SPECTRUM SENSING IN COGNITIVE RADIOS

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Dedication:

In the name of Allah, the Most Merciful, the Most Beneficent

We wish to dedicate our efforts and work to our families and our friends, who have always been a great support and a constant source of encouragement.

Declaration:

No portion of the work presented in this dissertation has been submitted in support of any other award or qualification either at this institution or elsewhere

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REFERENCES

Abstract:

For the past many decades, since wireless communication emerged, there have been regulatory bodies all over the world that license the frequencies to particular users for specified use. Gradually, with the ever increasing trend towards wireless communication, the frequency spectrum kept on getting more and more crowded until quite recently the FCC (Federal Communications Commission) realized the problem of spectrum scarcity.

The battle between the increasing demand for spectrum and its scarcity has forced us to come up with solutions for the efficient use of the existing spectrum and accommodate new users. The problem calls for a dire need of a system which can sense the spectrum and dynamically adapt to the changes in the environment and continue communication without the need of one fixed licensed band. Such a system is called a cognitive Radio and is the focus of this project.

In this dissertation, the reader can find deep research into the problem and into the characteristics of a new proposed system that aims to solve the problem. An algorithm has been devised for spectrum sensing in cognitive radios. After detailed review of the research, simulations that have been carried out on software have been explained which then make way for the hardware implementation portion of the project.

The project is not aimed to be a complete working system but can serve as a prototype on which future cognitive radios can be based.

The authors of this thesis have put all their efforts to make it as succinct and self explanatory for the reader as possible. Concepts have been built from the very foundations and left where future research can be done if the reader wishes.

Chapter 1

Introduction

1.1 Background

Wireless networks are regulated by a fixed spectrum assignment policy, i.e. the spectrum is regulated by governmental agencies and is assigned to license holders or services on a long term basis for large geographical regions. In addition, a large portion of the assigned spectrum is used sporadically as shown in *Fig 1*. The spectrum usage is

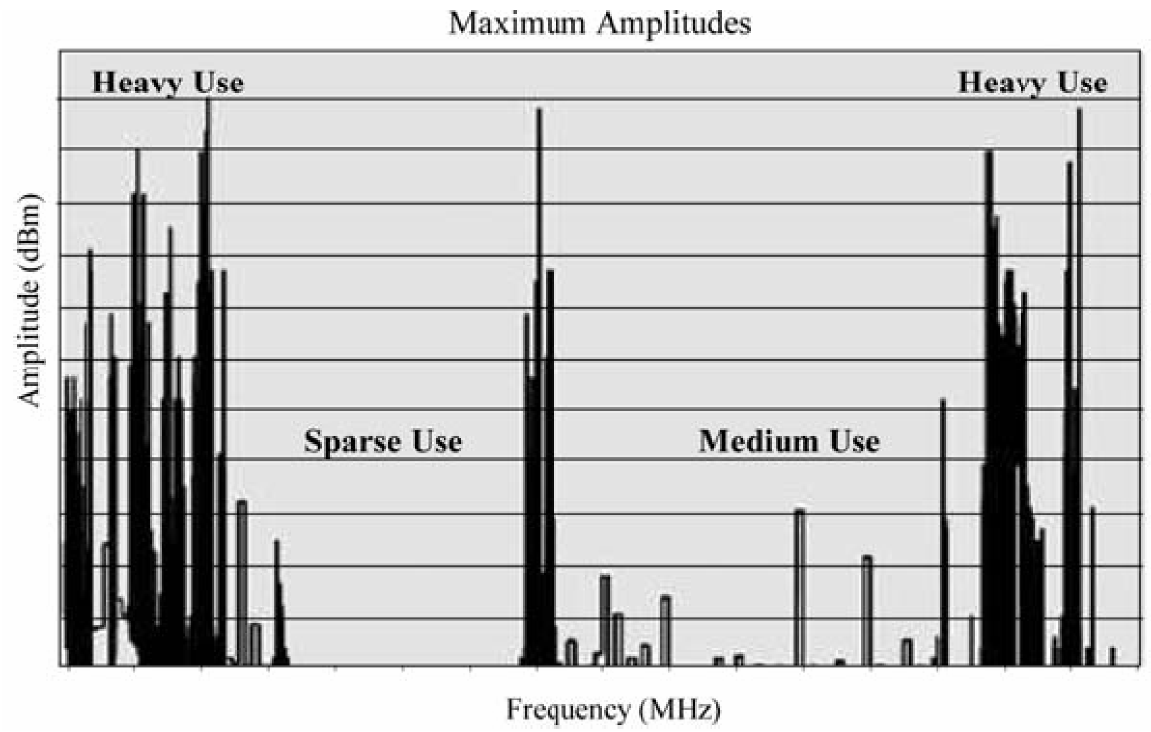


Fig.1 Spectrum Usage

concentrated on certain portions of the spectrum while a significant amount of the spectrum remains unutilized. Temporal and geographical variations in the utilization of the assigned spectrum vary greatly from time to time. The spectrum usage is concentrated on certain portions of the spectrum while a significant amount of the spectrum remains unutilized. This results in inefficient spectrum usage. According to Federal Communications Commission (FCC) temporal and geographical variations in the utilization of the assigned spectrum range from 15% to 85%. Although the fixed spectrum assignment policy generally served well in the past, there is a dramatic increase in the access to the limited spectrum for mobile services in the recent years. This increase is straining the effectiveness of the traditional spectrum policies, and is acting as a major hindrance to the implementation of new technologies that require the use of the frequency spectrum.

1.2 Present Scenario

As a result of the crowded spectrum regulators all across the world are trying to find new methods for spectrum access and utilization. These new methodologies recognize that fixed assignment of a frequency to one purpose across huge geographic regions (often across entire countries) is quite inefficient. Today, this type of frequency assignment results in severe underutilization of the precious and bounded spectrum resource.

1.3 Possible Solutions

The Federal Communications Commission (FCC; for commercial applications) and the National Telecommunications and Information Administration (NTIA; for federal applications) in the United States, as well as corresponding regulatory bodies of many other countries, are exploring the question of whether better spectrum utilization could be achieved given some intelligence in the radio and in the network infrastructure.

1.3.1 Aggregating Spectrum Demand and Use of Subleasing Methods

Many applications for wireless service operate with their own individual licensed spectra. It is rare that each service is fully consuming its available spectrum. Studies show that spectrum occupancy seems to peak at about 14 percent, except under emergency conditions, where occupancy can reach 100 percent for brief periods of time. Each of these services do not wish to separately invest in their own unique infrastructure. Consequently, it is very practical to aggregate these spectral assignments to serve a user community with a combined system. The industry refers to a collection of services of this type as a trunked radio. Trunked radio base stations have the ability to listen to many input frequencies. When a user begins to transmit, the base station assigns an input and an output frequency for the message and notifies all members of the community to listen on the repeater downlink frequency for the message. Trunking aggregates the available spectrum of multiple users and is therefore able to deliver a higher quality of service while reducing infrastructure costs to each set of users and reducing the total amount of spectrum required to serve the community.

Based on some what similar pattern new technologies are being developed to solve the problem of crowded spectrum.

1.3.2 Dynamic Spectrum Access (DSA)

The limited availability of spectrum and its inefficient use necessitate a new communication paradigm to exploit the existing wireless spectrum opportunistically Dynamic spectrum access (DSA) based intelligent radios are proposed to solve these current spectrum inefficiency problems. The NeXt Generation (xG) communication networks also called the Dynamic Spectrum Access Networks (DSAN's) based on intelligent radio's will provide high bandwidth to mobile users by the use of various dynamic spectrum access techniques. The present inefficient use of the available spectrum can be significantly improved with the use these xG networks. These networks have the potential of affecting the market place for radio devices and services as well as changing the means by which wireless communications policy is developed and implemented, however one of the key parameters which is to be addressed is the access to radio spectrum. Once the access is obtained, the capacity to manage interference becomes a key attribute for increase in the number of users. The ability of a device implemented using DSA; to be aware of its environment, adapt to enhance its performance, and the performance of the network, allows a transition from a manual, oversight process to an automated, device-oriented process. This ability has the potential to allow a much more intensive use of the spectrum by lowering of spectrum access barrier to entry for new devices and services. It also has the potential to radically change how policy should be developed in order to account for these new uses of the spectrum, and it can fundamentally change the role of the spectrum policy-maker and regulator.

1.3.3 Cognitive Radio

The key enabling technology of xG network is the *cognitive radio(CR)*. The techniques provided by these radios provide the capability to use or share the spectrum in an opportunistic manner. Dynamic spectrum access techniques allow the cognitive radio to operate in the best available channel.

It is defined as

"A radio that senses its environment and dynamically adapts to utilize radio resources in time, frequency and space domains on a real time basis while not interfering with licensed users and other CR's".

OR

"A 'Cognitive Radio' is a radio that can change its transmitter parameters based on interaction with the environment in which it operates."

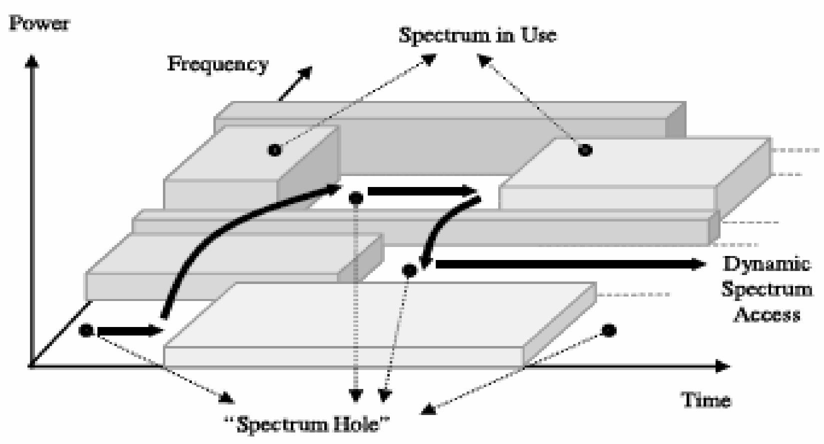


Fig.2 Spectrum Hole concept

The ultimate objective of the cognitive radio is to obtain the best available spectrum through cognitive capability and reconfigurability. As most of the spectrum is already assigned, the most important challenge is to share the licensed spectrum without interfering with the transmission of other licensed users as shown in Fig.2. The figure is a three dimensional representation of the RF environment, where the x-axis represents time, the y-axis is the power amplitude and the z-axis is the frequency. At the start on the time axis, the cognitive radio senses the spectrum (the YZ plane at x=0) and finds out the available free bands. It starts to communicate on what ever free band is most feasible for use. As soon as some licensed user comes in to operate on that band, the cognitive radio through is continual sensing and monitoring identifies a new empty band to which it can migrate. In this way the cognitive radio user keep hopping from frequency to frequency, without any prior license to operate in any specified frequency, and still not interfering those who have the license for those frequencies.

Cognitive radio can provide a wide variety of intelligent behaviors. It can monitor the spectrum and choose frequencies that minimize interference to existing communication networks. When doing so, it follows a set of rules that define what frequencies may be considered, what waveforms may be used, what power levels may be used for transmission etc. It may also be given rules about the access protocols by which spectrum access is negotiated with spectrum license holders, if any, and the etiquettes by which it must check with other users of the spectrum to ensure that no user hidden from the node wishing to transmit is already communicating.CR’s are powerful tools for mitigating and solving general and selective spectrum access issues, they help in improving wireless data network performance through increases user throughput and system reliability with their use more adaptability and less coordination is required between wireless networks.

1.4 Functions of a Cognitive Radio

More specifically, the cognitive radio technology will enable the users to:

- Spectrum Sensing:

  Determine which portions of the spectrum are available and detect the presence of licensed users when a user operates in a licensed band.

- Spectrum Management:

  Select the best available channel.

- Spectrum Sharing:

  Coordinate access to this channel with other users.

- Spectrum Mobility:

  Vacate the channel when a licensed user is detected.

1.4.1 Spectrum Sensing

To understand the spectrum sensing in cognitive radios, we first need to familiarize ourselves with a few basic terms that will be used repeatedly in this thesis:

a) Primary User:

   The user who has the license to operate in a certain frequency band.

b) Secondary User:

   The cognitive radio user or the unlicensed user who will carry out his transmission in both licensed and unlicensed bands without causing any interference to any primary user.

c) White Space:

   The free or vacant band in the RF spectrum. Also referred to as a spectrum hole.

d) Dark Space:

The occupied band in the RF spectrum where some other primary or secondary user is already carrying out his transmission.

Now that we have acclimatized ourselves to the basic cognitive radio terminologies, we are all set to understand how it senses the spectrum.

Spectrum sensing means to detect spectrum holes, this function enables the CR to adapt to its environment. The most efficient way to detect spectrum holes is to detect the primary users that are working within the range of the CR, in reality it is however difficult for a CR to have a direct measurement of a channel between the primary user and the transmitter, thus emphasis is laid on the detection of the primary transmitter as oppose to the primary user. In general the sensing techniques are classified as shown in *Fig.3*

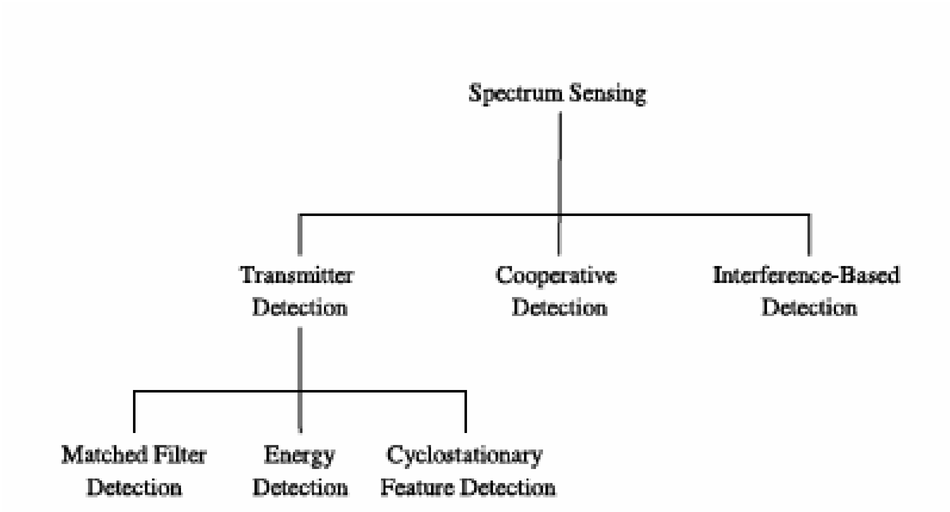


Fig.3 Classification of Spectrum Sensing Techniques

Here we concern ourselves only with the Transmitter based detection. The transmitter based detection is further sub-divided into three different types:

1.4.1.1 Matched Filter Detection

In the case of matched filter detection it is imperative to have the prior knowledge of the signal type which is to be received; mostly Gaussian noise is the matched filter as it maximizes the Signal to Noise ratio (SNR). While the main advantage of the matched filter 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. Hence, if this information is not accurate, then the matched filter performs poorly. However, since most wireless network systems have pilot, preambles, synchronization word or spreading codes, these can be used for the coherent detection.

1.4.1.2 Energy Detection

If the receiver is not able to gather enough information about the receiving signal than the method to be used for detection is energy based detection. In order to measure the energy of the received signal, the output signal of band pass filter with bandwidth W is squared and integrated over the observation interval T. Finally, the output of the integrator, Y, is compared with a threshold, k, to decide whether a licensed user is present or not. This is also a quicker method to find out spectrum holes and involves less mathematical computations as compared to other methods.

1.4.1.3 Cyclostationary Feature Detection

An alternative detection method is the cyclostationary feature detection. 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. These features are detected by analyzing a spectral correlation function. 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. However, it is computationally complex and requires significantly long observation time. For more efficient and reliable performance, the enhanced feature detection scheme combining cyclic spectral analysis with pattern recognition based on neural networks can also be used.

1.4.2 Spectrum Management

In xG networks, in which cognitive radios are to be used the unused spectrum bands will be spread over wide frequency range including both unlicensed and licensed bands. These unused spectrum bands detected through spectrum sensing show different characteristics according to not only the time varying radio environment but also the spectrum band information such as the operating frequency and the bandwidth. Since cognitive radios should decide on the best spectrum band to meet the QoS requirements over all available spectrum bands, new spectrum management functions are required for xG networks, considering the dynamic spectrum characteristics. We classify these functions as spectrum sensing, spectrum analysis, and spectrum decision, which are discussed further on.

1.4.3 Spectrum Sharing

In xG networks, employing cognitive radio's one of the main challenges in open spectrum usage is the spectrum sharing. Spectrum sharing can be regarded to be similar to generic medium access control (MAC) problems in existing systems. However, substantially different challenges exist for spectrum sharing in xG networks. The coexistence with licensed users and the wide range of available spectrum are two of the main reasons for these unique challenges.

1.4.4 Spectrum Mobility

*Spectrum mobility is defined as the process when an xG user changes its frequency of operation.*xG networks target to use the spectrum in a dynamic manner by allowing the radio terminals; the cognitive radio, to operate in the best available frequency band. This enables ''Get the Best Available Channel'' concept for communication purposes. To realize the ''Get the Best Available Channel'' concept, an xG radio has to capture the best available spectrum.

1.5 Physical Architecture of a Cognitive Radio

The generic architecture of a cognitive radio is shown in *Fig.4*

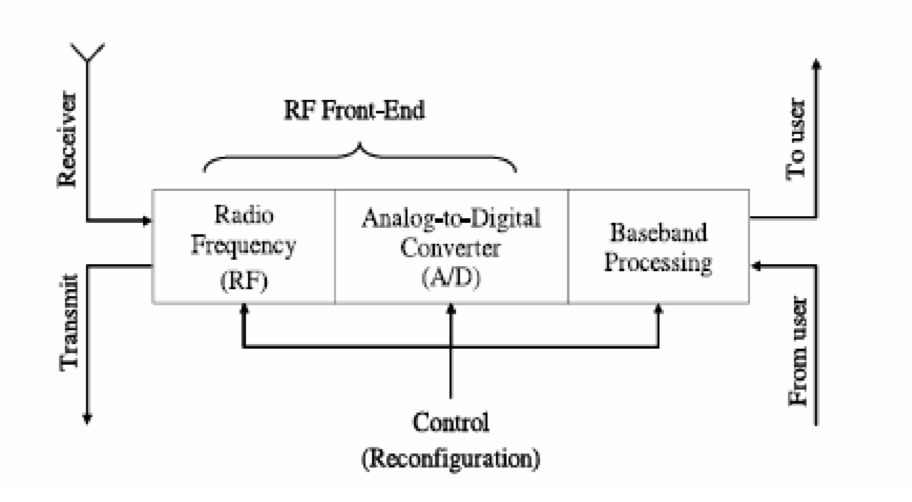


Fig.4 Cognitive Radio Transceiver

The main components of a cognitive radio transceiver are the radio front end and the baseband processing unit. Each component can be re-configured depending on the ever changing radio environment. In the RF front end the received signal is amplified, mixed and A/D converted. In the baseband processing unit, the signal is modulated/demodulated and encoded/encoded. The baseband processing unit of the cognitive radio is similar to that of other transceivers however the main difference is in the RF front end.

The main novel characteristic of the RF front end of the cognitive radio is its wide band sensing capability; this function is mainly related to the RF hardware technologies such as wide band antennas, power amplifier and adaptive filter. The RF front end of the cognitive radio should be capable of tuning to any frequency within the spectrum of interest; this kind of spectrum sensing enables real-time measurements of spectrum information from radio environment. Generally the wideband front end architecture for a cognitive radio as a structure as shown in *Fig.5*

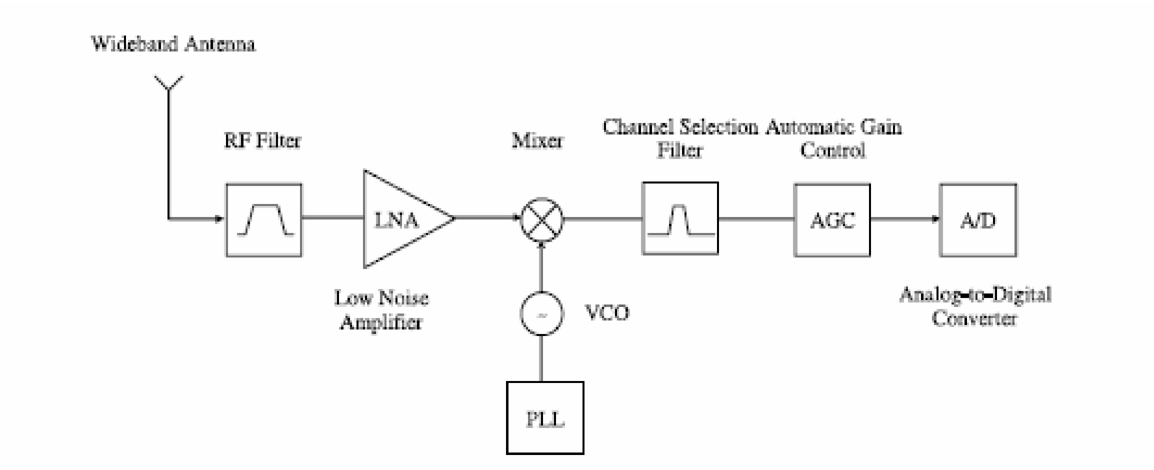


Fig.5 Wide band RF front end architecture

RF Filter: The RF filter selects the desired band by bandpass filtering the received RF signal.

Low noise amplifier (LNA): The LNA amplifies the desired signal while simultaneously minimizing noise component.

Mixer: In the mixer, the received signal is mixed with locally generated RF frequency and converted to the baseband or the intermediate frequency (IF).

Voltage-controlled oscillator (VCO): The VCO generates a signal at a specific frequency for a given voltage to mix with the incoming signal. This procedure converts the incoming signal to baseband or an intermediate frequency.

Phase locked loop (PLL): The PLL ensures that a signal is locked on a specific frequency and can also be used to generate precise frequencies with fine resolution.

Channel selection filter: The channel selection filter is used to select the desired channel and to reject the adjacent channels.

Automatic gain control (AGC): The AGC maintains the gain or output power level of an amplifier constant over a wide range of input signal levels.

1.6 Characteristics of Cognitive Radio

The two main characteristics of a cognitive radio are:

- *Cognitive Capability*
- *Reconfigurability*

1.6.1 Cognitive Capability

Cognitive Capability refers to the ability of a radio to capture or sense the information from it’s environment, this can’t be just simply be achieved by monitoring the power in some frequency band of interest but more sophisticated techniques are required in order to capture the temporal and spatial variations in the radio environment and avoid interference to other users. Through this capability, the portions of the spectrum that are unused at a specific time or location can be identified and best spectrum and appropriate operating parameters can be selected. The tasks required for this adaptive operation are shown in *Fig.6* called the *cognitive cycle.*

1.6.1.1 Cognitive Cycle

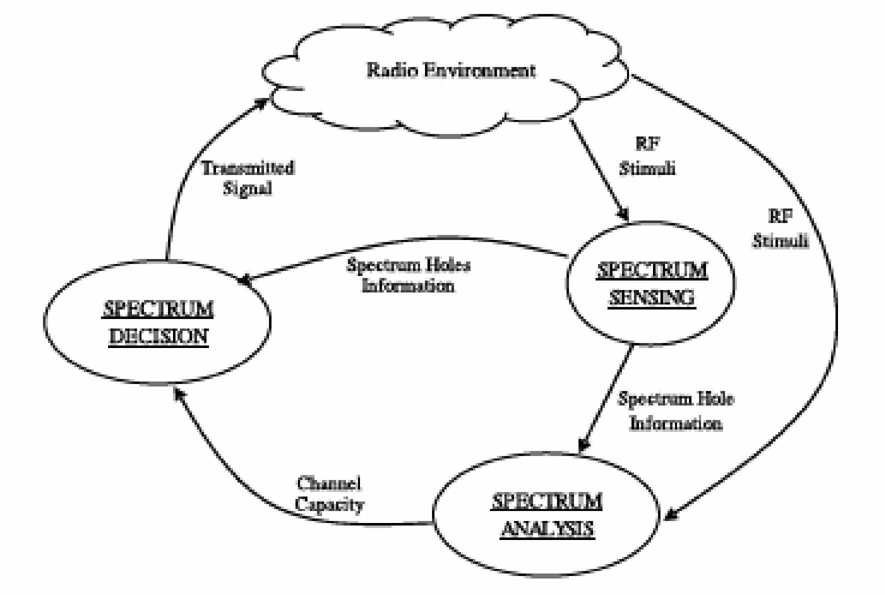


Fig.6 Cognitive Cycle

The cognitive cycle involves three main steps:

- Spectrum Sensing
- Spectrum Analysis
- Spectrum Decision

Spectrum Sensing:

In the spectrum sensing portion of the cognitive cycle the CR senses the concerned spectrum, captures its information based on the method being employed in the radio and finally detects the spectrum hole.

Spectrum Analysis:

In this part of the cycle analysis of the spectrum sensed in the first part is carried out with emphasis on spectrum holes which have been detected through spectrum sensing.

Spectrum Decision:

In this part of the cycle the CR determines the data rate, transmission mode and the bandwidth of the transmission, after which appropriate band is chosen according to the spectrum characteristics and user requirements.

After the successful completion of the cognitive cycle once the band of the concerned spectrum is determined communication can be performed over this band of the spectrum. However as the radio environment is continuously changing over time and space the CR must keep track of the changes of the radio environment in which it's operating. If the band in which the CR is operating becomes unavailable, the spectrum mobility function comes into action. Any environmental changes during the transmission such as appearance of a primary user, user movement or traffic variation can trigger this adjustment.

1.6.2 Re-configurability

Whereas cognitive capability enables CR to be aware of its environment reconfigurability enables it to be programmed dynamically according to the environment. Moreover cognitive radio can be programmed to transmit and receive on a wide range of frequencies and to use different transmission techniques supported by the hardware. This capability enables the cognitive radio to adapt easily to the ever changing radio environment. There are several reconfigurable parameters that are incorporated in the cognitive radio:

Operating Frequency:

One of the reconfigurable parameter in a CR is its operating frequency, based on the environment in which the radio is operating its operating frequency can reconfigured in order to get the best possible results.

Modulation:

A CR can also reconfigure the modulation scheme depending on the requirement of the user and the radio environment. For example in the case of delay sensitive applications where the data rate is more important than the error rate, a modulation scheme that enables higher spectral efficiency would be used, conversely ,the applications which are sensitive to loss would go for modulation scheme with low bit error rate.

Transmission Power:

Another reconfigurable parameter in CR's is the transmission power, this enables dynamic power configuration within the permissible power limit. If transmission at higher power is not required the cognitive radio can reduce the transmitter's power to a lower level to allow more users to share to share the spectrum and decrease the interference.

Communication Technology:

A cognitive radio can also be used to provide interoperability among different communication systems. The transmission parameters of a cognitive radio can be reconfigured not only at the beginning of the transmission but also during the transmission. According to the spectrum characteristics, these parameters can be reconfigured such that the cognitive radio is switched to a different spectrum band, the transmitter and receiver parameters are reconfigured and the appropriate communication protocol parameters and modulation schemes are used.

1.7 Previous work

It's only recently that the idea of dynamic spectrum access has surfaced in the telecommunications world. Work has been carried out on the physical and MAC layer issues relating to cognitive radios, only in bits and pieces. Only recently in November 2004, IEEE has organized a working group under the standard 802.22 whose job is to standardize the cognitive radio and secondary spectrum access technologies.

Some research is being done in the Wireless Research Center, University of Berkeley on the Cyclostationary Feature Detection algorithms and on the Available Resource Mapping. The research can be found under the name of "DySPAN" over the internet.

Other sources also provide other suggested methods for spectrum sensing, each one with its own pros and cons. Also some emulation platforms have been suggested for the cognitive radio test beds.

But all of this research is still a long way from a practical implementation of the cognitive radio system.

Chapter 2

Methodology

This project is another step towards developing an efficient spectrum sensing scheme in the cognitive radio environment. Extensive research has been carried out to arrive at the final results which shall be presented later in this thesis.

The methodology adopted in this project is depicted in the diagram given below:

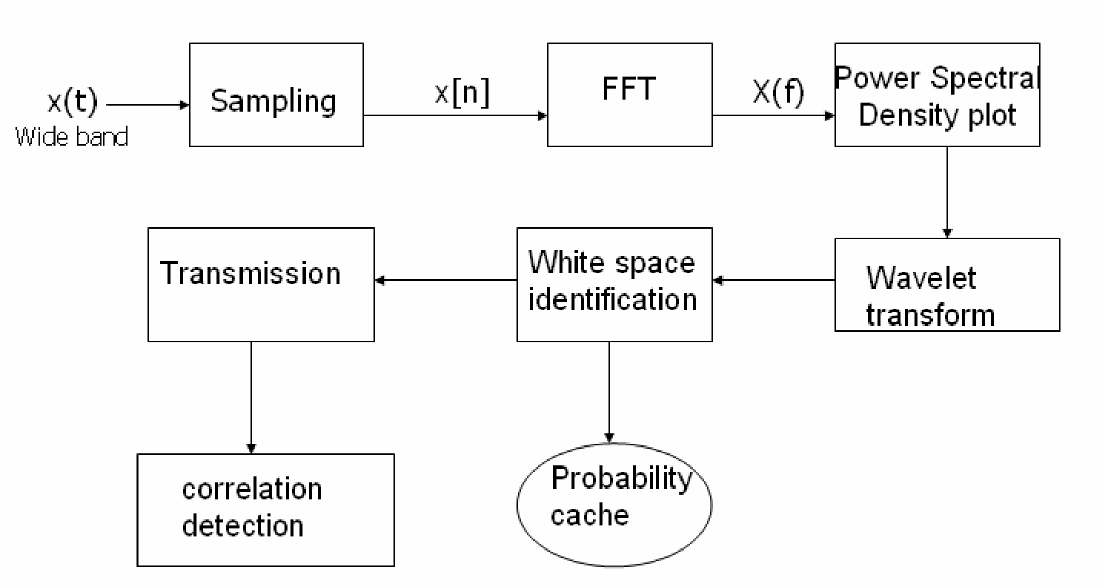


Fig 7: Methodology

2.1 Wideband signal

The input to the algorithm is a time domain wideband signal. A time domain signal is the one which varies with respect to time and signal's value is known for all real numbers (Continuous) or at discrete interval (discrete).In this case the signal is a continuous time domain signal, the term wideband refers to the wide range of frequencies present in the signal.

2.2 Sampling

Sampling refers to the conversion of continuous time signal to discrete time. A continuous signal is defined for all values for a given time interval whereas a discrete signal has values at individually distinct points. Let x(t) be a continuous signal which is to be sampled, and that sampling is performed by measuring the value of the continuous signal every T seconds. Thus, the sampled signal x[n] is given by:

$x[n] = x(nT)$, with $n = 0, 1, 2, 3, \ldots$

T is the sampling interval in the equation given above. The sampling rate or sampling frequency is defined as the number of samples obtained in one second, or $fs = 1/T$. The sampling rate is measured in hertz or in samples per second.

2.2.1 Nyquist-Shannon sampling theorem

Nyquist-shannon sampling theorem provides a condition for sampling a band pass signal. A bandpass signal is the one with a maximum frequency value. The theorem states that the sampling rate should be more than twice the maximum frequency. Nyquist rate is the equal to the twice maximum frequency component for which the sampling frequency has to be exceeded. The frequency equal to one-half of the sampling rate is therefore a bound on the highest frequency that can be unambiguously represented by the sampled signal. This frequency (half the sampling rate) is called the Nyquist frequency of the sampling system. Frequencies above the Nyquist frequency fN can be observed in the sampled signal, but their frequency is ambiguous. That is, a frequency component with frequency f cannot be distinguished from other components with frequencies NfN + f and NfN – f for nonzero integers N. This ambiguity is called aliasing. To handle this problem most analog signals are filtered with a low pass filter with cutoff near the nyquist frequency before conversion to sampled discrete representation.

2.2.2 Bandpass Sampling Theorem

In contrast to nyquist theorem, the bandpass sampling theorem can significantly lower the sampling rate. As stated before, a continuous-time signal with highest frequency fmax can be uniquely represented by samples taken at the minimum rate (Nyquist rate) of 2fmax samples per second. However, if the signal is a band-pass signal with frequencies components in the band f1 ≤ f ≤ f2, a blind application of the sampling theorem would have us sampling the signal at a rate of 2f2 samples per second. If that were the case and f2 was an extremely high frequency, the sampling would be more difficult to perform.

If the sampling is to be performed for a signal using bandpass sampling theorem, the ratio of the highest frequency component is quite large.Real signals have Fourier spectra with symmetry about zero. That is, they have a negative-frequency spectrum that is a mirror image of the positive-frequency spectrum. Sampling effectively shifts both sides of the spectrum by multiples of the sampling frequency.For this a bandpass with low and high band limits fL and fH respectively, the condition for an acceptable sample rate is that shifts of the bands from fL to fH and from –fH to –fL must not overlap when shifted by all integer multiples of sampling rate fs.

The sampling rate for this is given by:

$$2\ fH / n < fs < 2\ fL / 2n\text{-}1$$

$$1 \leq n \leq fH / (fH - fL)$$

Here, n is an integer for which the condition is satisfied. The highest value for n corresponds to the lowest sampling rate and when n =1, the condition becomes equal to the nyquist rate.

Coming back to the time domain wideband signal, which we accepted as an input to the sampler, it will be sampled at twice the highest frequency component for all the frequency components to be available in the frequency domain. The signal bandwidth is equal to the highest maximum frequency component and which therefore leaves us with the nyquist criteria for sampling as discussed earlier. However, if the sampling is to be performed for a signal for which the ratio of the highest frequency component is quite large, for example a narrow band signal of high frequency, the bandpass theorem is equally valid.

2.3 Fast Fourier transform

The next step is to convert the discrete time wideband signal to the frequency domain for further analysis. A number of transformations lay before us, we discuss some of them and use which suits best for our case.

2.3.1 Fourier transform

A Fourier Transform is a mathematical operation that transforms a signal from the *time domain* to the *frequency domain*, and vice versa. In the time domain, the signal is expressed with respect to time. In the frequency domain, a signal is expressed with respect to frequency.

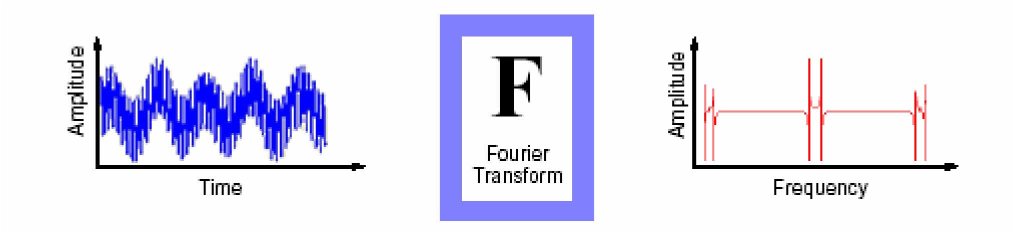


Fig 8: Fourier transform of a time domain signal

2.3.2 Discrete Fourier Transform

This is one of the forms of Fourier analysis. It accepts input in the discrete time domain form and converts it to frequency domain. This is done by sampling a continuous time domain signal, which is performed earlier in the algorithm. The DFT of an N point signal is given by the following equation:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N} kn} \qquad k = 0, \dots, N-1$$

The Fast Fourier Transform (FFT) is another method for calculating the DFT. While it produces the same result as the other approaches, it is incredibly more efficient and reduces the computation time by a considerable amount. Since the algorithm is focuses on real time processing, time is a major factor.

The FFT is a set of algorithms for computing the complex DFT. The following diagram depicts the difference between a real and complex FFT:

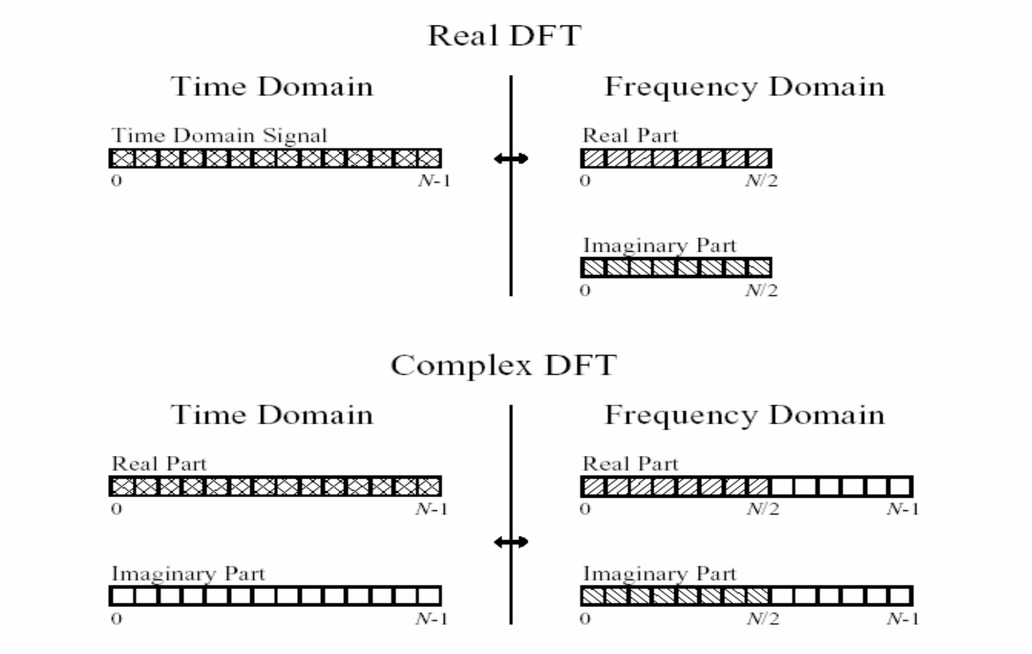


Fig 9: Comparison of real and complex DFT

The real DFT transforms an N point time domain signal into two N/2 point frequency domain signals. The two signals in the frequency domain are called the real part and the imaginary part, holding the amplitudes of the cosine waves and sine waves, respectively.

In comparison, the complex DFT transforms two N point time domain signals into two N point frequency domain signals. The two time domain signals are called the real part and the imaginary part, just as are the frequency domain signals. In spite of their names, all of the values in these arrays are just ordinary numbers.

Functionally, the FFT decomposes the set of data to be transformed into a series of smaller data sets to be transformed. Then, it decomposes those smaller sets into even smaller sets. At each stage of processing, the results of the previous stage are combined in special way. Finally, it calculates the DFT of each small data set. For example, an FFT of size 16 is broken into 2 FFT’s of size 8 which are broken into 4 FFT’s of size 4, which are broken into 8 FFT's of size 2, which are broken into 16 FFT's of size 1. A DFT of a single point is the same, so no further calculation is required.

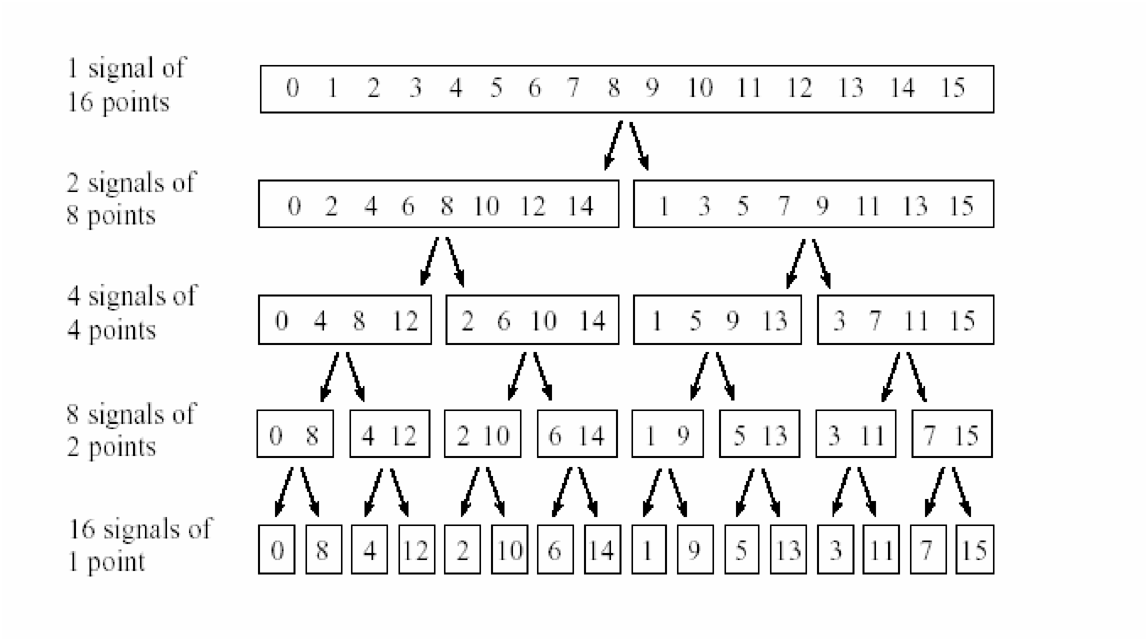


Fig 10: Fast Fourier Transform

The first stage breaks the 16 point signal into two signals each consisting of 8 points. The second stage decomposes the data into four signals of 4 points. This pattern continues until there are N signals composed of a single point. An interlaced decomposition is used each time a signal is broken in two, that is, the signal is separated into its even and odd numbered samples. A total of Log2(N) stages is required for the decomposition .A 16 point signal requires 4 stages, a 512 point signal requires 9 stages, a 4096 point signal requires 12 stages and so on. The decomposition is nothing more than a reordering of the samples in the signal. The figure below shows the rearrangement pattern required. On the left, the sample numbers of the original signal are listed along with their binary equivalents. On the right, the rearranged sample numbers are listed, also along with their binary equivalents. The important idea is that the binary numbers are the reversals of each other. Another way to look at this are that the final order is nothing more than a bit reversal. The MSB's become the LSB's and the vice versa for each number's binary equivalent.

Sample numbers in normal order			Sample numbers after bit reversal	
Decimal	*Binary*		*Decimal*	*Binary*
0	0000		0	0000
1	0001		8	1000
2	0010		4	0100
3	0011		12	1100
4	0100		2	0010
5	0101		10	1010
6	0110	⇨	6	0100
7	0111		14	1110
8	1000		1	0001
9	1001		9	1001
10	1010		5	0101
11	1011		13	1101
12	1100		3	0011
13	1101		11	1011
14	1110		7	0111
15	1111		15	1111

Fig 11: The FFT bit reversal sorting.

Now after the DFT of each single point is taken (which is the point itself) the last step is to rearrange the spectrum in exact reverse order in which the time-domain decomposition of the signal took place This is done using a special method often termed as the butterfly algorithm.

2.3.3 Butterfly algorithm

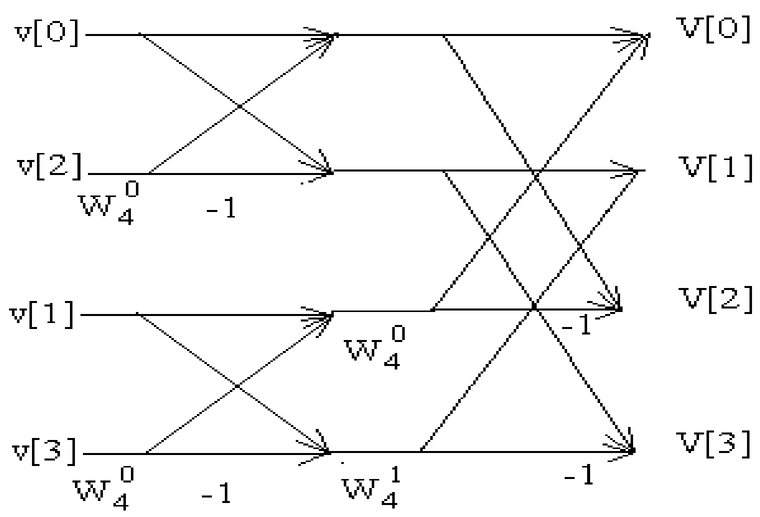


Fig 12: A butterfly diagram of 4 point FFT

This diagram is the essence of the FFT algorithm. The main trick is that you don't calculate each component of the Fourier transform separately. That would involve unnecessary repetition of a substantial number of calculations. Instead, you do your calculations in stages. At each stage you start with N numbers and "butterfly" them to obtain a new set of N complex numbers. Those numbers, in turn, become the input for the next stage. The calculation of a 4-point FFT involves two stages. The input of the first stage is the 4 original samples. Notice that each stage involves N multiplications. The number of stages is log2 (N). Altogether, the FFT requires on the order of Nlog2 (N) calculations.

2.3.4 Efficiency of FFT

The DFT takes N^2 operations for N points. For a FFT at any stage the computation required to combine smaller points into a large frequency spectrum is proportional to N, and there are log2(N) stages (for radix 2), the total computation is proportional to N*log2(N). Therefore, the ratio between a DFT computation and an FFT computation for the same N is proportional to N / log2 (N). In cases where N is small this ratio is not very significant, but when N becomes large, this ratio gets very large. Every time when N is doubled, the numerator doubles, but the denominator only increases by 1.

In dynamic spectrum sensing, speed is a major issue and thus faster algorithms are employed to sense spectrum in real time thus the FFT is a good choice. If a 1024 point FFT is compared to DFT, the ratio comes to 102.4 which means the number of computations is reduced by more than a hundred times.

2.4 Power Spectral Density Plot

The Power spectral density function (PSD) shows the strength of the variations (energy) as a function of frequency. In other words, it shows at which frequencies variations are strong and at which frequencies variations are weak. The unit of PSD is energy per frequency (width) and energy within a specific frequency range can be obtained by integrating PSD within that frequency range. Computation of PSD is done directly by the method called FFT or computing autocorrelation function and then transforming it.

PSD is a very useful tool for identifying oscillatory signals and their amplitude. PSD is still useful even if data do not contain any purely oscillatory signals. We quite often compute and plot PSD to get an idea of data at an early stage of time series analysis. Looking at PSD is like looking at simple time series plot except that we look at time series as a function of frequency instead of time. Here, we could say that frequency is a transformation of time and looking at variations in frequency domain is just another way to look at variations of time series data. PSD tells us at which frequency ranges variations are strong and that might be quite useful for further analysis.

Since the data is already in the frequency domain and that is done by taking the FFT of the time domain signal. To convert the data into a PSD plot in MATLAB the square of the FFT is taken and divided by the number of points of the FFT.The algorithm employed for spectrum sensing is an energy detection based thus it is necessary to take the PSD plot of the frequency domain signal. This gives us strength of different frequency present in the signal. The PSD is used for edge detection by the wavelet transform which is further used in the determining of licensed user signals in the wide band frequency spectrum.

2.5 Wavelet transforms

One of the shortcomings of the Fourier Transform is that it does not give any information on the time at which a frequency component occurs. This is not a problem for signals not varying with time but is a constraint for time varying signals, such that in our case. The short-time Fourier transform (STFT), or alternatively short-term Fourier transform, is a Fourier-related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time.

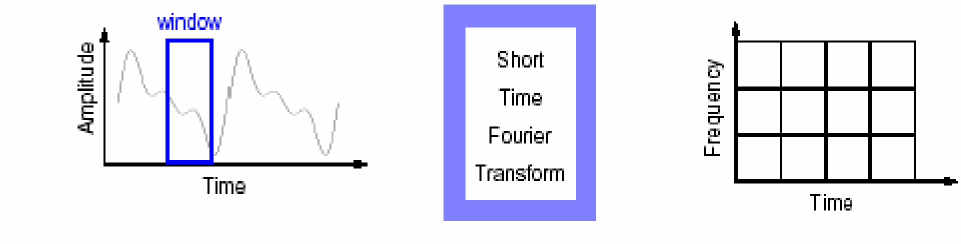


Fig 13: STFT of a time domain signal

In short time Fourier transforms (STFT), a moving window is applied to the signal and the Fourier transform is applied to the signal within the window as the window is moved. This gives us a two dimensional plot of the frequency and time. The drawback of this is that the window size chosen initially to compute the STFT of the time domain signal remains the same for complete time. The frequency and time information of an abrupt changing signal maybe compromised. Since the window size is not variable, the precision of the mentioned parameters is limited.

In the discrete time case, the data to be transformed could be broken up into chunks or frames and then Fourier transformed, with the results added together to give magnitude and phase for each time in frequency and time.

Previously, we discussed different methods to convert a time domain signal to a frequency domain signal. A wavelet is no different in the sense; it converts a signal from a time-domain to a frequency domain. However, the signal approaching this algorithm block is not only converted to the frequency domain but plotted with its power spectral density. Before moving onto the purpose of using wavelet transform in this project, it is necessary to develop a further insight into wavelet transform.

The word wavelet comes from a French word "ondellete" meaning a small waveform. Generically, it is a waveform of effectively limited duration that has an average value of zero. Compare wavelets with sine waves, which are the basis of Fourier analysis. Sinusoids do not have limited duration — they extend from minus to plus infinity. And where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric.

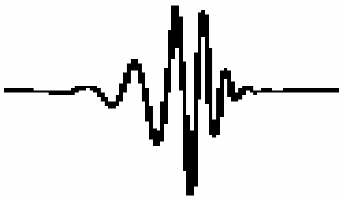


Fig 14: A wavelet

Moreover, the Fourier is focused on breaking a signal into sinusoidal components whereas a wavelet analysis is the breaking of signal into shifted and scaled version of the original wavelet. The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function :

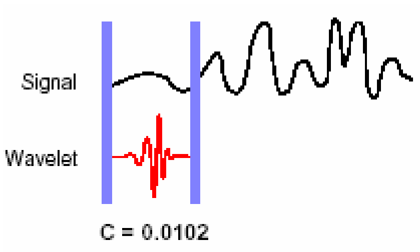
$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)\,dt$$

This produces wavelet coefficients that are a function of scale and position. It's really a very simple process. In fact, here are the five steps for creating a CWT:

The Continuous Wavelet Transform

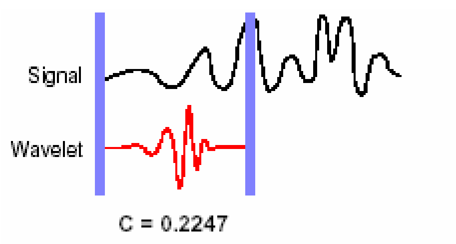
1. Take a wavelet and compare it to a section at the start of the original signal.

2 .Calculate a number, C, that represents how closely correlated the wavelet is with this section of the signal. The higher C is, the more the similarity. More precisely, if the signal energy and the wavelet energy are equal to one, C may be interpreted as a correlation coefficient. The results will depend on the shape of the wavelet you choose.



3 Shift the wavelet to the right and repeat steps 1 and 2 for the complete signal

4 Scale (stretch) the wavelet and repeat steps 1 through 3.



5. Repeat steps 1 through 4 for all scales.

Once we have the coefficients produced at different scales by different sections of the signal. The coefficients constitute the results of a regression of the original signal performed on the wavelets. Then a plot is made on which the x-axis represents position along the signal (time), the y-axis represents scale, the color at each x-y point represents the magnitude of the wavelet. The colour at each point represents the magnitude of the coefficient C. These are the coefficient plots generated by the graphical tools.

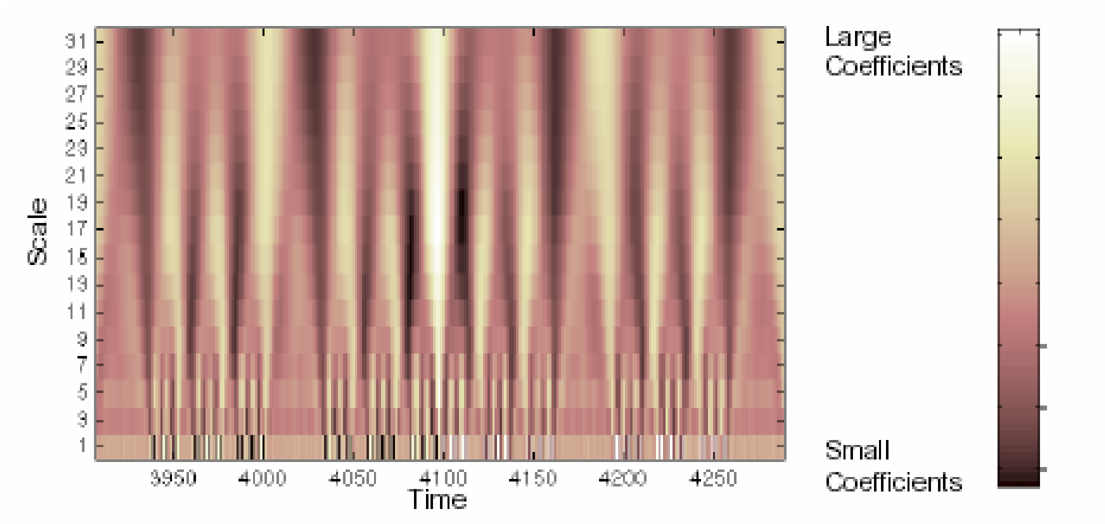


Fig 15: Wavelet Transform Result

2.5.1 Scale and Frequency

The scales in the coefficients plot (shown as y-axis labels) run from 1 to 31. The higher scales correspond to the most "stretched" wavelets. The more stretched the wavelet, the longer the portion of the signal with which it is being compared, and thus the coarser the signal features being measured by the wavelet coefficients. Thus, there is a correspondence between wavelet scales and frequency as revealed by wavelet analysis:

- Low scale = Compressed wavelet = Rapidly changing details = High frequency.

• High scale = Stretched wavelet = Slowly changing features = Low frequency.

Unlike the discrete wavelet transform, the CWT can operate at every scale, from that of the original signal up to some maximum scale that you determine by trading off your need for detailed analysis with available computational processing power.

The purpose of the analysis is to determine:

•The site of the change (e.g., time or position)

•The type of change

•The amplitude of the change

The table below gives names of some the wavelet families:

Wavelet Family Short Name	Wavelet Family Name
'haar'	Haar wavelet.
'db'	Daubechies wavelets.
'sym'	Symlets.
'coif'	Coiflets.
'bior'	Biorthogonal wavelets.
'rbio'	Reverse biorthogonal wavelets.
'meyr'	Meyer wavelet.
'dmey'	Discrete approximation of Meyer wavelet.
'gaus'	Gaussian wavelets.
'mexh'	Mexican hat wavelet.
'morl'	Morlet wavelet.
'cgau'	Complex Gaussian wavelets.
'shan'	Shannon wavelets.
'fbsp'	Frequency B-Spline wavelets.
'cmor'	Complex Morlet wavelets.

Fig 16: Names of Wavelet Families

The tables below give an overview of the properties of different wavelets:

Property	rbioNr.Nd	gaus	dmey	cgau	cmor	fbsp	shan
Crude		•		•	•	•	•
Infinitely regular		•		•	•	•	•
Arbitrary regularity	•						
Compactly supported orthogonal							
Compactly supported biothogonal	•						
Symmetry	•	•	•	•	•	•	•
Asymmetry							
Near symmetry							
Arbitrary number of vanishing moments	•						
Vanishing moments for ϕ							
Existence of ϕ	•						
Orthogonal analysis							
Biorthogonal analysis	•						
Exact reconstruction	•	•	$\simeq$	•	•	•	•
FIR filters	•		•				
Continuous transform	•	•					
Discrete transform	•		•				
Fast algorithm	•		•				
Explicit expression	For splines	•		•	•	•	•
Complex valued				•	•	•	•
Complex continuous transform				•	•	•	•
FIR-based approximation			•				

Fig : Wavelet Properties.

Property	morl	mexh	meyr	haar	*dbN*	symN	coifN	biorNr.Nd
Crude	•	•						
Infinitely regular	•	•	•					
Arbitrary regularity					•	•	•	•
Compactly supported orthogonal				•	•	•	•	
Compactly supported biothogonal								•
Symmetry	•	•	•	•				•
Asymmetry					•			
Near symmetry						•	•	
Arbitrary number of vanishing moments					•	•	•	•
Vanishing moments for ϕ							•	
Existence of ϕ			•	•	•	•	•	•
Orthogonal analysis			•	•	•	•	•	
Biorthogonal analysis			•	•	•	•	•	•
Exact reconstruction	$\simeq$	•	•	•	•	•	•	•
FIR filters				•	•	•	•	•
Continuous transform	•	•	•	•	•	•	•	•
Discrete transform			•	•	•	•	•	•
Fast algorithm				•	•	•	•	•
Explicit expression	•	•		•				For splines

Fig 17: Wavelet Properties

The input to this stage of the algorithm is the PSD plot of the frequency domain signal.As dicussed above,the wavelet is a good tool for identifying sharp changes or dicontinuties in the signal.Therefore, the continous wavelet transform is used for detecting the discontinuties in the PSD plot. The discontinuties correspond to the high frequencies and for this reason low scaled wavelets are employed to detect them.The shifted versions of the low scale wavelet are moved on the entire signal to give values for wavelet coefficients.The values of the coeffcients are higher at places where discontinuties occur or at places where the edges of the PSD occur.These values are then compared to the noise threshold to determine where the primary suer signal exists and further classify them as white or dark spaces.

2.6 Probability Cache

The project under discussion employs a probability algorithm that is simple, yet works optimally. A probability cache is maintained which contains probability values for all the frequencies in the wide band. These probabilities are interpreted to be the chance that a white space will continue to persist in the spectrum at the same location as it is now. The probability model is based on a slow learning process. From the moment the Cognitive Radio is switched on, it first initialized the probability cache. The initialization step involves incrementing the value of probability on a certain frequency by 1 every time a spectrum hole is detected on that frequency and no increment for a dark space. This process is carried out on all the frequencies. The frequency to frequency accuracy of the probability cache depends upon the frequency resolution of the system. The more the number of points taken while taking the FFT of the signal, the better the frequency resolution, and the narrower the width of each channel to which a single value of probability is assigned. After all the values have been initialized, they are divided by the total number of scans run during the initialization. For example, if the Cognitive Radio was given 10 scans to initialize its probability cache, and out of these 10 times, on a certain frequency, 6 times a white space was detected and 4 times a dark space was detected. It final probability value will be (1+1+1+1+1+1)/10 = 0.6

Once the initialization is complete, we switch to the probability weighting mode. Here we define a variable called the 'rate of change' which defines how much change the latest scan brings about in the probability value. Weighting is carried out using the following law:-

$$\mu_{j,t} = (1-\rho)\mu_{j,t-1} + \rho x_t$$

Where,

j = Channel number in the spectrum

t = Time instant

p = Rate of change

u = probability cache values

x = latest scan array

Selection of the best white space among all the white spaces available is done on the basis of the highest probability value.

2.7 Fine sensing

We come to the fine sensing part only after the Cognitive Radio has started transmission in the most probable white space detected through the coarse sensing. The reason that fine sensing is not employed to sense the whole of the wide band of interest is its limitation as far as the speed is concerned. If the Cognitive Radio were to detect primary user signals within the whole of the wide band, using fine sensing, it will take too much time to find our the holes and by the time the Cognitive Radio begins its transmission, the holes might have changed their locations in the frequency axis.

The fine sensing thus, only works in the transmission band i.e. the band in which the Cognitive Radio is transmitting its own signals. The fine sensing involves an elaborate DSP algorithm to detect primary user signals that might be getting interfered due to the CR signal transmission within the same frequency band. Ideally if a primary user signal does appear in the band where the Cognitive Radio is carrying out its own transmission, the energy detector should show a dark space there, and the cognitive radio should migrate to another white space, but a situation can occur when the SNR of the primary user is so low (even blow the noise level threshold), that the energy detector passes it as a white space. Under such circumstances, the fine sensing comes in handy to distinguish between a user signal and the noise on the basis of periodicity.

To further elaborate on this, the fine sensor can differentiate between user signal and noise as opposed to the energy detector. This is due to the fact that the energy detector simply integrates the energy content of a signal irrespective of its properties. On the contrary the fine sensor, detects the user signal on the basis of its cyclo-stationary properties which include its periodicity that's inherent into all sorts of modulated signals due to the periodic carrier that modulates the data. However, noise is a wide sense stationary process, and does not have any cyclo-stationary properties associated with it. So even if the SNR of the signal is low, the fine sensor still can detect the user signal from within the noise.

The method used for fine sensing can be either of the following two:

1) Matched Filter Detector

2) Cyclo Stationary Feature Detector or Correlation Detector.

2.7.1 Matched filter detector

This technique is used when the primary user information is known. It is a linear filter which maximizes the signal to noise ratio. The main advantage of this filter is that it requires less time to achieve high processing gain because of the coherency. However it requires a prior knowledge of primary signal such as modulation scheme, pulse shape, packet format. All this information can be saved in cognitive radio memory, however if this information is not accurate i.e. not coherent then the results could be poor. Performance could be improved by using pilot symbols, preambles, synchronization codes, equalization in the primary signal and thus could be used for coherent detection. For example CDMA systems use spreading codes for pilot and synchronization channels, OFDM systems use preambles. The main disadvantage with this technique is that it would require a dedicated receiver for every primary user

2.7.2 Cyclostationary Feature Detection

An alternative method for the detection of primary signals is Cyclostationary Feature Detection in which modulated signals are coupled with sine wave carriers, pulse trains, repeated spreading, hopping sequences, or cyclic prefixes. This results in built-in periodicity. These modulated signals are characterized as cyclostationary because their mean and autocorrelation exhibit periodicity.

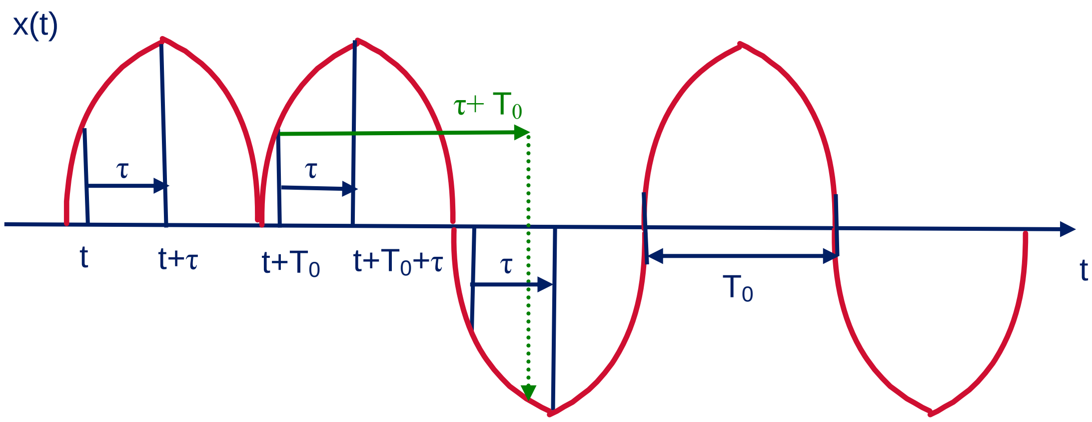


Fig 18: Modulated signals are cyclo-stationary signals

$$R_x(t,\tau) = R_x(t+T_0,\tau)$$

This periodicity is introduced in the signal format at the receiver so as to exploit it for parameter estimation such as carrier phase, timing or direction of arrival. These features are detected by analyzing a spectral correlation function. The main advantage of this function is that it differentiates the noise from the modulated signal energy. This is due to the fact that noise is a wide-sense stationary signal with no correlation however modulated signals are cyclostationary due to embedded redundancy of signal periodicity. Analogous to autocorrelation function spectral correlation function (SCF) can be defined.

Spectral correlation function is also known as cyclic spectrum. While power spectral density (PSD) is a real valued one dimensional transform, SCF is a complex valued two dimensional transform. The parameter á is called the cycle frequency. If á = 0 then SCF gives the PSD of the signal. Because of the inherent spectral redundancy signal selectivity becomes possible. Analysis of signal in this domain retains its phase and frequency information related to timing parameters of modulated signals. Due to this, overlapping features in power spectral density are non overlapping features in cyclic spectrum. Hence different types of modulated signals that have identical power spectral density can have different cyclic spectrum. Because of all these properties cyclostationary feature detector can perform better than energy detector in discriminating against noise. However it is computationally complex and requires significantly large observation time. For more efficient detection, the enhanced feature detection scheme combined with cyclic spectrum analysis and pattern recognition based on neural networks is proposed.

2.7.3 Correlation Detector

The correlation detector simply correlates the incoming received signal, with some sample signals stored in the cache of the cognitive radio. Correlation is defined as:

$$C = (1/\sqrt{EgEx}) \int_{-\infty}^{\infty} g(t)^{*}x(t)\, dt$$

g(t) = Memory Carrier with variable frequency

x(t) = Received signal within the communication band

Eg = Energy of g(t).

Ex = Energy of x(t)

It can have a value in the range of 0 to 1. Where 0 means that the signals are orthogonal to each other, and 1 means that both the signals are identical.

To eliminate the need of priory knowledge of the frequency of the incoming signal, the detector keeps sweeping within the narrow transmission band from the lowest to highest frequency. And if at some frequency it detects a high correlation value, a primary user has been found.

As soon as any primary user signal is detected in the cognitive radio transmission band, either through coarse sensing or through fine sensing, the band is vacated for the licensed user to take, and the cognitive radio user migrates to the next best white space available having the maximum probability of persistence.

This process continues, thus enabling interference free and license less, dynamic spectrum access.

Chapter 3

Simulations

Simulations for this project have been carried out on MATLAB 7.0. By reading through what's given below, the reader can have a clear step by step understanding of how each module in the Cognitive Radio has been modeled and coded:

3.1 Creating a random RF environment

The radio frequency environment consists of a number of primary users, who can vary their frequencies and power at any time without any prior knowledge of the secondary user. These have been modeled through matrices containing random data that refreshes at every sampling instant to generate new random values.

The random data is generated through the uniform probability distribution model which is defined as:-

If range of values is X=[a ,b]

$F_x(x)= 1/(b-a) \qquad 1 \le x \le b$

$E[X] = (a + b)/2$

$VAR[X] = (b – a)^2/12$

The frequency band of interest can be specified by the user, and the sampling frequency is automatically set to be the double of the maximum frequency in the band of interest (Nyquist Rate). The number of primary users within the band of interest can also be changed or altered as desired.

Further the channel is assumed to be an AWGN (Additive White Guassian Noise) and fading channel.

To model the Additive White Guassian Noise, random values having guassian (normal) distribution have been added into the primary user signals generated earlier. Fading and dispersion has been modeled through the smoothing function which smoothes the signal by employing a moving average filter (convolving with a boxcar of specified width).

3.2 Power Spectral Density

The PSD is plotted for the environment generated in the last step. A new PSD will appear every time the environment changes. The frequency resolution of the PSD can be altered by changing the number of points in the FFT of the time domain signal. The PSD shows the amount of energy present at different frequencies within the band of interest.

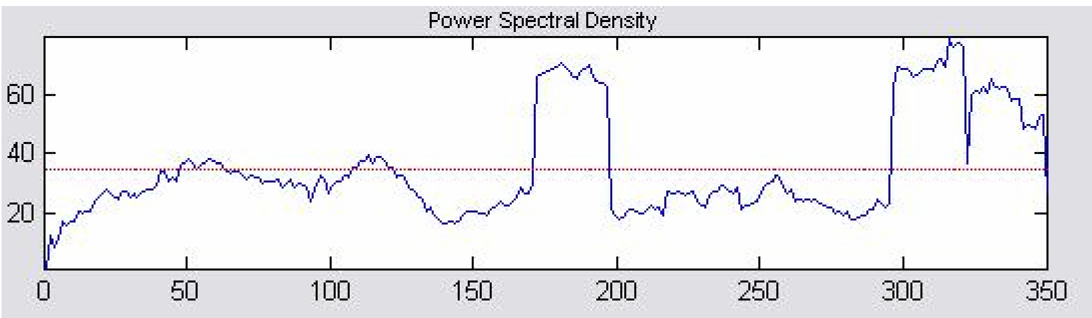


Fig 19: Power Spectral Density Plot for the simulation

3.3 Edge Detection

Edges in the PSD plot have been detected using the wavelet transform (described earlier). A small scale is used to find out the edges as edges represent the high frequency areas of a signal, and can only give a high value of wavelet coefficient when a wavelet of low scale (less width) is passed over it. Wavelet toolbox has been used for finding out the wavelet transform of the varying PSD signal.

Once the wavelet transform values have been computed, the indices of all the edges are stored in a temporary array and also the indices of the mid points between every two edges are stored in another array.

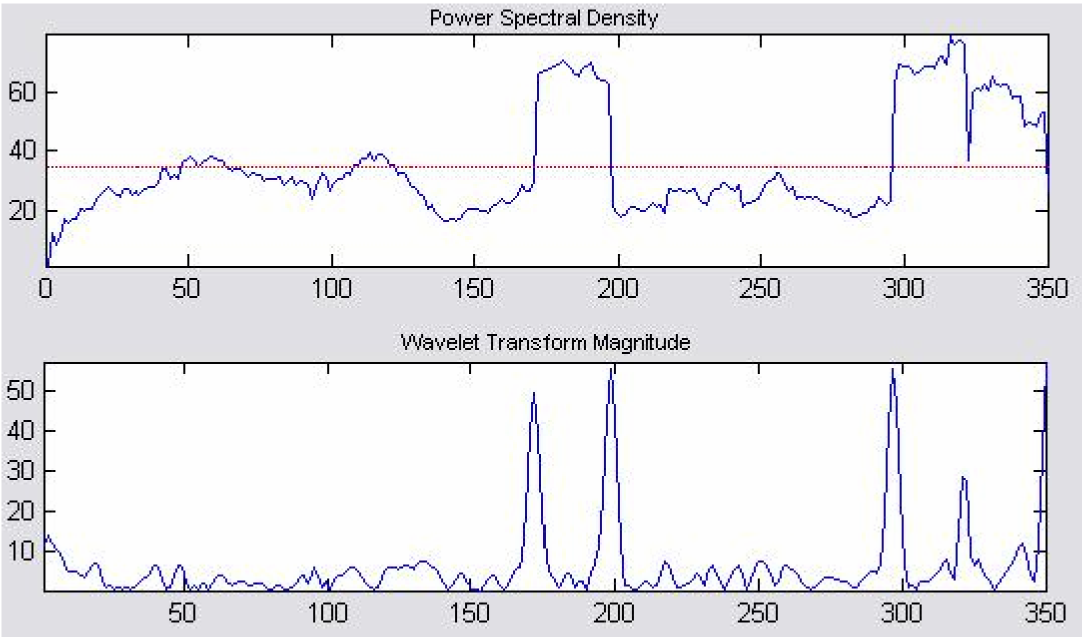


Fig 20: Edges for the PSD

3.4 Identification of White and Dark Spaces

Now the problem is greatly simplified. Only the values of the power of the signal at the frequencies specified by the mid points calculated above are compared with the noise threshold. The white spaces are identified as follows:

$P(x) \geq$ noise threshold → Dark Space

$P(x) <$ noise threshold → White Space

The beauty of the algorithm lies in the fact that instead of comparing each and every point in the PSD against the noise threshold to determine whether it's a dark or white space, we only need to check a few points. That is only one point in between every two edges, since we know that in between every two edges, the value of the PSD is almost the same.

3.5 Probability Cache

The probability cache has been explained earlier in the thesis. Here it will only suffice to say that the probability cache is not only stored in memory to be used as a decision criterion for selection of the best white space, but also shown graphically next to the white space/ dark space configuration diagram for the ease of selection. It updates automatically with each new scan.

3.6 Transmission

The Cognitive Radio user transmission band is identified to be the white space with maximum probability of persistence. This frequency is highlighted in on the frequency axis and automatically shifts to the next best available white space as soon as a dark space appears where the CR user was communicating. Although a complete cognitive radio will be able to adapt to the changes in environment by altering its symbol rate, its modulation scheme, its transmitted power, but in our simulations we have only catered for the operating frequency. The cognitive radio user hops from frequency to frequency without interfering with the primary user transmission.

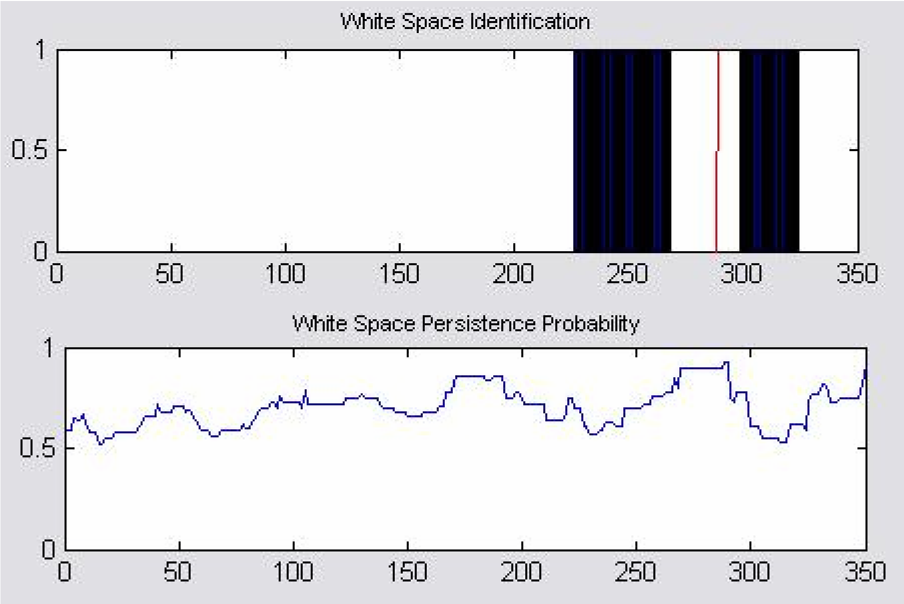


Fig 21: White - Dark Space identification, Probability values and CR Transmission

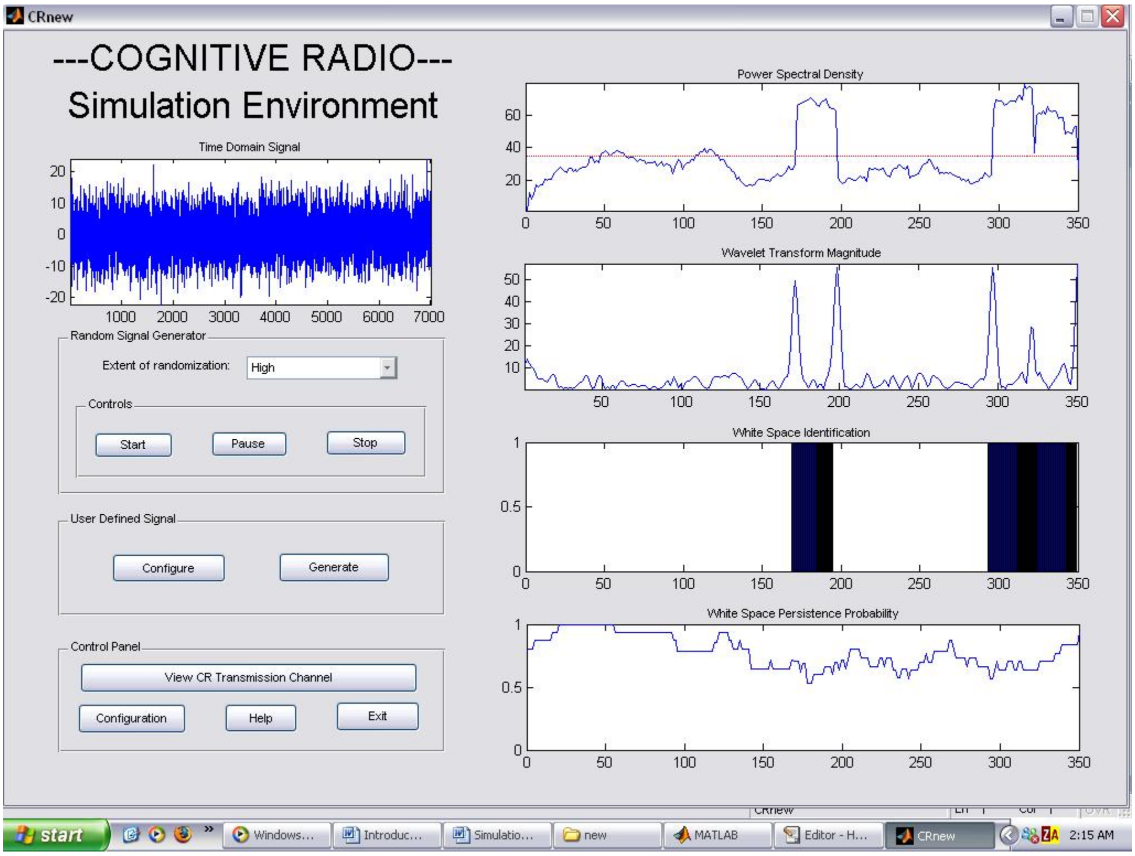
3.7 Correlation Detector

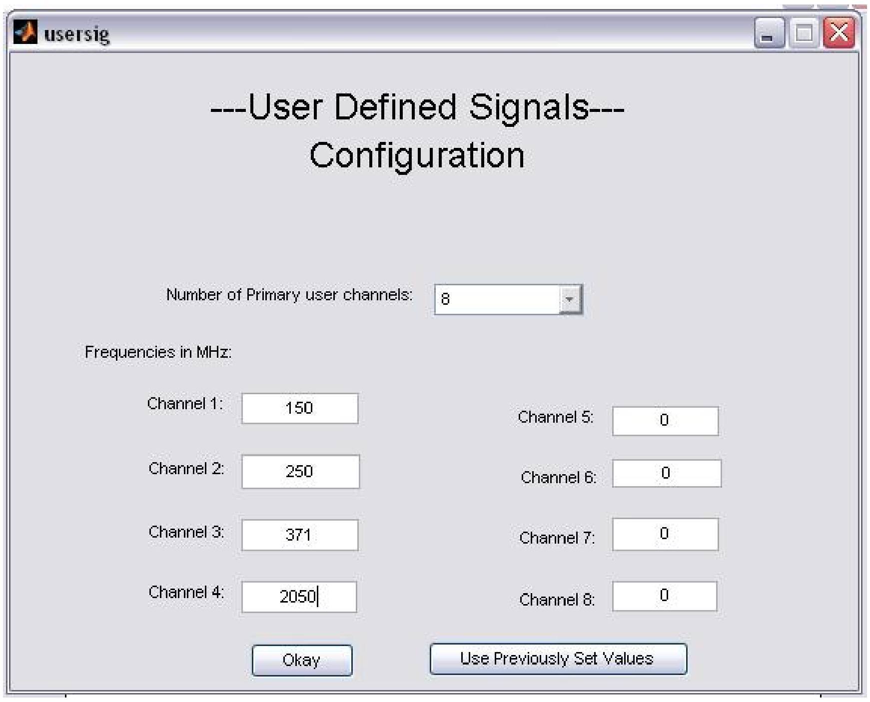
A sample carrier is stored in the memory of the cognitive radio, whose frequency can be varied. The inputs to the fine sensing block are the frequency limits of the transmission band in which communication of the cognitive radio is being carried out, and the received signal within that frequency band (the rest of the spectrum has been filtered out). The sample carrier is correlated with the received signal by carrying the frequency of the sample carrier from the lowest frequency in the transmission band to the highest frequency. If at any frequency or frequencies, the value of the correlation is above a certain threshold, the primary user is said to be present at that frequency.

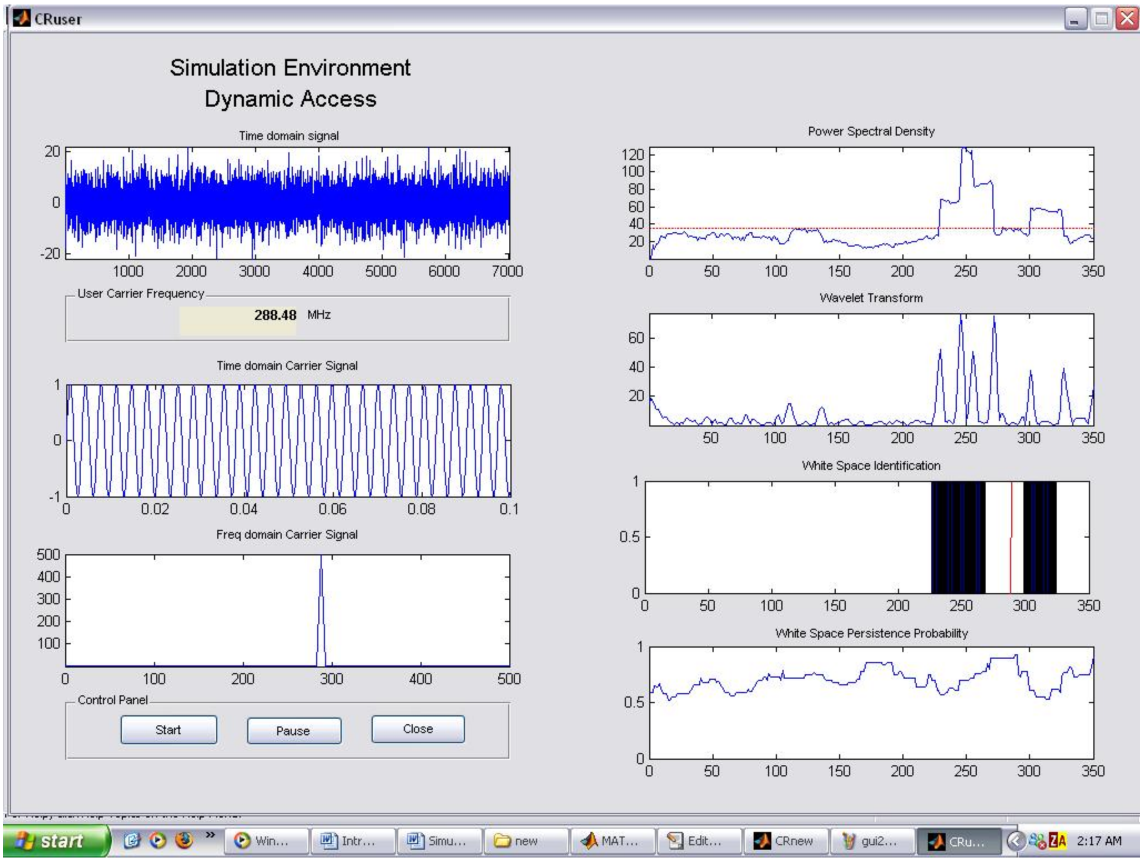
The advantage of this scheme lies in the fact that, this method is irrespective of the phase lags in the received signal, as the memory carrier and the received signals are correlated with all possible leads and lags (similar to a convolution between two signals without flipping any of the signals).

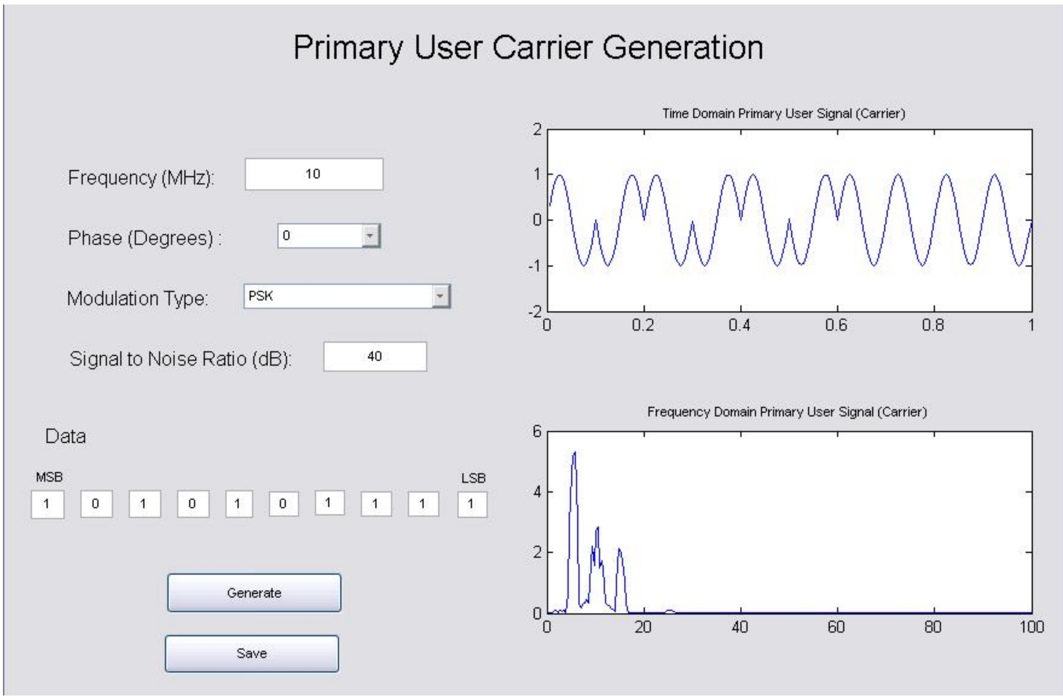
3.8 Graphical User Interface

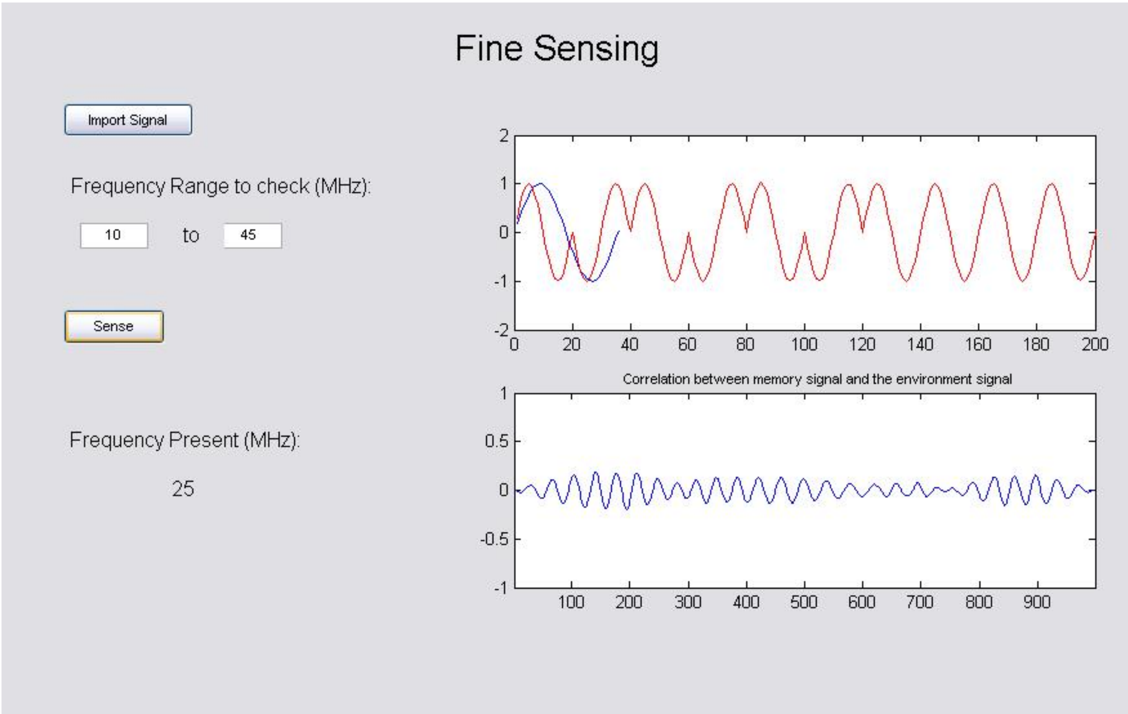
Finally every thing is integrated together within the "CRSE" (Cognitive Radio Simulation Environment). A user friendly GUI, in which all sorts of values can be tailored to the users own desires and simulations can be carried out just as in a real time scenario with constantly changing RF environment. Following is a complete view of the GUI's different windows.




usersig
---User Defined Signals---
Configuration
Number of Primary user channels:
8
Frequencies in MHz:
Channel 1:
150
Channel 2:
250
Channel 3:
371
Channel 4:
2050
Channel 5:
0
Channel 6:
0
Channel 7:
0
Channel 8:
0
Okay
Use Previously Set Values


CRuser
Simulation Environment
Dynamic Access
Time domain signal
User Carrier Frequency
288.48
MHz
Time domain Carrier Signal
Freq domain Carrier Signal
Control Panel
Start
Pause
Close
Power Spectral Density
Wavelet Transform
White Space Identification
White Space Persistence Probability
start
2:17 AM





Figs 22: Graphical User Interface

Chapter 4

Hardware Implementation

4.1. DSP KIT

As technology continues to progress, the presence of digital signal processors (DSPs) in everyday life is increasingly apparent. DSPs are used in devices such as cellular telephones, global positioning systems, and computers. These types of devices are constantly receiving, analyzing, and modifying data in real-time to perform their given task. Digital signal processors are fast special-purpose microprocessors with a specialized type of architecture and an instruction set appropriate for signal processing, such as the TMS320C6x (C6x) family of processors. The C6x notation is used to designate a member of Texas Instruments' (TI) TMS320C6000 family of digital signal processors. The C6x is considered to be TI's most powerful processor. Digital signal processors are used for a wide range of applications, from communications and controls to speech and image processing.

This chapter introduces DSP kit by highlighting its features, supporting tools, overview of code composer studio, useful types of files and its integration with Simulink.

4.1.1 Key Features

Main features associated with the subject kit are following:-

1. TMS320C6713 DSP - 225 MHz, floating point, 256 Kb internal RAM/Cache

2. CPLD - Programmable "glue" logic

3. External SDRAM – 16 Megabytes, 32-bit Interface

4. External Flash - 512Kbytes, 8-bit interface (256Kb usable)

5. AIC23 - Stereo, 8 KHz –96KHz sample rate, 16 to 32 bit samples, jacks, microphone, line-in, line-out and speaker

6. User LEDS - Writable through CPLD

7. User DIP Switches – Readable through CPLD

8. Configuration Switches – Selects Power, Configuration and boot modes

9. Daughter card Expansion Interface- allows user to enhance functionality with add-on daughter card.

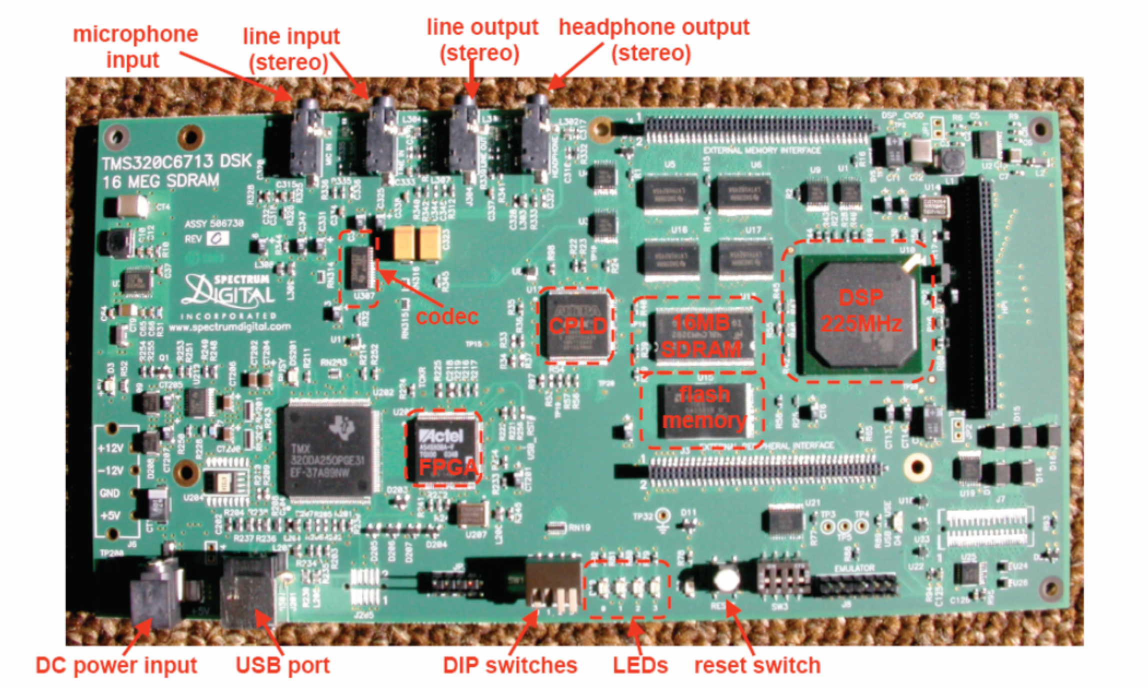
4.1.2 DSK Support Tools

The DSK package includes:

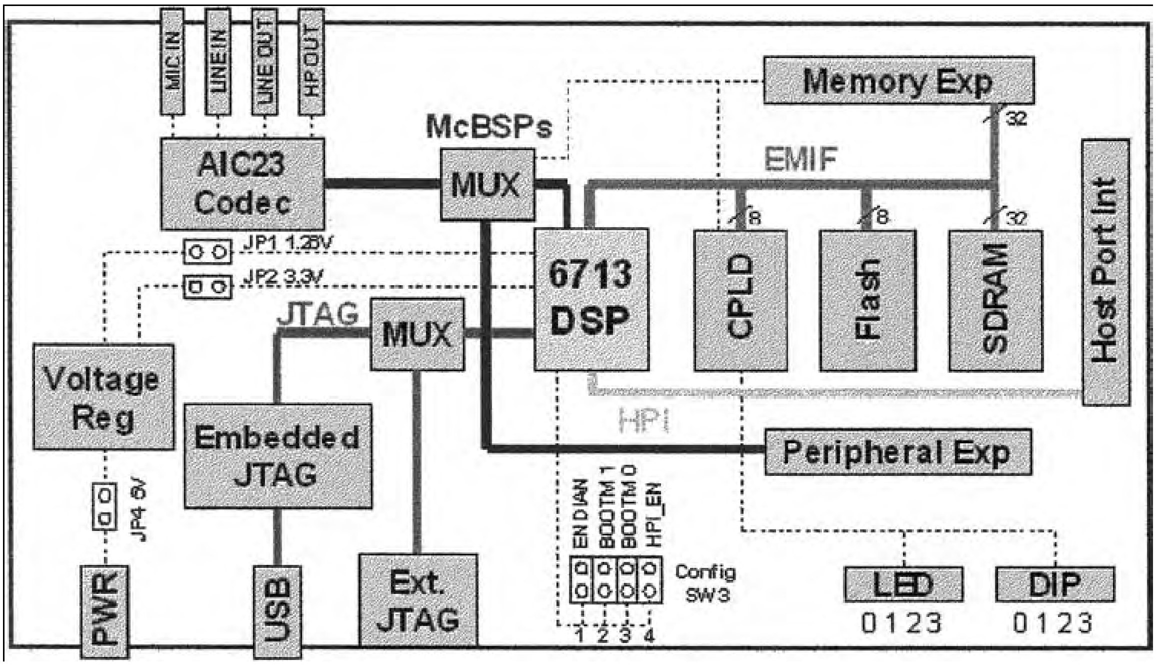
- Code Composer Studio (CCS), which provides the necessary software support tools. CCS provides an integrated development environment (IDE), bringing together the C compiler, assembler, linker, debugger, and so on.
- A universal serial bus (USB) cable for host interface.
- 5V power supply for the DSK board.
- An oscilloscope, signal generator, and speakers.(optional)

4.1.3 DSK Board

The DSK package is with the necessary hardware and software support tools for real-time signal processing. It is a complete DSP system. The DSK board includes the C6713 floating-point digital signal processor and a 32-bit stereo codec TLV320AIC23 (AIC23) for input and output.



(a)



(b)

Figure 23 TMS320C6713-based DSK board: (a) board; (b) diagram.

The onboard codec AIC23 provides ADC and DAC. It connects to a 12-MHz system clock. Variable sampling rates from 8 to 96 kHz can be set readily. A daughter card expansion is also provided on the DSK board. Two 80-pin connectors provide for external peripheral and external memory interfaces. The DSK board includes 16MB (megabytes) of synchronous dynamic random access memory (SDRAM) and 256kB (kilobytes) of flash memory. Four connectors on the board provide input and output: MIC IN for microphone input, LINE IN for line input, LINE OUT for line output, and HEADPHONE for a headphone output (multiplexed with line output). The status of the four user dip switches on the DSK board can be read from a program and provides the user with a feedback control interface. The DSK operates at 225MHz. Also onboard the DSK are voltage regulators that provide 1.26 V for the C6713 core and 3.3 V for its memory and peripherals.

4.2 Code Composer Studio

CCS provides an IDE to incorporate the software tools. CCS includes tools for code generation, such as a C compiler, an assembler, and a linker. It has graphical capabilities and supports real-time debugging. It provides an easy-to-use software tool to build and debug programs. The C compiler compiles a C source program with extension .c to produce an assembly source file with extension .asm. The assembler assembles an .asm source file to produce a machine language object file with extension .obj. The linker combines object files and object libraries as input to produce an executable file with extension .out.

This executable file represents a linked common object file format(COFF). This executable file can be loaded and run directly on the C6713 processor. A linear optimizer optimizes this source file to create an assembly file with extension .asm (similar to the task of the C compiler). To create an application project, one can “add” the appropriate files to the project. Compiler/linker options can readily be specified. A number of debugging features are available, including setting breakpoints and watching variables; viewing memory, registers, and mixed C and assembly code and graphing results.

4.2.1 Useful Types of Files

A user would be working with a number of files with different extensions. They include:

a. file.pjt: to create and build a project named file
b. file.c: C source program
c. file.asm: assembly source program created by the user, by the C compiler, or by the linear optimizer
d. file.sa: linear assembly source program.The linear optimizer uses file.sa as input to produce an assembly program file.asm
e. file.h: header support file
f. file.lib: library file, such as the run-time support library file rts6700.lib file.cmd: linker command file that maps sections to memory
g. file.obj: object file created by the assembler
h. file.out: executable file created by the linker to be loaded and run on the C6713 processor
i. file.cdb: configuration file when using DSP/BIOS

4.3 Integration of Matlab Tools for DSP Code Generation

The Embedded Target for TI C6000 DSP platform integrates Simulink and Matlab with Texas Instrument express DSP(tm) tools. The software suite allows a user to develop DSP designs from concept through code and automates rapid prototyping on the C6713 DSP starter kit. The Build process builds a Code Composer Studio (CCS) project from the C code generated by Real-Time Workshop. The CCS project is automatically compiled and linked, and the executable is loaded on the board, and run on the C6713 DSP.

4.3.1 Software Requirements

For using Simulink for code generation and in turn allowing rapid prototyping following soft wares are required.

a. Matlab 7.0.4 Release 14, Service Pack 2
b. Code Composer Studio v3.1

4.4 Getting Started with DSK

4.4.1 POST(Power on Self Test)

a. Power up DSK and watch LEDs
b. Power On Self Test (POST) program stored in FLASH memory automatically executes POST takes 10-15 seconds to complete All DSK subsystems are automatically tested
c. During POST, a 1kHz sinusoid is output from the AIC23 codec for 1 second Listen with headphones or watch on oscilloscope
d. If POST is successful, all four LEDs blink 3 times and then remain on

4.4.2 DSK Diagnostic Utility

a. Install CCS 3.1
b. Directions in "Quick Start Installation Guide"
c. Diagnostic utility automatically installed

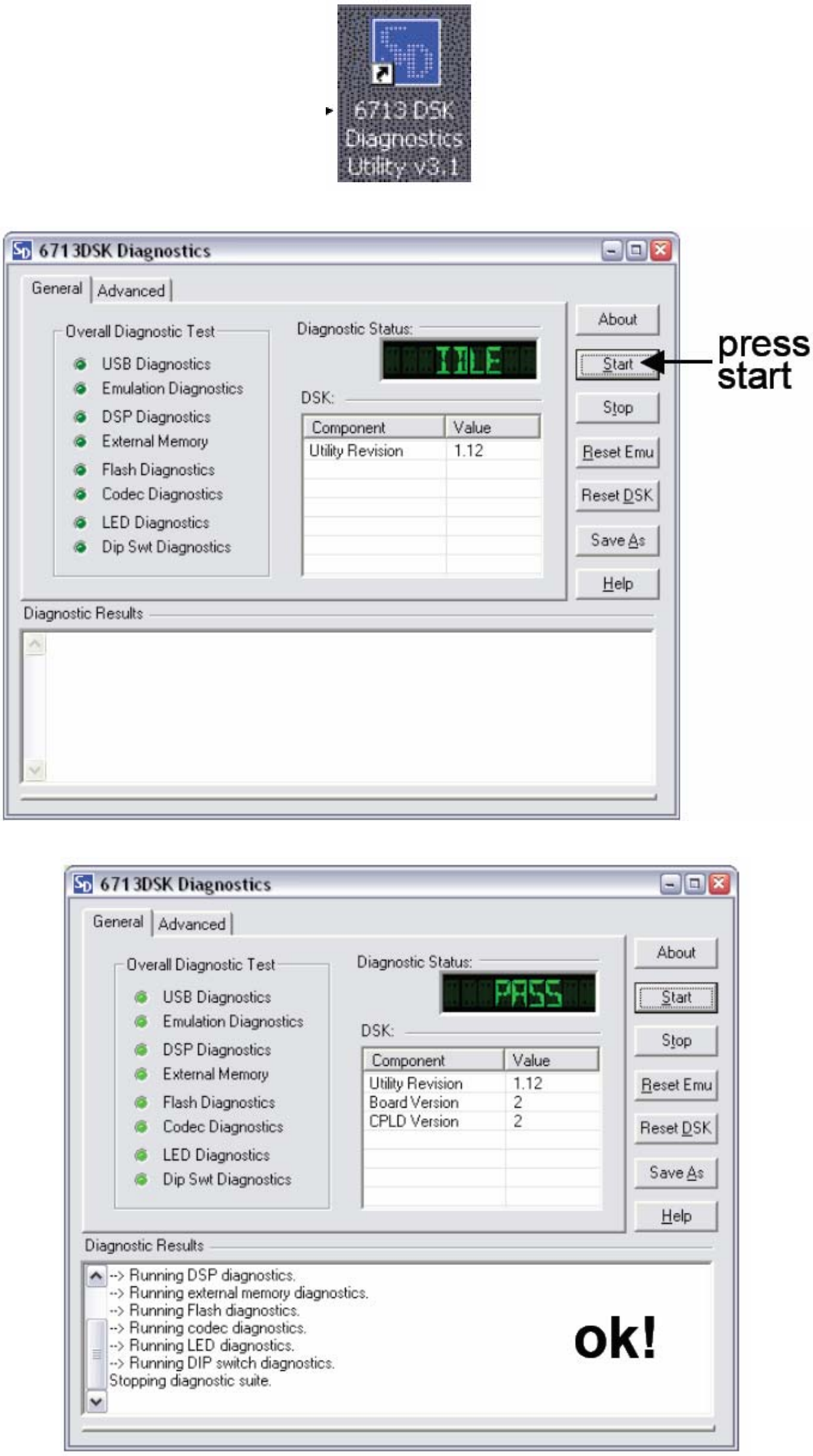


Figure 24: Diagnostic Utility

4.4.3 Code Composer Studio IDE

a. Connect power supply to DSK

b. Wait for POST to complete

c. Connect USB cable from PC to DSK

d. If this is the first time connecting the DSK, you may be asked to install a driver. The driver is on the Code Composer Studio CD and will automatically be found by Windows if the CD is in the drive.

e. Launch Code Composer Studio C6713 DSK

f. CCS will load and wait for your input

4.5 Work done on the kit

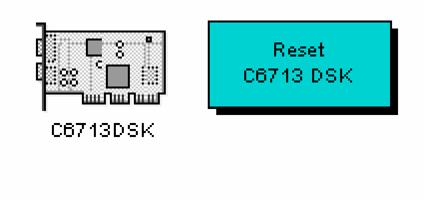
White space identification from the PSD has been done on the DSP kit.

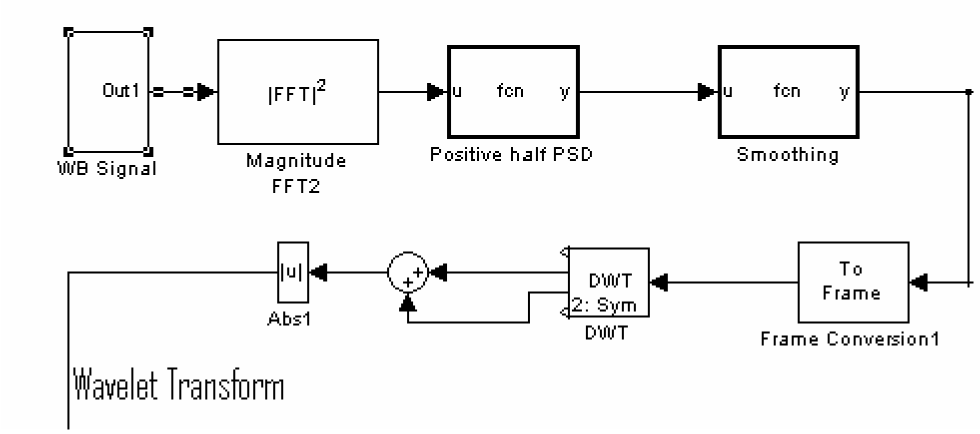
4.5.1 Objective

The purpose of using the dsp kit in our project is to provide a hardware platform for the implementation of our project. We successfully implemented till the white space identification of the spectrum.

4.5.2 Simulink Model

The path followed is the development of Simulink model and its implementation on the kit. The following model was developed in Simulink:





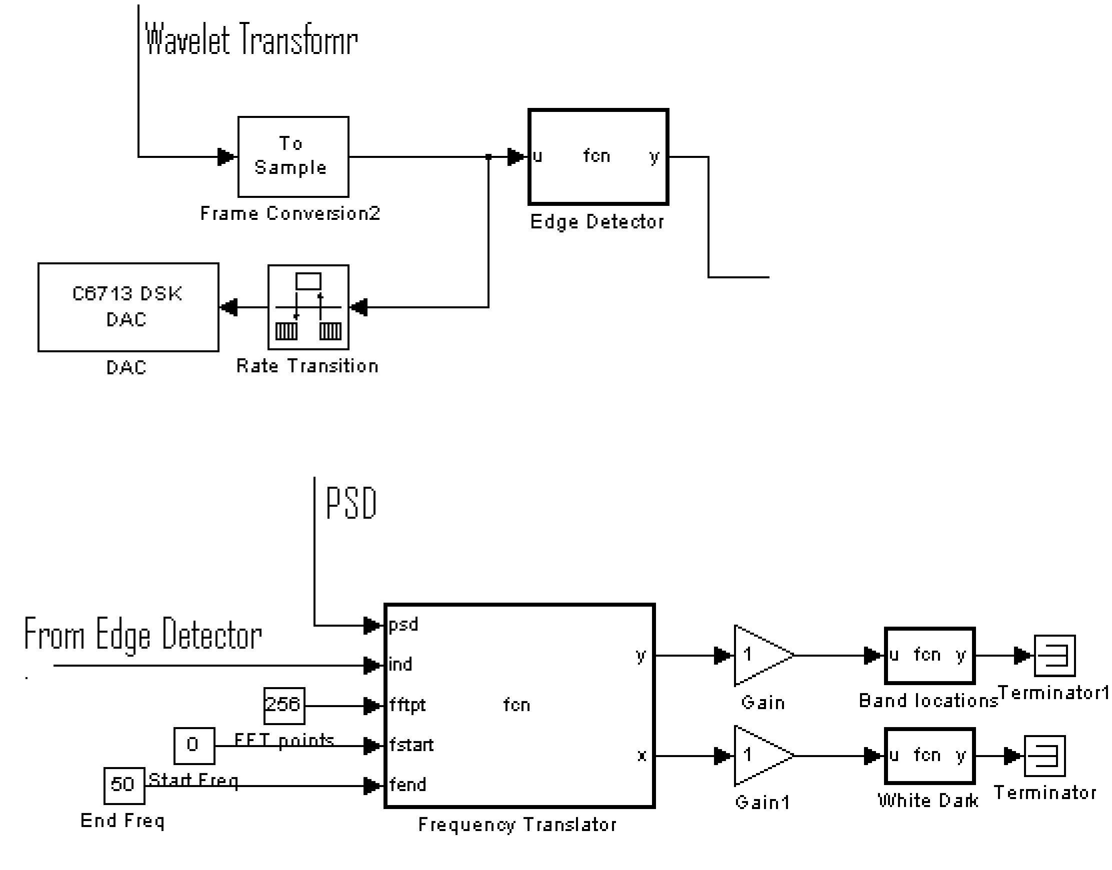
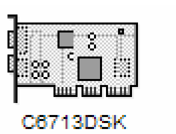


Figure 25: Simulink Model

Each block shown in the above model performs a specific task, major block are elaborated in details:

Embedded Target for Taxes Instrument C6713 DSK



Options on the block mask allow the features of code generation for the C6713 DSP Starter Kit target to be set. Adding this block to the Simulink model provides access to the processor hardware settings needed to be configured when the code is generated from Real-Time Workshop to run on the target. Any model that is targeted to the C6713 DSK must include this block, or the Custom C6000 target preferences block. Real-Time Workshop returns an error message if a target preferences block is not present in the model.

This block must be in the model at the top level and not in a subsystem. It does not connect to any other blocks, but stands alone to set the target preferences for the model. This block mainly includes the target board information, memory mapping and layout, and how to allocate the various code sections, such as compiler, DSP/BIOS, and custom sections.

Setting the options included in this block result in identifying the target to Real-Time Workshop, Embedded Target for TI C6000 DSP, and Simulink, and configuring the memory map for target. Both are essential steps in the process of targeting any board, custom or explicitly supported like the C6711 DSK or the DM642 EVM. Unlike most other blocks, the dialog for this block cant be opened unless it is added to the model. When the block is opened it attempts to connect to the target. It cannot make the connection when the block is in the library and returns an error message.

Embedded Matlab function block

The Embedded MATLAB Function block allows MATLAB code in models intended to be deployed as stand-alone executables generated by Real-Time Workshop. The function accepts multiple input signals and produces multiple output signals.

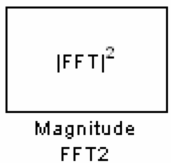
Embedded MATLAB Function block can call any of the following functions:

Sub functions: Sub functions are defined in the body of the Embedded MATLAB block. In the preceding example, avg is a sub function.

Embedded MATLAB run-time library functions: Embedded MATLAB run-time library functions are a subset of the functions that you call in MATLAB. When you build targets for your model, these functions generate C code that conforms to the memory and variable type requirements of embedded environments. In the preceding example, length, sqrt, and sum are Embedded MATLAB run-time library functions.

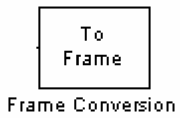
MATLAB functions: Function calls that cannot be resolved as sub functions or Embedded MATLAB run-time library functions are resolved in the MATLAB workspace. These functions do not generate code; they execute only in the MATLAB workspace during simulation of the model.

FFT Block



This block is used to calculate the square of the magnitude of Fast Fourier Transform of the input signal which is used to obtain the Power Spectral Density Plot of the concerned signal.

Frame Converter

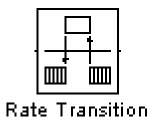


This block is used to convert the input data obtained from the previous block into frames. This is done because the DWT block being used accepts input only in frames.

Discrete Wavelet Transform

The DWT block computes the discrete wavelet transform (DWT) of each column of a frame-based input. By default, the output is a sample-based vector or matrix with the same dimensions as the input. Each column of the output is the DWT of the corresponding input column.

Rate Transition



The Rate Transition block handles periodic (fast to slow and slow to fast) and asynchronous transitions. When inserted between two blocks of differing sample rates, the Rate Transition block automatically configures its input and output sample rates for the appropriate type of transition; you do not need to specify whether a transition is slow-to-fast or fast-to-slow

C6713 DSK Digital to Analog Converter

Adding the C6713 DSK DAC (digital-to-analog converter) block to the simulink model provides the means to output an analog signal to the analog output jack on the C6713 DSK. When the C6713 DSK DAC block is added to the model the digital signal received by the codec is converted to an analog signal. After converting the digital signal

Option	Affected Hardware
Overflow mode	TMS320C6713 Digital Signal Processor
Scaling	TMS320C6713 Digital Signal Processor
Word length	Codec

to analog form (digital-to-analog (D/A) conversion), the codec sends the signal to the output jack. One of the configuration options in the block affects the codec. The remaining options relate to the model that is being used in Simulink and the signal processor on the board. In the following table, you find each option listed with the C6713 DSK hardware affected by your selection.

Chapter 5

Applications

Cognitive Radio methods can have a number of applications as discussed below:-

1) To counter for the problem of spectrum scarcity by allowing dynamic unlicensed access to the spectrum. A proposed application is in the TV bands within the UHF and VHF ranges.
2) In emergency situations or in military environments, where the troops have to carry out communication without the availability of any interference free licensed band.

3) For use by the regulatory authorities, to sense the spectrum and be able to find out what frequencies are occupied at what time.

Chapter 6

Future Avenues of Research

This project is just the start of a new upcoming and advanced technology. A great amount of research is required before it can finally be implemented on a commercial scale.

Research has to be done on the design of a fast and efficient Radio front end that can feed time domain data into this algorithm at fast rates.

Also work has to be done on the MAC layer issues for cognitive radios. This is of greater importance in cooperative sensing case, where a number of cognitive terminals have to coordinate their sensing with each other in a network and cater for problems such as hidden node problem.

Future work is also proposed on the development of a hybrid fine sensing scheme, which has all the plus points from correlation detection, cyclo-stationary feature detection and matched filter detection schemes.

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