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Spectrum Sensing for Cognitive Radio

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***Abstract*— Around the globe static allocation of spectrum scheme is commonly used which is also known as command and control. In this method, the radio spectrum is divided into spectrum bands that are allocated to specific technology based services, such as mobile, fixed, broadcast, fixed satellite and mobile satellite services on exclusive basis. This command-and-control-based spectrum management framework guarantees that the radio frequency spectrum will be exclusively licensed to a license user and can use the spectrum without any interference.**

I. INTRODUCTION

Cognitive radio has emerged as a promising technology for maximizing the utilization of the limited radio bandwidth while accommodating the increasing amount of services and applications in wireless networks. A cognitive radio (CR) transceiver is able to adapt to the dynamic radio environment and the network parameters to maximize the utilization of the limited radio resources while providing flexibility in wireless access. The key features of a CR transceiver are awareness of the radio environment (in terms of spectrum usage, power spectral density of transmitted/received signals, wireless protocol signaling) and intelligence. This intelligence is achieved through learning for adaptive tuning of system parameters such as transmit power, carrier frequency, and modulation strategy (at the physical layer), and higher-layer protocol parameters.

Cognition

In a way, it can be argued that cognitive radio draws its inspiration from cognitive science. The roots of cognitive science are intimately linked to two scientific meetings that were held in 1956:

- The Symposium on Information Theory, which was held at the Massachusetts Institute of Technology (MIT). That meeting was attended by leading authorities in the information and human sciences, including Allen Newell (computer scientist), the Nobel Laureate, Herbert Simon (political scientist and economist), and Noam Chomskey (linguist). As a result of that symposium, linguists began to theoretize about language, which was to be found subsequently in the theory of computers: the language of information processing.
- The Dartmouth Conference, which was held at Dartmouth College, New Hamp- shire. The conference was attended by the founding fathers of artificial intelligence, namely, John *mccarthy*, Marvin Minsky and Allen Newel. The goal of this second meeting was to think about intelligent machines. The Dartmouth Conference was also attended by Frank Rosenblatt (psychologist), the founder of (artificial) neural networks. At the conference, Rosenblatt described a novel method for supervised learning, which he called the perceptron. However, interest in neural networks was short lived: in a monograph published in 1969, Minsky and Papert used mathematics to demonstrate that there are fundamental limits on what Rosenblatt's perceptron could compute. The Minsky-Papert monograph, coupled with a few other factors, contributed to the dampening of interest in neural networks in the 1970s. We had to wait for the pioneering contributions of John Hopfield on neurodynamic systems and Rumlehart, Hinton and Williams on supervised learning in the 1980s for the revival of research interest in neural networks.

In a book entitled “The Computer and the Mind,” Johnson-Laird postulated the following tasks of a human mind:

- To perceive the world
- To learn, to remember and to control actions
- To think and create new ideas
- To control communication with others
- To create the experience of feelings, intentions and self-awareness.

Johnson-Laird, a prominent psychologist and linguist, went on to argue that theories of the mind should be modeled in computational terms. Much of what has been identified by Johnson-Laird as the mind's main tasks and their modeling in computation terms apply equally well to cognitive radio. Indeed, we can go on to offer the following definition for cognitive radio involving multiple users.

The cognitive radio network is an intelligent multiuser wireless communication system that embodies the following list of primary tasks:

- To perceive the radio environment (i.e., outside world) by empowering each user's receiver to sense the environment on continuous time
- To learn from the environment and adapt the performance of each transceiver to statistical variations in the incoming RF stimuli
- To facilitate communication between multiple users through cooperation in a self-organized manner.
- To control the communication processes among competing users through the proper allocation of available resources
- To create the experience of intentions and self-awareness
- The primary objective of all these tasks, performed in real time, is twofold:
- To provide highly reliable communication for all users

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- To facilitate efficient utilization of the radio spectrum in a fair-minded way

Two Complementary Visions of Cognitive Radio

In the first doctoral dissertation on cognitive radio published in 2000, Joseph Mitola described how a cognitive radio could enhance the flexibility of personal wireless services through a new language called the radio knowledge representation language. Mitola followed this dissertation with the publication of a book on cognitive radio architecture. A distinctive feature of both publications is a cognitive computer cycle, which encapsulates the various actions expected from a cognitive radio, as depicted in Fig.2.1. Through deployment of the right software control, it is envisioned that a cognitive radio could orient itself by establishing priorities, then create plans decide and finally take the appropriate action in response to sensing of the RF environment. As envisioned in Fig. 2.1, provisions are also made for the cognitive radio to do two things:

- Bypass the planning phase and go directly to the decision phase in the event of an urgent situation
- Bypass the two phases of planning and decision-making by proceeding immediately to the action phase in the event of an emergency.

In the first journal paper published in 2005, Simon Haykin presented detailed expositions of the signal-processing, adaptive and learning procedures that lie at the heart of cognitive radio. In particular, the paper identifies three specific tasks:

1. Radio-scene analysis (RSA), which encompasses
   - Estimation of interference temperature of the radio environment localized around a user's receiver
   - Detection of spectrum holes
   - Predictive modeling of the environment.
2. Channel identification, which is needed for improved spectrum utilization and coherent detection of original information-bearing signal at the user's receiver.
3. Dynamic spectrum management (DSM) and transmit-power control (TPC), which culminates in decision-making and action taken by the user's transmitter in response to the analysis of RF stimuli picked up by the receiver.

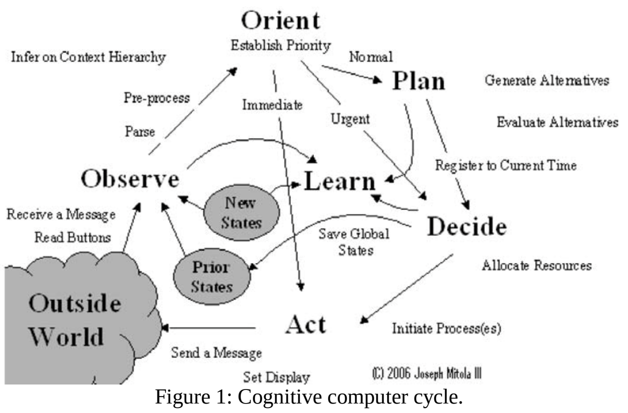

Figure 1: Cognitive computer cycle.

Tasks (1) and (2) are performed in the receiver, and task (3) is performed in the transmitter, as depicted in the cognitive signal-processing cycle in Figure 1. The depiction is presented in the context of a multiuser network. For the transmitter to work harmoniously with the receiver there is an obvious need for a feedback channel connecting the receiver to the transmitter as shown in above figure1. Through the feedback channel, the receiver is enabled to convey to the transmitter two essential forms of information:

- Information on the performance of the forward link for adaptive modulation
- Information on the spectral state of the RF environment in the local neighborhood of the receiver.

The cognitive radio is therefore, by necessity, an example of a global closed-loop feedback control system.

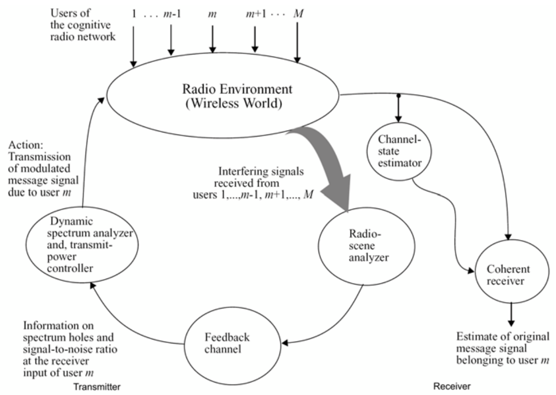

Figure 2: Basic signal-processing cycle for user m in a cognitive radio network; the diagram also includes elements of the receiver of user m.

II. FFT-AVERAGING RATIO ALGORITHM

In this project, we will be dealing with Energy Detection based Spectrum Sensing. Here a Fast Fourier transform (FFT) based spectrum sensing algorithm will be proposed. The proposed algorithm is called FAR denoting FFT-averaging-ratio. The FFT-based spectrum sensing algorithm FAR is more implementation-friendly. To have a decision threshold insensitive to noise level, FAR uses ratio formed from one or more blocks of received signal samples as a decision variable.

A. Algorithm

Step1 – A random signal is generated.
Step2 – Segmentation of the signal is done into T frames.
Step3 – Multiplication of frames with a window function.
Step4 – FFT is applied to the windowed frame.
Step5 – Power spectral density is calculated.
Step6 – Averaging of T consecutive frames is calculated.
Step7 –Formation of decision variable
Step8 – Finally Threshold is applied and decisions on channel states are made.

B. Flow Chart

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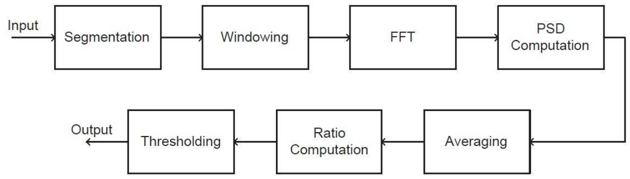

Figure 3: Flow Chart of FAR Algorithm.

III. DESCRIPTION

A. Window Function

The segmented frames are multiplied with the rectangular window function to get the desired spectral shape. A window function (also known as an apodization function or tapering function) is a mathematical function that is zero-valued outside of some chosen interval. For instance, a function that is constant inside the interval and zero elsewhere is called a rectangular window, which describes the shape of its graphical representation. When another function or waveform/data-sequence is multiplied by a window function, the product is also zero-valued outside the interval: all that is left is the part where they overlap; the "view through the window".

Windowing of a simple waveform, like cos ωt causes its Fourier transform to develop non-zero values (commonly called spectral leakage) at frequencies other than ω. The leakage tends to be worst (highest) near ω and least at frequencies farthest from ω. The rectangular window has excellent resolution characteristics for sinusoids of comparable strength, but it is a poor choice for sinusoids of disparate amplitudes. This characteristic is sometimes described as low-dynamic-range.

At the other extreme of dynamic range are the windows with the poorest resolution. These high-dynamic-range low-resolution windows are also poorest in terms of sensitivity; this is, if the input waveform contains random noise close to the frequency of a sinusoid, the response to noise, compared to the sinusoid, will be higher than with a higher-resolution window. In other words, the ability to find weak sinusoids amidst the noise is diminished by a high-dynamic-range window. High-dynamic-range windows are probably most often justified in wideband applications, where the spectrum being analyzed is expected to contain many different components of various amplitudes.

In between the extremes are moderate windows, such as Hamming and Hann. They are commonly used in narrowband applications, such as the spectrum of a telephone channel. In summary, spectral analysis involves a trade-off between resolving comparable strength components with similar frequencies and resolving disparate strength components with dissimilar frequencies. That trade off occurs when the window function is chosen. When the input waveform is time-sampled, instead of continuous, the analysis is usually done by applying a window function and then a discrete Fourier transform (DFT). But the DFT provides only a coarse sampling of the actual DTFT spectrum. Applications of window functions include spectral analysis, filter design, and beam forming. In typical applications, the window functions used are non-negative smooth "bell-shaped" curves, though rectangle, triangle, and other functions can be used.

The window used in this project is rectangular window. The rectangular window, also sometimes called `uniform window', is given by:

$$w(n) = 1$$

i.e. equivalent to using no window at all. Its transfer function and characteristic bandwidths are shown in Figure 4.

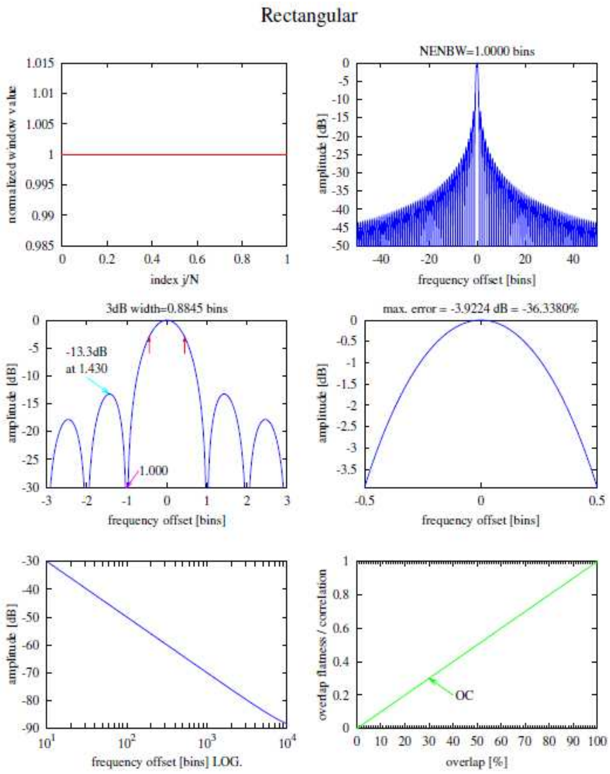

Figure 4: Rectangular window

NENBW = 1:0000 bins
W3 dB = 0:8845 bins
emax = -3:9224 dB = -36:3380%

The first zero is located at f = ±1:00 bins. The highest side lobe is -13:3 dB, located at f = ±1:43 bins. The side lobes drop at a rate of f-1. Over lapping makes no sense for the Rectangular window. While W3 dB is the narrowest of all windows, emax and the spectral leakage are the worst of all windows considered here.

B. Fast Fourier Transform

A fast Fourier transform (FFT) is an algorithm to compute the discrete Fourier transform (DFT) and its inverse. There are many different FFT algorithms involving a wide range of mathematics, from simple complex-number arithmetic to group theory and number theory; below we gives an overview of the available techniques and some of their general properties, while the specific algorithms are described in subsidiary articles linked below.

The DFT is obtained by decomposing a sequence of values into components of different frequencies. This operation is useful in many fields but computing it directly from the definition is often too slow to be practical. An FFT is a way to compute the same result more quickly: computing the DFT of N points in the naive way, using the definition, takes O(N2) arithmetical operations (O only denotes an upper bound), while an FFT can compute the same DFT in only O(N log N) operations. The difference in speed can be substantial, especially for long data sets where N may be in the thousands or millions. In practice, the computation time can be reduced by several orders of magnitude in such cases, and the improvement is roughly proportional to N/log(N). This huge improvement made the calculation of the DFT practical; FFTs are of great importance to a wide variety of applications, from digital signal processing and solving partial differential equations to algorithms for quick multiplication of large integers.

An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the only difference is that an FFT is much faster.

Let x0, ..., xN-1 be complex numbers. The DFT is defined by the formula

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k\frac{n}{N}} \qquad k = 0,\ldots,N-1$$

Evaluating this definition directly requires O(N2) operations: there are N outputs Xk, and each output requires a sum of N terms. An FFT is any method to compute the same results in O(N log N) operations. More precisely, all known FFT algorithms require O(N log N) operations, although there is no known proof that a lower complexity score is impossible.

To illustrate the savings of an FFT, consider the count of complex multiplications and additions. Evaluating the DFT's sums directly involves N2 complex multiplications and N(N−1) complex additions [of which O(N) operations can be saved by eliminating trivial operations such as multiplications by 1]. The well-known radix-2 Cooley–Tukey algorithm, for N a power of 2, can compute the same result with only (N/2)log2(N) complex multiplies (again, ignoring simplifications of multiplications by 1 and similar) and Nlog2(N) complex additions.

In practice, actual performance on modern computers is usually dominated by factors other than the speed of arithmetic operations and the analysis is a complicated subject, but the overall improvement from O(N2) to O(N log N) remains.

Algorithms used for FFT

The Cooley–Tukey algorithm is the most common fast Fourier transform (FFT) algorithm. It re-expresses the discrete Fourier transform (DFT) of an arbitrary composite size N = N1N2 in terms of smaller DFTs of sizes N1 and N2, recursively, in order to reduce the computation time to O(N log N) for highly-composite N (smooth numbers).

Radix-2 decimation-in-time (DIT) FFT is the simplest and most common form of the Cooley–Tukey algorithm. Radix-2 DIT divides a DFT of size N into two interleaved DFTs (hence the name "radix-2") of size N/2 with each recursive stage. The discrete Fourier transform (DFT) is defined by the formula:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N} nk}$$

Where is an integer ranging from 0 to N-1.

Radix-2 DIT first computes the DFTs of the even-indexed inputs x2m (x1, x2 …..xN-2) and of the odd-indexed inputs x2m+1 (x1, x3 …..xN-2) , and then combines those two results to produce the DFT of the whole sequence. This idea can then be performed recursively to reduce the overall runtime to O (N log N). This simplified form assumes that N is a power of two; since the number of sample points N can usually be chosen freely by the application, this is often not an important restriction.

The Radix-2 DIT algorithm rearranges the DFT of the function xn into two parts: a sum over the even-numbered indices n=2m and a sum over the odd-numbered indices n=2m+1 :

$$X_k = \sum_{m=0}^{N/2-1} x_{2m} e^{-\frac{2\pi i}{N}(2m)k} + \sum_{m=0}^{N/2-1} x_{2m+1} e^{-\frac{2\pi i}{N}(2m+1)k}$$

One can factor a common multiplier out of the second sum, as shown in the equation below. It is then clear that the two sums are the DFT of the even-indexed part x2m and the DFT of odd-indexed part of the function . Denote the DFT of the Even-indexed inputs by and the DFT of the odd-indexed inputs by and we obtain:

$$X_k = \underbrace{\sum_{m=0}^{N/2-1} x_{2m} e^{-\frac{2\pi i}{N/2}mk}}_{\text{DFT of even-indexed part of } x_m} + e^{-\frac{2\pi i}{N}k} \underbrace{\sum_{m=0}^{N/2-1} x_{2m+1} e^{-\frac{2\pi i}{N/2}mk}}_{\text{DFT of odd-indexed part of } x_m} = E_k + e^{-\frac{2\pi i}{N}k} O_k.$$

However, these smaller DFTs have a length of N/2, so we need compute only N/2 outputs: thanks to the periodicity properties of the DFT, the outputs for $N/2 \le k < N$ from a DFT of length N/2 are identical to the outputs for . That is, $E_{k+N/2} = E_k$ and $O_{k+N/2} = O_k$. The phase factor $\exp[-2\pi ik/N]$ (called a twiddle factor) obeys the relation:

$$\exp[-2\pi i(k+N/2)/N] = e^{-\pi i}\exp[-2\pi ik/N = -\exp[-2\pi ik/N]$$

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flipping the sign of the terms. Thus, the whole DFT can be calculated as follows:

$$X_k = \begin{cases} E_k + e^{-\frac{2\pi i}{N}k} O_k & \text{if } k < N/2 \\ E_{k-N/2} - e^{-\frac{2\pi i}{N}(k-N/2)} O_{k-N/2} & \text{if } k \geq N/2. \end{cases}$$

This result, expressing the DFT of length N recursively in terms of two DFTs of size N/2, is the core of the radix-2 DIT fast Fourier transform. The algorithm gains its speed by re-using the results of intermediate computations to compute multiple DFT outputs. Note that final outputs are obtained by a +/− combination of and , which is simply a size-2 DFT (sometimes called a butterfly in this context); when this is generalized to larger radices below, the size-2 DFT is replaced by a larger DFT (which itself can be evaluated with an FFT).

C. Power spectral density

For continued signals that describe, for example, stationary physical processes, it makes more sense to define a power spectral density (PSD), which describes how the power of a signal or time series is distributed over the different frequencies. Here, power can be the actual physical power, or more often, for convenience with abstract signals, can be defined as the squared value of the signal. The total power P of a signal is the following time average:

$$P = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} x(t)^2\, dt$$

In analyzing the frequency content of the signal , one might like to compute the ordinary Fourier transform ; however, for many signals of interest this Fourier transform does not exist. Because of this, it is advantageous to work with a truncated Fourier transform, where the signal is integrated only over a finite interval [0, T]:

$$\hat{x}_T(w) = \frac{1}{\sqrt{T}} \int_0^T x(t) e^{-iwt}\, dt$$

Then the power spectral density can be defined as:

$$S_{xx}(w) = \lim_{T\to\infty} E[|\hat{x}_T(w)|^2]$$

Here E denotes the expected value; explicitly, we have

$$E[|\hat{x}_T(w)|^2] = E\left[\frac{1}{T}\int_0^T x^*(t)e^{iwt}dt \int_0^T x(t')e^{-iwt'}dt'\right] = \frac{1}{T}\int_0^T\int_0^T E[x^*(t)x(t')e^{iw(t-t')}dt\,dt'$$

Using such formal reasoning, one may already guess that for a stationary random process, the power spectral density and the autocorrelation function of this signal

$$\gamma_{(T)} = \langle X(t)X(t+T)\rangle$$

should be a Fourier transform pair. Provided that is absolutely integrable, which is not always true, then

$$S_{xx}(w) = \int_{-\infty}^{\infty} \gamma_{(T)} e^{-iw\tau} dt = \hat{\gamma}(w)$$

The power of the signal in a given frequency band can be calculated by integrating over positive and negative frequencies,

$$\int_{w_1}^{w_2} S_{xx}(w) + S_{xx}(-w)dw = F(w_2) - F(-w_2)$$

Where Fis the integrated spectrum whose derivative is More generally, similar techniques may be used to estimate a time-varying spectral density. The definition of the power spectral density generalizes in a straightforward manner to finite time-series with $1 \leq n \leq N$, such as a signal sampled at discrete times for a total measurement period $T = N\Delta t$.

$$S_{xx}(w) = \frac{(\Delta t)^2}{T}\left|\sum_{n=1}^{N} x_n e^{-2n}\right|^2$$

In a real-world application, one would typically average this single-measurement PSD over several repetitions of the measurement to obtain a more accurate estimate of the theoretical PSD of the physical process underlying the individual measurements. This computed PSD is sometimes called periodogram. If two signals both possess power spectral densities, then a cross-spectral density can be calculated by using their cross-correlation function.

Properties of the power spectral density

Some properties of the PSD include:

- The spectrum of a real valued process is an even function of frequency:

$$S_{xx}(-w) = S_{xx}(w)$$

- If the process is continuous and purely indeterministic, the autocovariance function can be reconstructed by using the Inverse Fourier transform.

The integrated spectrum or power spectral distribution is defined as

$$F(w) = \int_{-\infty}^{w} S_{xx}(w')dw'$$

IV. RESULTS

The input to the cognitive radio is the random signal that we generate using random variables and the input random signal is shown in Fig 5 below

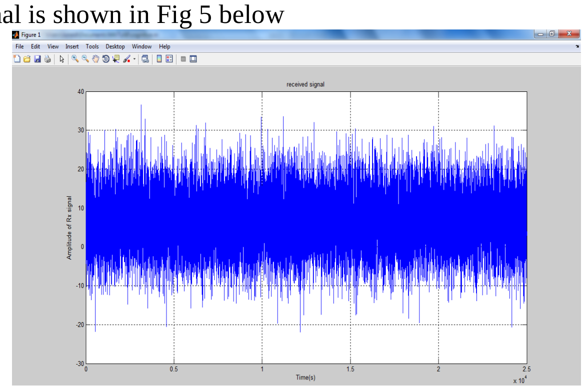

Figure 5: input random signal to the receiver

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The output is a set of vectors that show the available channels that can be used for transmission of data as well as reception of data. The cognitive radio will change its reception as well as transmission parameters according to the available channels. The available channels are shown in figure 6.

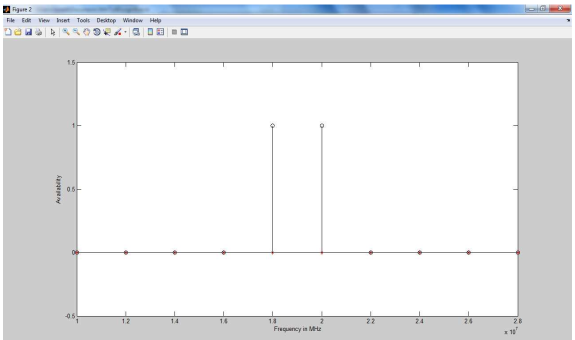

Figure 6: available channels

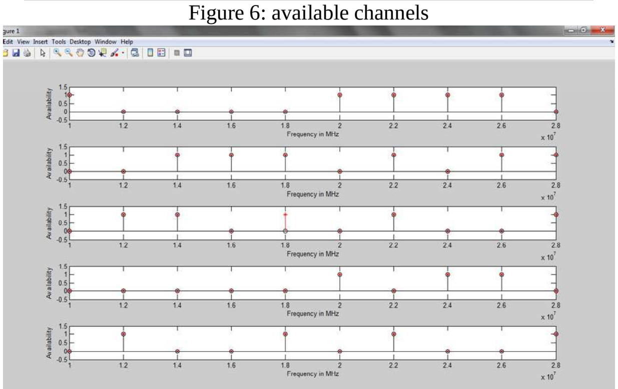

Figure7: Plot of Primary User Availability Vs Frequency

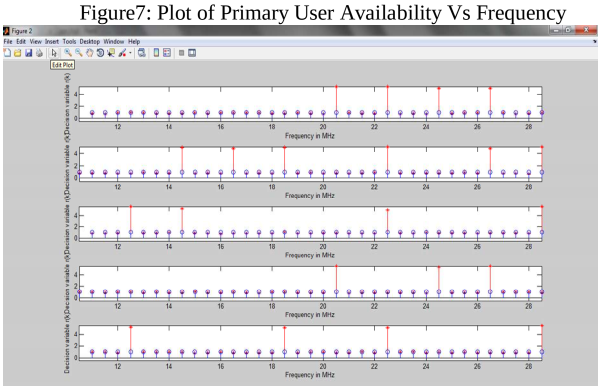

Figure8: Plot of Decision Variable VS Frequency

V. ADVANTAGES AND DISADVANTAGES

Advantages:

- Effective to detect signals at low Signal to Noise ratio (SNR)
- Efficient Bandwidth (BW) use
- Less complexity
- Low power consumption
- Friendly to Hardware Implementation

Limitations

Although energy detection based FAR algorithm has low computational and implementation complexities, it is quite sensitive to noise uncertainty. Also the Sensing time taken may be high

VI. CONCLUSION AND FUTURE WORK

Spectrum is a very valuable resource in wireless communication systems and it has been a major research topic from last several decades. Cognitive radio is a promising technology which enables spectrum sensing for opportunistic spectrum usage by providing a means for the use of white spaces. Considering the challenges raised by cognitive radios, the use of spectrum sensing method appears as a crucial need to achieve satisfactory results in terms of efficient use of available spectrum and limited interference with the licensed primary users. As described in this report, the development of the cognitive radio network requires the involvement and interaction of many advanced techniques, including distributed spectrum sensing, interference management, cognitive radio reconfiguration management, and cooperative communications.

Furthermore, in order to fully realize the CR system in wireless communications for efficient utilization of scarce RF spectrum, the method used in identifying the interference and/or spectrum sensing should be reliable and prompt so that the primary user will not suffer from CR system to utilize their licensed spectrum. We presented the different signal processing methods by grouping them into three basic groups and their details in turn. We have also presented the pros and cons of different spectrum sensing methods, and performed the comparison in terms of operation, accuracies, complexities and implementations. There exist number of issues to be addressed in terms of primary signal detection time, hardware requirements and computational complexities. FAR algorithm for spectrum sensing has been proposed and selection for major parameters of FAR algorithm has been discussed. FAR algorithm is designed to compromise between the performance and implementation complexity. In particular, FAR algorithm has a constant threshold feature which is greatly in favor of blind sensing.

In future I would like to go for real time spectrum sensing for cognitive radio using FPGA's and also try to minimize the disadvantages by enhancing the algorithm.

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