this technique is reduced interference. In interference based detection, cognitive radio relates decision to cumulative RF energy from transmitter measured at the receiver. Hence, due to its simplicity and feasible implementation, we hose energy detection method. In Matched filter detection, which provides an optimal detection performance, but requires prior knowledge of primary signal; has lower accuracy. This technique is used when the xG user knows the information (various parameters) of the primary user signal. The optimal detector in stationary Gaussian noise is the matched filter since it maximizes the received signal-to-noise ratio (SNR) [40]. While the main advantage of the matched filter detector is that it requires less time to achieve high processing gain due to coherency, It requires a prior knowledge of the primary user signal such as the modulation type and order, the pulse shape, and the packet format. Alternately, if this information is not accurate, then the matched filter performs poorly. The Cyclostationary method is more accurate, but has increased complexity. Cyclostationary detection is typically a statistical test based on the estimated autocorrelation function of one or several known cyclic frequencies. The advantage being that the autocorrelation is periodic.

This enables detection under very low SNR, Hence Robust in low SNR and robust to interference. It also requires partial knowledge of primary signal and has high computational cost. Modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading, hopping sequences, or cyclic prefixes, which result in built-in periodicity. These modulated signals are characterized as cyclostationarity since their mean and autocorrelation exhibit periodicity. The main advantage of the spectral correlation function is that it differentiates the noise energy from modulated signal energy, which is a result of the fact that the noise is a wide-sense stationary signal with no correlation, while modulated signals are cyclostationary with spectral correlation due to the embedded redundancy of signal periodicity. Therefore, a cyclostationary feature detector can perform better than the energy detector in discriminating against noise due to its robustness to the uncertainty in noise power [42]. The other method, Energy Detection is widely used: simple, optimal under no knowledge of primary signal.

A cyclostationary process [43] has statistical properties which vary periodically over time. A wide sense cyclostationary process (the analogue of a wide sense stationary process) has an autocorrelation function which is cyclic with a certain periodicity T, i.e., R(t, s) = R(t+T, s) for all time indices s and t. Communication signals are typically cyclostationary with multiple periodicities, e.g., the symbol frequency. Other periodicities may be related to coding and guard periods [44]. Cyclostationary detection is typically a statistical test based on the estimated autocorrelation function of one or several known cyclic frequencies. Fig. 6.2 plots all methods we discussed, our aim would be to get a method so that we have to have maximum accuracy and minimum complexity. As depicted, since matched filter requires no knowledge of primary user , it is quite simple but results can be contradictory. Similarly, energy detection has added complexity (due to multiple cognitive radio systems) but accuracy is not increased as expected. Cyclostationary detection exploits more knowledge (i.e., the cyclic frequencies) about the process one wishes to detect than energy detection does. Hence, cyclostationary detection will only be able to detect a limited amount of systems for which the communication signals possess known cyclostationary properties, but, on the other hand, these systems can be explicitly identified by the cyclostationary detector. There are various approaches for spectrum detection but wavelet based approach proposed in [37, 45] is very precise even when the signal and noise level are very close to each other. This technique was tested with the help of computer simulations. We have proposed some modification in it which will be explained in further sections.

6.2 Hybrid Model

The hybrid model for transmitter based detection is the combination of all the three techniques (matched filter, energy detection and cyclostationary detection). With the proper channelization of the technique has been done under this approach which will help in detecting the idle spectrum bands (spectrum holes that is the underutilized sub bands of the radio spectrum) opportunistically with better utilization of the spectrum under non cooperative sensing with increase in the overall spectrum efficiency. [46]

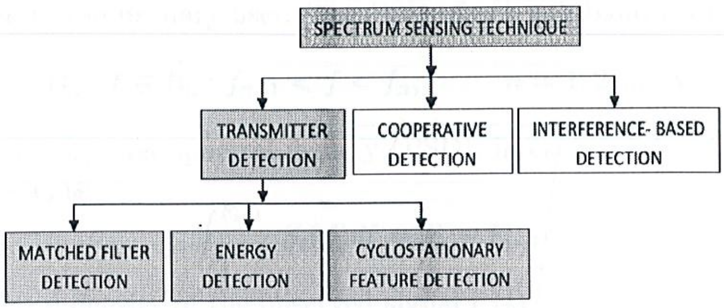


Figure 6.1: Block diagram of different sensing techniques(Shaded techniques being preferred here)

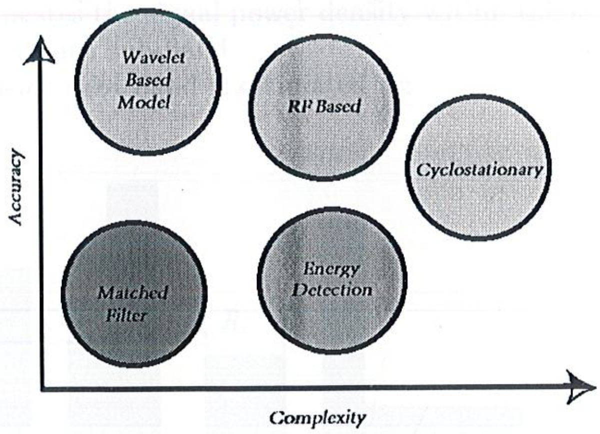


Figure 6.2: Plot of complexity verses accuracy for various spectrum sensing techniques.

6.3 Spectrum Sensing Techniques

6.3.1 Original Sensing Method

In [34] spectrum sensing has been treated as edge detection problem. In this edge detection technique has been implemented to find the spectrum hole. Let us assume a frequency band of interest (Fig. 3) which is further divided into N sub-bands consecutively, with their frequency boundaries located at $f_0 < f_1 < \ldots < f_n$. The idea is to locate any vacant spaces between the two adjacent sub bands so that a secondary user can utilize it without any interference to the primary user. The PSD of n^th sub-band is defined by:

$$B_n : f \in B_n : f_{n-1} < f < f_n, \qquad n = 1, 2, ...N \tag{6.1}$$

The normalized power spectral density (PSD), in each sub-band, in the absence of noise, is:

$$\int_{F_i}^{F_{i-1}} S_i(f)df = F_i - F_{i-1} \tag{6.2}$$

Power spectral density of the observed signal r (t):

$$S_r(f) = \sum_{n=1}^{N} \alpha_n^2 S_n(f) + S_w(f), \qquad f \in [f_0, f_n] \tag{6.3}$$

Where α_n^2 indicates the signal power density within the n^th band
S_n(f) is PSD of each sub-band.
PSD inside each sub=band is estimated as:

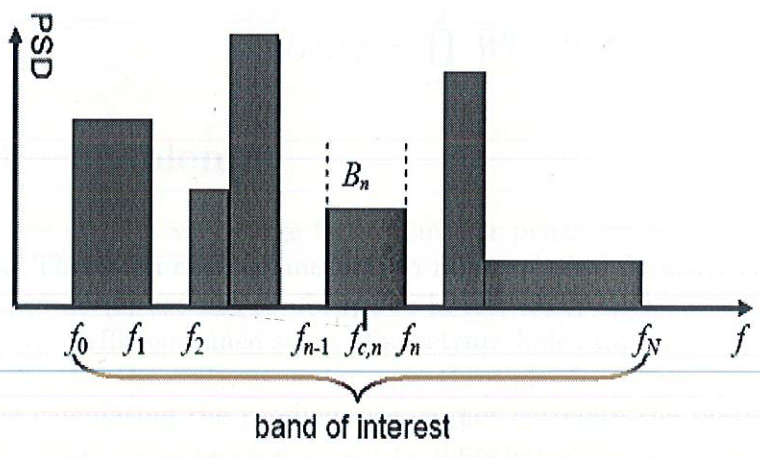


Figure 6.3: The PSD inside each sub-band

$$B_i = \frac{1}{F_i - F_{i-1}} \int_{F_i}^{F_{i-1}} S_r(f) \tag{6.4}$$

The identification of the frequency boundaries between successive sub-bands is done using properties of the wavelet transform [47]. The dilation of the wavelet functions by one scale is

$$\psi_s(f) = \frac{1}{s} * \psi(\frac{f}{s}) \tag{6.5}$$

The continuous wavelet transform is defined as

$$W_s S_r(f) = S_r * \psi_s(f) \tag{6.6}$$

At fine scales, it provides localized information of S_r (f), to find the edges and irregularities in it we have to find its first and second derivatives. The first derivative is

$$W_s^1 S_r(f) = s\frac{d}{df}(S_r * \psi_s)(f) \tag{6.7}$$

The second derivative is

$$W_s^2 S_r(f) = s^2 \frac{d^2}{df^2}(S_r * \psi_s)(f) \tag{6.8}$$

Edges and discontinuities propagate to different scales s. In [48], the CWT is obtained with dyadic scales s=2^j, i=1, 2, 3 ...,j. In order to track the propagation of edges and discontinuities in multiple scales, the multi scale product of the J CWT gradients is done [49].

$$U_J S_r(f) = \prod_{j=1}^{J} W_{S=S_j}^1 S_r(f) \tag{6.9}$$

6.4 Problems

If value of 'j' is very large fig.(d) smaller peaks are dissolved among larger ones. This is an efficient method to remove noise. In other cases, where the borders S_r (f) are not so abrupt or in less noisy environments, this method is quite inefficient since some of spectrum holes would be ignored. Value of 'S_j' denotes the scale, as we increase the scale, frequency span widens, hence while calculating the product; we cannot correlate the boundaries of every peak. Thus, boundaries may not be detected with a good precision.

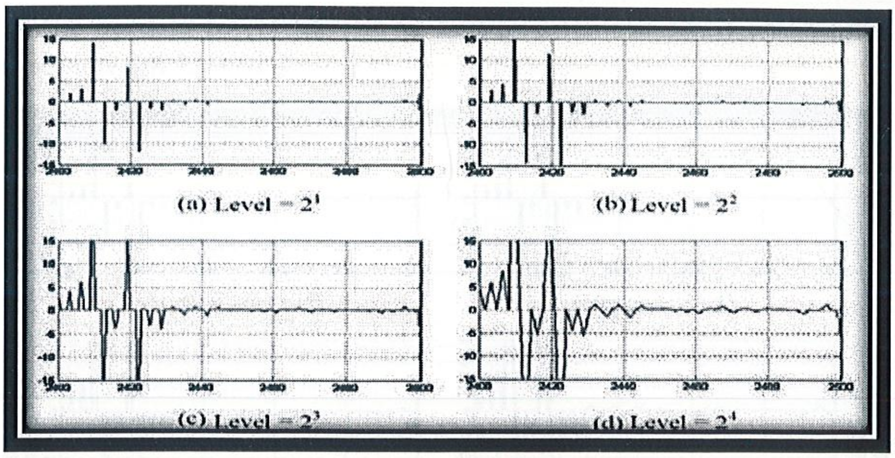


Figure 6.4: Showing the CWT coefficients with different values of j (a) j=1 (b) j=2 (c) j=3 (d) j=4

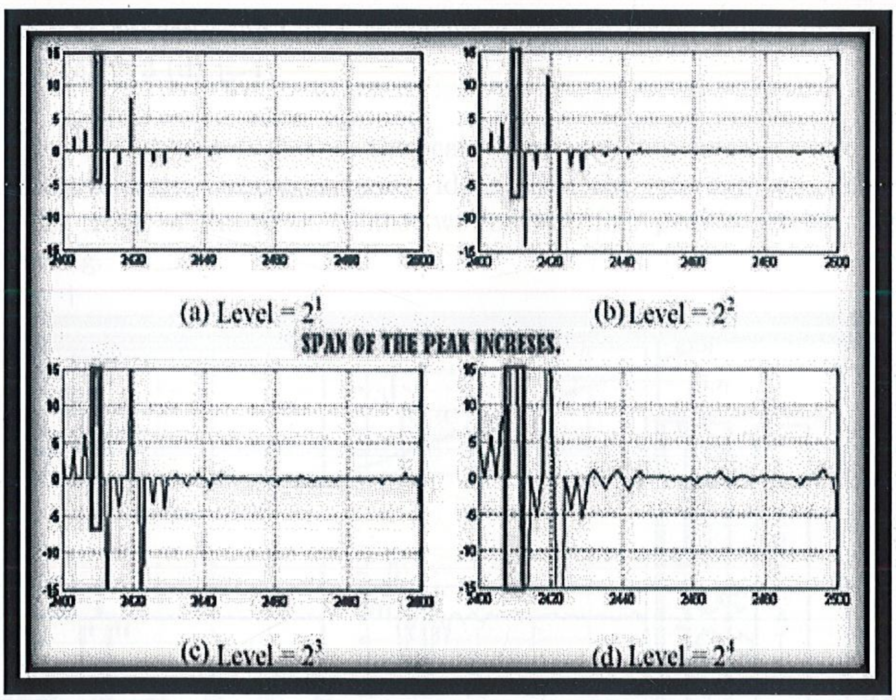


Figure 6.5: Showing the CWT coefficients with different values of j (a) j=1 (b) j=2 (c) j=3 (d) j=4

6.5 Solution and Proposed Model

Value of 'j' can be a little large than required fig. (d), so that smaller peaks are dissolved among larger ones. This will remove noise. In other cases, where the borders S_r (f) are not so abrupt or in less noisy environments, j value should not exceed 4.

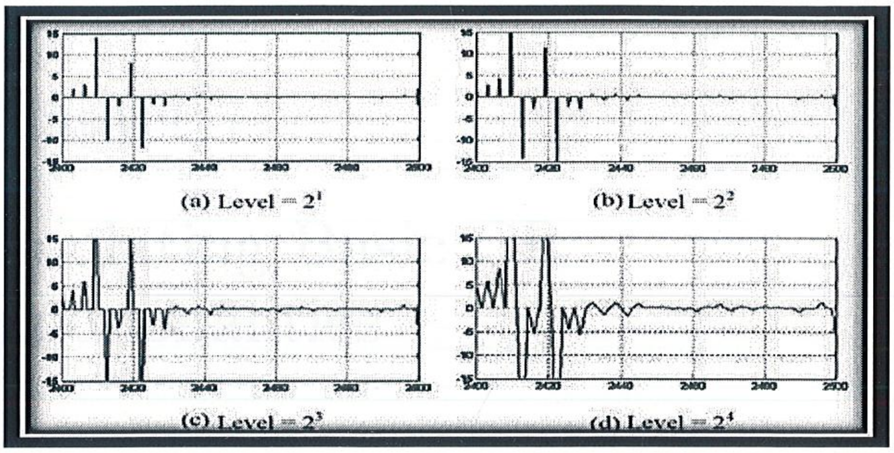


Figure 6.6: showing the CWT coefficients with different values of j (a) j=1 (b) j=2 (c) j=3 (d) j=4

Value of 'S_{jk}' would denote the scale corresponding to each peak. As we increase the scale, frequency span widens. But the reference no. 'k' would keep the track of the peak. Thus, we know which peak's product we are calculating.

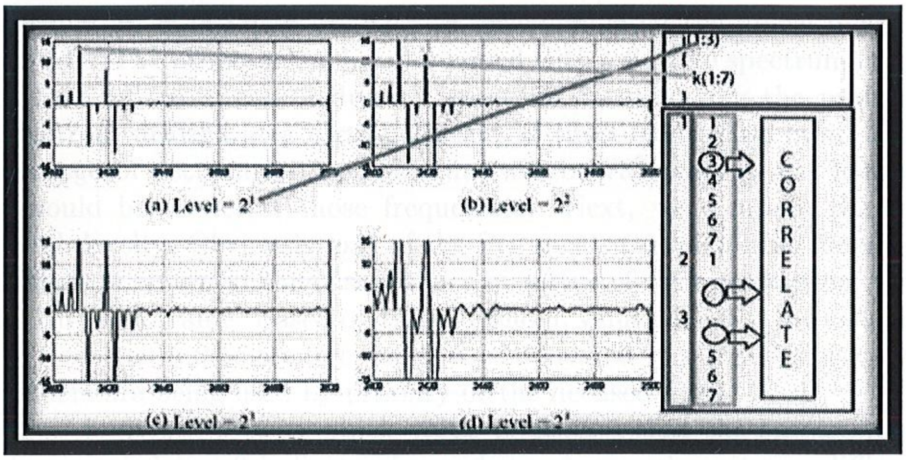


Figure 6.7: Showing the CWT coefficients with different values of j (a) j=1 (b) j=2 (c) j=3 (d) j=4

Chapter 7

Simulating Basic CR Functionalities

So far whatever functionalities of CR we have worked on, we wrote a small collective code for the same. Hence, it can be called as basic simulation of CR that performs the most important function of spectrum sensing, allocation and deallocation of spectru to primary as well as secondary users and deals with all these features at run-time i.e. according to users discretion.

7.1 Simulation

Using matlab R2008a[50, 51, 52], we have simulated the above mentioned algorithm. The program has been designed with a flexible spectrum creation such that we can create a dummy spectrum by inputting the probability of spectrum utilized at a certain instant of time. e.g. if we input 25% as percentage of occupancy, the spectrum will be 75% vacant and hence our aim would be to detect those frequencies. Next, we compute the power spectral density. Obviously, psd of the free spectrum value is far below than the values of allocated bands and hence by virtue of their proportion, we find out a threshold value. Based on this threshold, values below it are considered to be frequencies that are free and can be allocated to secondary users while the others are being used by primary or the licensed users.

Fig.7.8 gives a plot in which value 1 signifies that the spectrum is already occupied and 0 indicates free values. Again, since it was difficult to obtain actual spectrum plot on any analyzer, we created a dummy spectrum to see how our code works on the spectrum. This is the input data that is fed to the algorithm mentioned above and it gives the result as Fig. 7.8 which shows values below the threshold are vacant and can be allocated. The

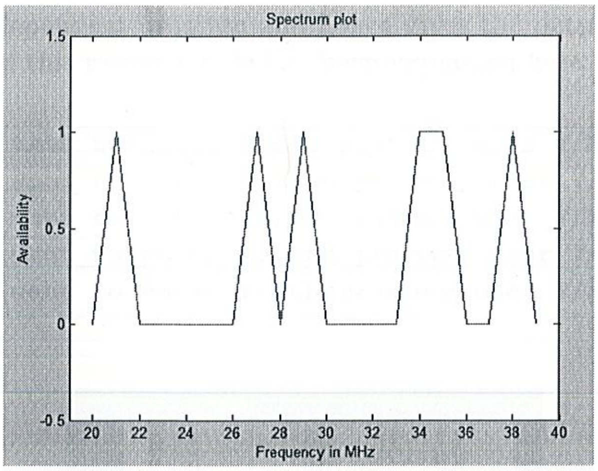


Figure 7.1: Creating a dummy spectrum in matlab to run the code to find free frequency band in the spectrum.

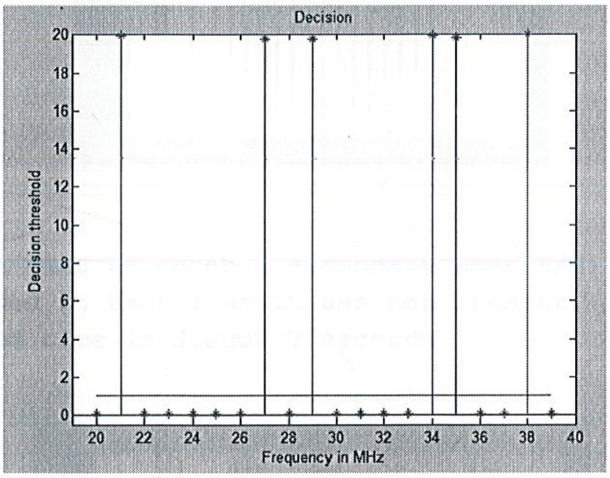
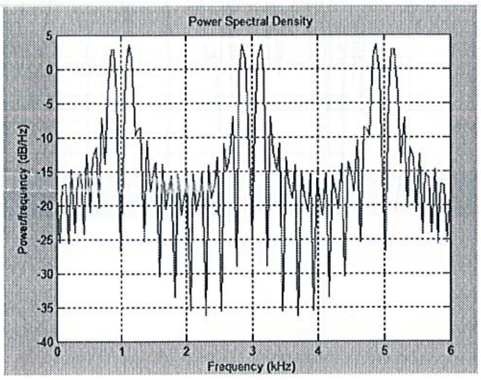


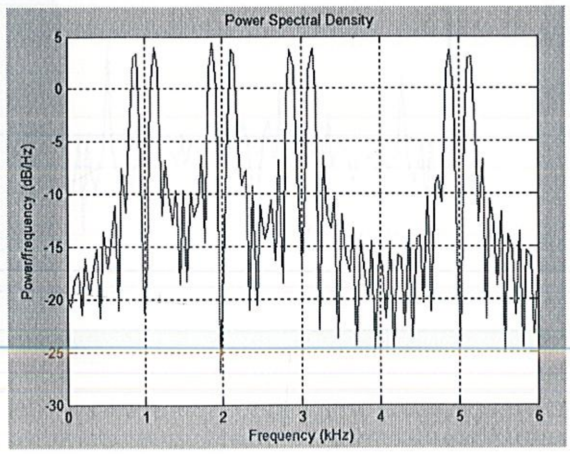
Figure 7.2: Plot of psd to the frequency. Comparing it to fig 7, we can clearly define free frequency values.

other simulation we had was simulation of cognitive radio, and performing the most important operation of spectrum sensing, allocating and deallocating the spectrum at run time. In the program, we first have certain vacant spaces in a particular spectral band and we allocate them to the primary users first, once they had been allocated to the primary users, we allocate the vacant spaces to the secondary users, once the spectrum is completely filled, we can fire a slot and allocate it to another user. Then we have minor functionalities of adding noise or changing amplitude of the signal. This is totally a user dependent program and hence gives the output on users will. One iteration of this running code has been explained here.

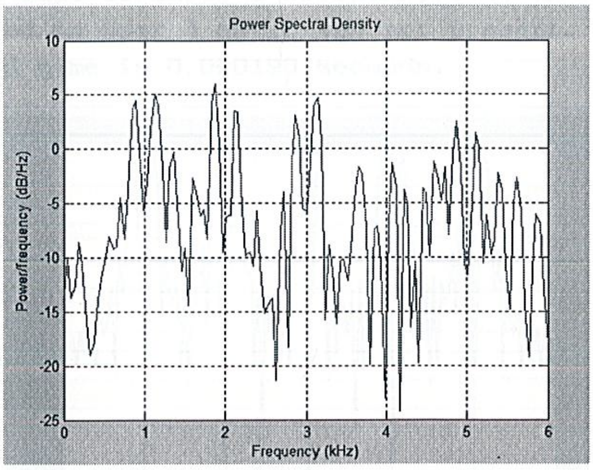
```
Do you want to enter first primary user Y/N:  y
Do you want to enter second primary user Y/N:  n
Do you want to enter third primary user Y/N:  y
Do you want to enter fourth primary user Y/N:  n
Do you want to enter fifth primary user Y/N:  y
```



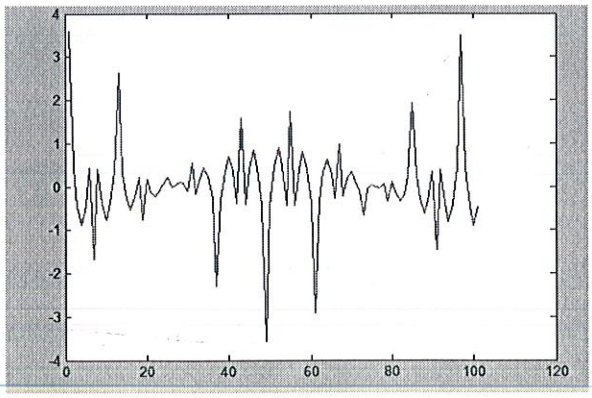

```
Do you want to enter a secondary user Y/N:  y
Assigned to User 2 as it was not present.
Elapsed time is 0.000277 seconds.
```



```
do u want to add noise: y
Enter the SNR in dB:   2
adding noise
```

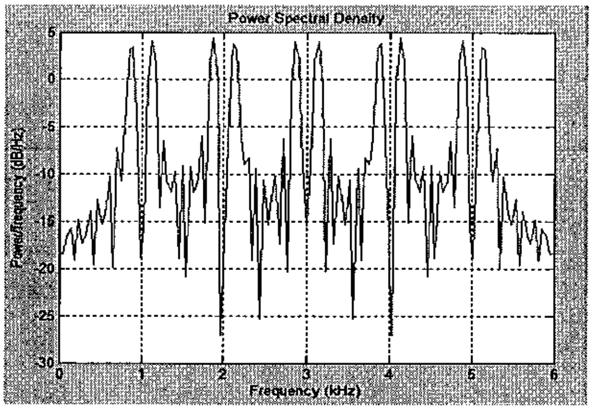



```
Do you want to attenuate the signals? [Y/N]:    y
Enter the percentage to attenuate the signal:   10
attenuating
```



```
Do you want to re-run the program? [Y/N]:     y
\n\nEnter the users again.\n\n

Do you want to enter a secondary user Y/N:  y
Assigned to User 4 as it was not present.
Elapsed time is 0.000190 seconds.
```




```
Do you want to enter a secondary user Y/N:  y
all user slots in use. try again later,
Elapsed time is 0.000034 seconds.

do u want to empty a slot:      y
which slot do u want to empty for ur entry:     3
slot3 is fired
```

7.2 Conclusion and Results of the Simulation

Here we have pointed out the problems in the original model and also suggested the improvement we can do. We have also simulated major feature of cognitive radio of spectrum sensing and tried to allocate and deallocate spectrum at run time with minimal computation time. The computation time of our algorithm comes out to be 0.000167(on an average), however, we ran the same code on a no. of systems and realized this was the CPU time which depends on the strength of CPU. In future we would be simulating the proposed idea for better and more functional and realistic cognitive radio and try to produce precise experimental results. We would also try to run the code for an actual spectrum data rather than using dummy self constructed spectrum plot. This second segment of simulation of a CR system has no boundaries and can be extended up to any level with more and more features and functionalities.

Chapter 8

Conclusions and Future Direction

In this chapter we summarize the work done in the thesis, draw the conclusions, and suggest directions for further research.

8.1 Conclusions

Wavelets and cognitive radio are the terms that the wireless community has heavily exposed to over the recent years. It is anticipated that in the near future, the wireless community will be encountering that these terms are mentioned jointly in the context of the spectrum efficiency and opportunistic spectrum usage and eliminate the concept of coarse spectrum allocation, thereby minimizing the cost and increasing efficiency and security. In the light of this expectation, in this thesis,an implementation of some features (as spectrum sensing and denoising of signals) are given. The cognitive radio concept is introduced, and its requirements and objectives are explained in detail. The seeds of the 'future' have been sown, and hence, it is proven that wavelet is a very appropriate candidate both for implementing or supporting cognitive radio. The individual studies and their scope have already been discussed at end of the chapters.

8.2 Scope and Future Direction

In this part of the thesis, we will discuss the scope of cognitive radio and scope of increasing its performance and major challenges faced.

8.2.1 Scope

As new and more complex communication standards are developed around the globe, the demand for new transceivers architectures will also grow. However, more and more often the available capital, both cash and human, limit the designs that can be tackled. Fortunately, CR will be available for a select and growing group of these architectures that allow a single platform to leverage into many diverse designs. As seen here, this has many distinct advantages and is not limited to interoperability, investment retention and great flexibility. As with any software project, quite often the potential is only limited by the imagination of the designer. Fortunately, the last decade has seen significant advances in semiconductor technology that has caused impressive gains not only in performance but also in cost. CR is one area that has greatly benefited from these varied technologies and will continue to do so as the meaning of SDR is developed just as the history of programming languages has done. While CR will be the solution to all communication problems, it will offer robust solutions to challenging design issues in the coming years. However, there are still some challenges preventing full acceptance of this technology. The two main issues are cost and power. Interestingly, these two have a first order positive relationship; solve one problem and the other will only get better. The issues we faced were basically regarding the material available. Since it is a recently developed area, it is difficult to find the exact material you are looking for.There are only limited no. of results available on the search engines. Despite these challenges, CR is a revolutionizing concept that would help to build integrated devices(gadgets) composed of PDA's ,pagers and many more single purpose gadgets we use today.

8.2.2 Future Directions

The CR that has been simulated in this thesis is only an initialization phase. Only the spectrum sensing, allocation and de-allocation of spectrum at rum time has been simulated with denoising of signal and minor changes in waveforms can be done at run-time according to user's will. This task is a process of imparting knowledge (artificial intelligence) to a system and hence is a never ending experience. Spectrum sensing by far is the most important component for the establishment of cognitive radio. However, the components of the cognitive radio concept are the ability to measure, sense, learn and be aware of the parameters related to the radio channel characteristics, availability of spectrum and power, radios operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. Therefore, further research could focus on better implementation of CR and enhancing and adding more features in order to closely simulate real life systems. This thesis could be extended by adding more functionalities such as deciding modulation types, carrier frequency, signal recovery etc. So that our system can counteract the noise and interference problems of a communication systems, thereby minimizing the costs and processing times. Again, it is a totally creativity based thesis and challenges the reader or pursuer of the thesis to think out of the box and excavate new ways of making cognitive radio a reality.

Appendix

A-Code for Sensing allocation

```
clc;
close all;
clear all;

t = 0:0.00001:0.001;
cf1 = 1000;
cf2 = 2000;
cf3 = 3000;
cf4 = 4000;
cf5 = 5000;
Fs = 12000;
y1 = 1; y2 = 0; y3 = 0; y4 = 0; y5 = 0; Y = 0; y = 0;

x1 = cos(2*pi*1000*t);

inp = input('\nDo you want to enter first primary user ? (Y/N)  ','s');


if(inp == 'Y' | inp == 'y')
    y1 = ammod(x1,cf1,Fs);

end

inp = input('Do you want to enter second primary user ? (Y/N)  ','s');

if(inp == 'Y' | inp == 'y')
```

```
        y2 = ammod(x1,cf2,Fs);

    end

    inp = input('Do you want to enter third primary user ? (Y/N)  ','s');

    if(inp == 'Y' | inp == 'y')
        y3 = ammod(x1,cf3,Fs);

    end

    inp = input('Do you want to enter fourth primary user ? (Y/N)  ','s');

    if(inp == 'Y' | inp == 'y')
        y4 = ammod(x1,cf4,Fs);

    end

    inp = input('Do you want to enter fifth primary user ? (Y/N)  ','s');

    if(inp == 'Y' | inp == 'y')
        y5 = ammod(x1,cf5,Fs);

    end

    y = y1 + y2 + y3 + y4 + y5;

while(1)

        Pxx = periodogram(y);
        Hpsd = dspdata.psd(Pxx,'Fs',Fs);
        plot(Hpsd);


  inp = input('\nDo you want to enter a secondary user ? (Y/N)  ','s');

    if(inp == 'Y' | inp == 'y')


        tp=0;
```

```
chek1 = Pxx(25)*10000;
chek2 = Pxx(46)*10000;
chek3 = Pxx(62)*10000;
chek4 = Pxx(89)*10000;
chek5 = Pxx(105)*10000;

if(chek1 < 8000)
    disp('Assigned to User 1 as the slot was empty.');
    y1 = ammod(x1,cf1,Fs);


elseif (chek2 < 8000)
    disp('Assigned to User 2 as the slot was empty.');
    y2 = ammod(x1,cf2,Fs);


elseif(chek3 < 8000)
    disp('Assigned to User 3 as the slot was empty.');
    y3 = ammod(x1,cf3,Fs);


elseif(chek4 < 8000)
    disp('Assigned to User 4 as the slot was empty.');
    y4 = ammod(x1,cf4,Fs);


elseif(chek5 < 8000)
    disp('Assigned to User 5 as the slot was empty.');
    y5 = ammod(x1,cf5,Fs);
else
    disp('all user slots in use. try again later,');
    tp=1;
end

figure
y = y1 + y2 + y3 + y4 + y5 ;
Pxx = periodogram(y);
Hpsd = dspdata.psd(Pxx,'Fs',Fs);
plot(Hpsd);

%deallocation
```

```
        if(tp==1)
        inpu=input('do u want to empty a slot:      ','s');
        if(inpu=='y')
            inpu=input('which slot do u want to empty for the new user:       ','s
            switch(inpu)

                case ('1')
                    y1=0;
                    disp('slot1 is deallocated');
                    y = y1 + y2 + y3 + y4 + y5;
                    Pxx = periodogram(y);
                    Hpsd = dspdata.psd(Pxx,'Fs',Fs);
                    plot(Hpsd);
%                     break;

                case('2')
                    y2=0;
                    disp('slot2 is deallocated');
                    y = y1 + y2 + y3 + y4 + y5;
                    Pxx = periodogram(y);
                    Hpsd = dspdata.psd(Pxx,'Fs',Fs);
                    plot(Hpsd);
%                     break;

                case('3')
                    y3=0;
                    disp('slot3 is deallocated');
                    y = y1 + y2 + y3 + y4 + y5;
                    Pxx = periodogram(y);
                    Hpsd = dspdata.psd(Pxx,'Fs',Fs);
                    plot(Hpsd);
%                     break;

                case('4')
                    y4=0;
                    disp('slot4 is deallocated');
                    y = y1 + y2 + y3 + y4 + y5;
                    Pxx = periodogram(y);
                    Hpsd = dspdata.psd(Pxx,'Fs',Fs);
                    plot(Hpsd);
                  % break;
```

```
            case('5')
                 y5=0;
                disp('slot5 is deallocated');
                y = y1 + y2 + y3 + y4 + y5;
                Pxx = periodogram(y);
                Hpsd = dspdata.psd(Pxx,'Fs',Fs);
                plot(Hpsd);
%                 break;

            otherwise disp('invalid slot number entered');
               %break;
        end  %switch end
end
end
%////////////////////Adding Noise////////////////////
inpu=input('do u want to add noise: ','s');
if(inpu=='y'|inpu=='Y')
d = input('Enter the SNR in dB:   ');
figure
Y = awgn(y,d);
Pxx1 = periodogram(Y);
Hpsd = dspdata.psd(Pxx1,'Fs',Fs);
plot(Hpsd);
disp('adding noise');

chek1 = Pxx1(25).*10000;
chek2 = Pxx1(36).*10000;
chek3 = Pxx1(62).*10000;
chek4 = Pxx1(89).*10000;
chek5 = Pxx1(105).*10000;

if(check1 < 8000)
    disp('User 1 is not present.');
else
    disp('User 1 is present.');
end

if(check2 < 8000)
    disp('User 2 is not present.');
    else
```

```
    disp('User 2 is present.');
end

if(check3 < 8000)
    disp('User 3 is not present.');
    else
    disp('User 3 is present.');
end

if(check4 < 8000)
    disp('User 4 is not present.');
    else
    disp('User 4 is present.');
end

if(check5 < 8000)
    disp('User 5 is not present.');
else
    disp('User 5 is present.');
end

end

%%%%%%%%%%%%%%%%%%%%%%%%Attenuating the signal%%%%%%

temp = input('Do you want to attenuate the signals? [Y/N]:     ','s');
if(temp == 'Y' | temp == 'y')
Yff=0;
aF = input('Enter the percentage to attenuate the signal:    ');

figure
tem = aF/100;
tm = 1-tem;
Z = y.*tm;
disp('attenuating...');

grid on
plot(Z);

figure
```

```
Pxx4 = periodogram(Z);
Hpsd = dspdata.psd(Pxx4,'Fs',Fs);
plot(Hpsd);

check1 = Pxx4(25).*10000;
chec\qquad k2 = Pxx4(36).*10000;
check3 = Pxx4(62).*10000;
check4 = Pxx4(89).*10000;
check5 = Pxx4(105).*10000;

if(check1 < 8000)
    disp('User 1 is not present.');
else
    disp('User 1 is present.');
end

if(check2 < 8000)
    disp('User 2 is not present.');
    else
    disp('User 2 is present.');
end

if(check3 < 8000)
    disp('User 3 is not present.');
    else
    disp('User 3 is present.');
end

if(check4 < 8000)
    disp('User 4 is not present.');
    else
    disp('User 4 is present.');
end

if(check5 < 8000)
    disp('User 5 is not present.');
else
    disp('User 5 is present.');
end
```

```
        end

    end

    %if rerun the program
    temp = input('Do you want to re-run the program? [Y/N]:     ','s');

     if(temp == 'Y' | temp == 'y')
         disp('Enter the users again');
     else
         break;
     end
end
```

Bibliography

[1] U. Varshney, The status and future of 802.11 based WLANs", IEEE computer, Vol. 36, No. 6, June 2003.

[2] Federal Communications Commission - First Report, and Order and Further Notice of Proposed Rulemaking, Unlicensed operation in the TV broadcast bands," FCC06-156, Oct. 2006.

[3] FCC, Spectrum policy task force report," ET. Docket No. 02-155, Nov. 2002.

[4] J. Mitola,Cognitive radio for flexible mobile multimedia communications," Proc. IEEE Int. Workshop on Mobile Multimedia Communication, pp. 3-10, 1999.

[5] Q. Zhao and B. M. Sadler, A survey of dynamic spectrum access," IEEE Signal Processing Magazine, vol. 24, pp. 79-89, May 2007.

[6] P.Demestichas, V.Stavroulaki, L.Papadopoulou, A.Vasilakos, M.Theologou, "Service configuration and distribution in composite radio environments", IEEE Transactions on Systems, Man and Cybernetics Journal, vol. 33, No. 4, pp. 69-81, Nov. 2003

[7] S. Haykin, Cognitive radio: brain-empowered wireless communication," IEEE J. Selected Areas of Communications, vol. 23, no. 2, pp. 201-220, 2005.

[8] A Friendly Guide to Wavelets, Birkhauser-Boston (1994; sixth printing 1999).

[9] Ten lectures on wavelets, Daubechies, Ingrid.

[10] Fundamentals of Signals and Systems, M.J. Roberts, February 9, 2007.

[11] Signals and Systems by Alan V. Oppenheim, Aug 2008.

[12] A Friendly Guide to Wavelets, by G. Kaiser.

[13] Stearns Samuel D., Digital Signal Processing With Examples in Matlab, 2nd Edition; CRC, January 2011. ISBN 978-1439837825.

[14] Donoho, D. L., "Denoising via soft thresholding", IEEE Trans. on Information Theory, vol 41 , pp 613-627, 1995.

[15] Alexandru Isar, Dorina Isar: "Adaptive denoising of low SNR signals", Third International Conference on WAA 1003, Chongqing, P. R. China ,pp 721-726, 29-31 May, 2003.

[16] http//www.amara.com/IEEEwave/IW fourier ana.html(Dissimilarities between fourier and wavelet transform).

[17] Jonathan Berger, Ronald R. Coifman, Maxim J. Goldberg "Removing noise from music using. local trigonometric bases and wavelet packets", Journal of the Audio Engineering Society, vol 42, pp707–779, October 1994.

[18] P. J. Wolfe and S. J. Godsill, "Simple alternatives to the Ephraim and Malah suppression rule for speech enhancement", IEEE Workshop on Statistical Signal Processing, pp. 496-499, Aug. 2001.

[19] D.L.Donoho: "De-noising by Soft Thresholding",report vol 409, Stanford University, December 1992.

[20] Connexions module: DWT to denoise a signal Mark Eastaway,vol 9990.

[21] S. Mallat,"A Wavelet Tour of Signal Processing", pp462,Academic Press, 2nd edition,1999.

[22] O. Cappe, "Elimination of the musical noise phenomenon with the Ephraim and Malah Noise Suppressor", IEEE Trans. Speech and Audio Processing, vol2, pp345-349, Apr.1994.

[23] P. J. Wolfe and S. J. Godsill, "Audio signal processing using complex wavelets", vol 5729, 114th Convention of the Audio Engineering Society, 2003.

[24] D. Donoho and I. Johnstone, "Idea Spatial Adaptation via wavelet Shrinkage", Biometrika, vol. 81, pp. 425-455, 1994.

[25] R. R. Coifman and D. L. Donoho. Translation-invariant de-noising. In A. Antoniadis and G. Oppenheim, editors, Wavelets and Statistics, volume 103 of Springer Lecture Notes in Statistics, pages 125–150, New York, 1995

[26] Y. Xu, J. B. Weaver, D. M. Healy, Jr., and J. Lu, "Wavelet transform domain filters: A spatially selective noise filtration technique," IEEE Trans. Image Proc. 3, pp. 747–758, Nov. 1994.

[27] D. L. Donoho and I. M. Johnstone. Ideal spatial adaptation via wavelet shrinkage. Biometrika, 81:425–455, 1994.

[28] D. L. Donoho, "De-noising by soft-thresholding," IEEE Trans. Inform. Th. 41, pp. 613–627, May 1995.Statistics, pages 125–150, New York, 1995.

[29] A. K. Fletcher, K. Ramchandran, and V. K. Goyal, "Wavelet denoising by recursive cycle spinning," in Proc. IEEE Int. Conf. Image Proc., 2, pp. 873–876, (Rochester, NY), Sept. 2002.

[30] S. Mallat, A Wavelet Tour of Signal Processing, Academic Press, second ed., 1999.

[31] J. Mitola III and G.Q. Maguire Jr., Cognitive Radio: Making software Radios More Personal, IEEE Personal.

[32] S. Haykin, Cognitive Dynamic Systems, Proceedings of the IEEE, vol. 94, no. 11, pp. 1910-1911, November 2006.

[33] I. F. Akyildiz, W.-Y. Lee, M.C. Vuran, S. Mohanty, NeXt generation/dynamic spectrum access/cognitive radio wirelessnetworks: a survey, Computer Networks, vol. 50, no. 13, pp. 2127-2159 , September 2006.

[34] A. Taherpour, S. Gazor, and M. Nasiri-Kenari, "Wideband spectrum sensing in unknown white Gaussian noise", IET Communications, vol.2, issue 6, pp. 763-771, July 2008.

[35] Z. Quan, S. Cui, A.H. Sayed, and H.V. Poor, "Wideband spectrum sensing in cognitive radio networks," IEEE International Conference on Communications, 2008. (ICC'08), pp. 901-906, May 2008.

[36] Z. Tian, G. B. Giannakis, A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios, 1st International Conference on Cognitive

Radio Oriented Wireless Networks and Communications, 2006, pp. 1-5, June 2006.

[37] S. Mallat e W. L. Hwang, Singularity Detection and processing with Wavelets, Information Theory, IEEE Transactions on, volume 38, pp. 617-643, March 1992.

[38] H. Urkowitz, Energy detection of unknown deterministic signals, Proceedings of the IEEE, vol. 55, no. 4, pp. 523-531, April 1967.

[39] A. V. Dandawate and G. B. Giannakis, Statistical tests for presence of cyclostationarity, IEEE Transactions on SignalProcessing, vol. 42, no.9pp.2355-2369,September1994.

[40] A. Sahai, N. Hoven and R. Tandra, "Some fundamental limits in cognitive radio," Allerton Conf. on Commun, Control and Computing 2004, October 2004.

[41] T.X. Brown, "An analysis of unlicensed device operation in licensed broadcast service bands,": Proc. IEEE DySPAN 2005, November 2005, pp. 11–29.

[42] A. Huttunen, J. Pihlaja, V. Koivunen, J. Junell, and K. Kalliojärvi, "Collaborative, distributed spectrum sensing for cognitive radio," in Wireless World Research Forum Meeting 20, Ottawa,Canada,22–24 April,2008.

[43] Y. Hur, J. Park, W. Woo, K. Lim, C.-H. Lee, H. S. Kim, and J. Laskar,"A wideband analog multi-resolution spectrum sensing technique forcognitive radio systems," IEEE International Symposium on Circuits and Systems (ISCAS'06), pp. 4090-4093, May 2006.

[44] Non-Cooperative Spectrum Sensing: A Hybrid Model Approach Shipra Kapoor and Ghanshyam Singh Department of Electronics and Communication Engineering, Jaypee University of Information Technology.

[45] H. Poor, An Introduction to Signal Detection and Estimation, 2nd ed.New York: Springer-Verlag, 1998.

[46] Y. Hur, J. Park, W. Woo, K. Lim, C.-H. Lee, H. S. Kim, and J. Laskar, "A wideband analog multi-resolution spectrum sensing technique for cognitive radio systems," in IEEE International Symposium on Circuits and Systems, Island of Kos, Greece, May 2006.

[47] C. han Lee and W. Wolf, "Multiple access-inspired cooperative spectrum sensing for cognitive radio," in IEEE Military Communications Conference, Orlando, FL, October 2007.

[48] S. Enserik and D. Cochran, "A cyclostationary feature detector," in 28th Asilomar Conf on Signals, Systems and Computers, CA, Oct 1994.

[49] T. C. Aysal, S. Kandeepan, and R. Piesiewicz, "Cooperative spectrum sensing over imperfect channels," in Proc of BWA Workshop at the IEEE Conf on GLOBECOM, 30 Nov - 3 Dec 2008.

[50] What Every Engineer Should Know About MATLAB and Simulink, Biran / Breiner, CRC Press, Inc.2011.

[51] MATLAB: A Practical Introduction to Programming and Problem Solving, Attaway Elsevier Science, 2009.

[52] Numerical Methods for Engineers and Scientists: An Introduction with Applications Using MATLAB, Gilat / Subramaniam, John Wiley and Sons, Inc. 2008.

Brief Bio-data (Resumè) of Students

AKSHAY DHAWAN
Department of Electronics and Communication Engineering,
Jaypee University of Information Technology,
Waknaghat, Solan (H.P.)
Year : 2011
C.G.P.A: **8.2** (84.17%, Up Till 7^{th} sem)

RAVI ANAND
Department of Electronics and Communication Engineering,
Jaypee University of Information Technology,
Waknaghat, Solan (H.P.)
Year : 2011
C.G.P.A: **8.2** (84.17%, Up Till 7^{th} sem)

SHEFALI ARORA
Department of Electronics and Communication Engineering,
Jaypee University of Information Technology,
Waknaghat, Solan (H.P.)
Year : 2011
C.G.P.A: **7.5** (79%, Up Till 7^{th} sem)

Publication:
International Conference on Computational Intelligence and Communication Networks (CICN) 2011, Gwalior, India