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Spectrum Sensing Implementations for Software Defined Radio in Simulink

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Abstract

The lack of spectrum for communication and for research is a bottleneck as far as technology and business development is considered. It is a fact that the availability of useful spectrum is limited by hardware constraints. The studies conducted by the Federal Communications Commission found that that there are many areas of the radio spectrum which are not fully utilized in different geographical areas of the country and FCC recommended locating and utilizing these unused spectrum spaces by other users. This is where spectrum sensing comes into use. From then on different spectrum sensing algorithms were developed. The paper implements four of those major sensing spectrum algorithms in MATLAB-Simulink and also does a performance comparison among them.

Keywords: Spectrum Sensing; Software Defined Radio; MATLAB-Simulink;

1. Introduction

The electromagnetic spectrum is a finite natural resource. Initially there were only few services which utilized the electromagnetic spectrum. But later on the spectrum utilization increased and reached a condition where the problem of spectrum utilization overlap occurred i.e. the same band utilized by different services. To overcome this, the process of spectrum licensing was introduced and then the spectrum has been exclusively allocated to different wireless services by corresponding governments.

With the increase of wireless communications technology in the last two decades, in many countries, most of the existing radio spectrum has been allocated to players (primary users). But still the need for higher data rates increased, as a result of the transition from voice-only communications to multimedia type applications and high quality-of-service (QoS) applications [3]. Given the limitations of the natural frequency spectrum, it becomes obvious that the current static frequency allocation schemes cannot accommodate the requirements of an increasing number of higher data rate devices. The problem is particularly serious in communication-intensive situations such a massive emergency (e.g., the 9/11 attacks). During such situations the requirement of additional bandwidth became an essential requirement. On the other hand, major licensed bands, such as those allocated for television broadcasting, amateur radio, and paging, have been found to be grossly underutilized, resulting in spectrum wastage [1]. In the recent studies conducted by *the Federal Communications Commission* (FCC) and *Ofcom*, it was found

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that even though the spectrum space is licensed by different primary service providers, they never utilize the bandwidth completely at all times. FCC showed that the spectrum utilization in the 0–6 GHz band varies from 15% to 85% [1]. These measurements appear to indicate that there are many areas of the radio spectrum which are not fully utilized in different geographical areas of the country [2].

It was then recommended by FCC that, these free bands can be utilized by a secondary user until they cause any harm to primary user's transmission. This scanning of spectrum for holes is what we call by the name Spectrum Sensing. There are many techniques/algorithms developed for spectrum sensing. Some of them include Energy detection, Cyclostationary Detection, Eigen value based detection, SVD based detection, Waveform based detection etc. Cognitive radio (CR), viewed as a novel form of wireless communications, has been proposed to become a tempting solution to the spectrum underutilization problem [2]. According to the definition of CR by the Federal Communications Commission (FCC) [3], CR is the wireless communication system with intelligence, which senses its outside electromagnetic environment and learns from the surroundings, then adapts its internal states by changing certain operating parameters such as transmit-power, carrier-frequency, and modulation strategy in order to adapt to the change of its environment. The goal of this paper is to implement four of the major spectrum sensing algorithms in MATLAB- Simulink and then do a performance analysis among them.

2. Energy detection algorithm

For any spectrum sensing technique, the ultimate aim is to detect the presence or absence of a signal in a particular frequency band. Here, in energy detection algorithm this is achieved by detecting the energy of a particular band. And if the energy is found to exceed a certain threshold it is concluded that the band is assumed to have live signals and else vice versa. The threshold is set by detecting the energy variance of noise and it is fact that always a particular amount of uncertainty exists in this noise energy detection (1 to 2 dB). Hence due to this uncertainty the energy detection algorithm cannot detect a signal below certain energy levels. The main disadvantage of such a detection method is its inability to differentiate between the modulated signal, noise and the interference [11]. This defect prevents it from utilizing the prior information about a signal for detection purpose.

Let us assume that the received signal has the following simple form.

$$y(n) = s(n) + w(n) \tag{1}$$

where s(n) is the primary signal, w(n) is the additive white Gaussian noise (AWGN) sample, and n is the sample index. Note that s(n) = 0, when there is no transmission by primary user. The decision metric for the energy detector can be written as,

$$M = \sum_{n=0}^{N} \left| y(n) \right|^2 \tag{2}$$

where N is the size of the observation vector. The decision on the occupancy of a band can be obtained by comparing the decision metric M against a fixed threshold λ_E. This is equivalent to distinguishing between the following two hypotheses [21]:

$$H_0 : \mathrm{y(n)=w(n)}$$
$$H_1 : \mathrm{y(n)=s(n)+w(n)}$$

The accurate detection decision threshold λ_E requires both the signal and noise strength. Since it is difficult to obtain the signal strength, a certain false alarm rate is assumed and then a λ_E is selected. Here we have assumed that the noise term as a random variable that follows a Gaussian distribution with 0 mean and variance as σ_W^2 .

One can easily infer from equation 2 that M, the *Decision Metric*, follows a central chi-square distribution with 2N degrees of freedom under H_0 i.e. χ_{2N}^2 , and a non-central chi-square distribution with 2M degrees of freedom and a non-centrality parameter, $\mu = \sum_{n=1}^{N} |S(m)|^2 = 2NM$ under H_1. Thus $f_y(Y)$ which denotes the probability density function (pdf) of Y can be written as follows [7, 22],

$$f_y(Y) \sim \begin{cases} \chi_{2N}^2, & \mathrm{H}_0 \\ \chi_{2N}^2(\mu), & \mathrm{H}_1 \end{cases} \tag{3}$$

Then the false-alarm probability P_F can be expressed as [7, 22]

$$P_F = \frac{\Gamma\left(N, \frac{\lambda}{2}\right)}{\Gamma(N)} \tag{4}$$

where $\Gamma\left(N, \frac{\lambda}{2}\right)$ and $\Gamma(N)$ denote the gamma function and the upper incomplete gamma function with N degrees of freedom. Now provided we have the value of P_F , it would be possible to find out the value of threshold, λ from equation 4.

Once λ is determined, the detection probability P_D can be found out by,

$$P_D = \int_0^\infty Q_M\left(\sqrt{\mu}, \sqrt{\lambda}\right) f_\mu(\mu)\, d\mu \tag{5}$$

Hence for a constant SNR, if we assume different values for P_F and applying it to equation 4, we get different values of λ . Now by applying this value of λ 's onto equation 5, we get the corresponding P_D .

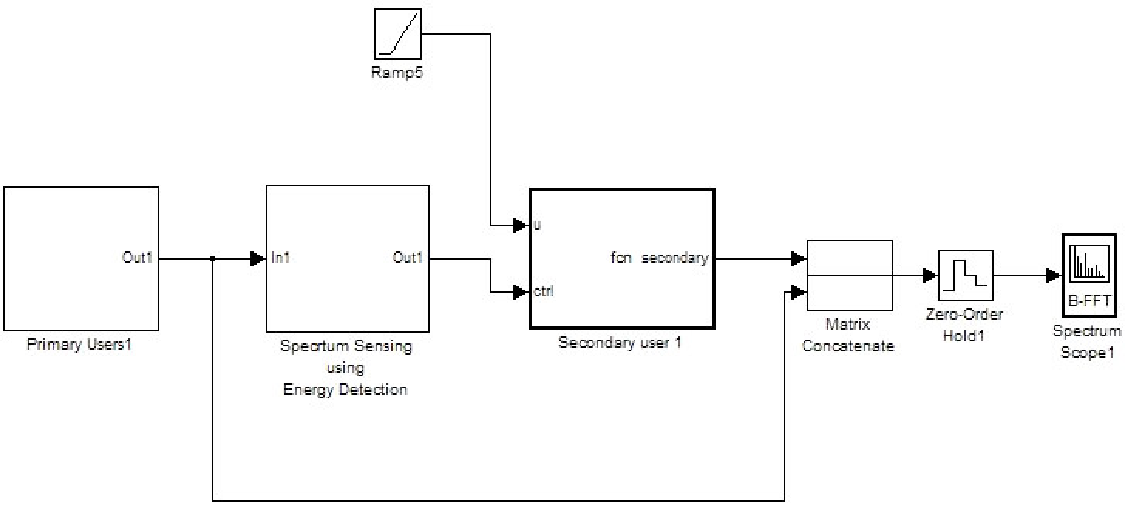

Figure 1: Energy Detection in Simulink

The energy detection based sensing is the simplest among the existing spectrum sensing methodologies. To test the sensing algorithm, one need to simulate a real transmission system. The figure 1 shows the MATLAB simulink model for implementing energy detection. The primary users are those who have been provided with the authority to transmit in their respective range of the spectrum. In our simulation we have five primary user transmissions happening simulatniously at 70 MHz, 80MHz, 90MHz, 100MHz and 110MHz and all these signals are generated from the ‘Primary user 1’ subsystem. The signal samples generated by the blocks are multiplex and transmitted through a single channel. In order to simulate a real FM signal we deliberately add Gaussian Noise to the signal. This is achieved using the block named ‘AWGN channel’. A ‘Zero Order hold’ is required at both ends of ‘AWGN Channel’ block to discretize the incoming signal. The ‘Energy Detection’ subsystem implements the energy detection algorithm and hence enabling the system to detect the presence or absence of primary transmission. The ‘Secondary User 1’ which emulates a secondary user, is an embedded Matlab code block. It aquire input from the ‘Energy Detection’ block. And depending on the input from the previous block the secondary user will have an idea about the free spectrum and can hence use the spectrum space for transmitting their own information. In this simulation the secondary transmissions are just sin waves which are transmitted at the frequencies where primary transmission is absent. We also have ‘Spectrum Scope’ blocks enable us to get an idea about the active and inactive bands in the scanned spectrum.

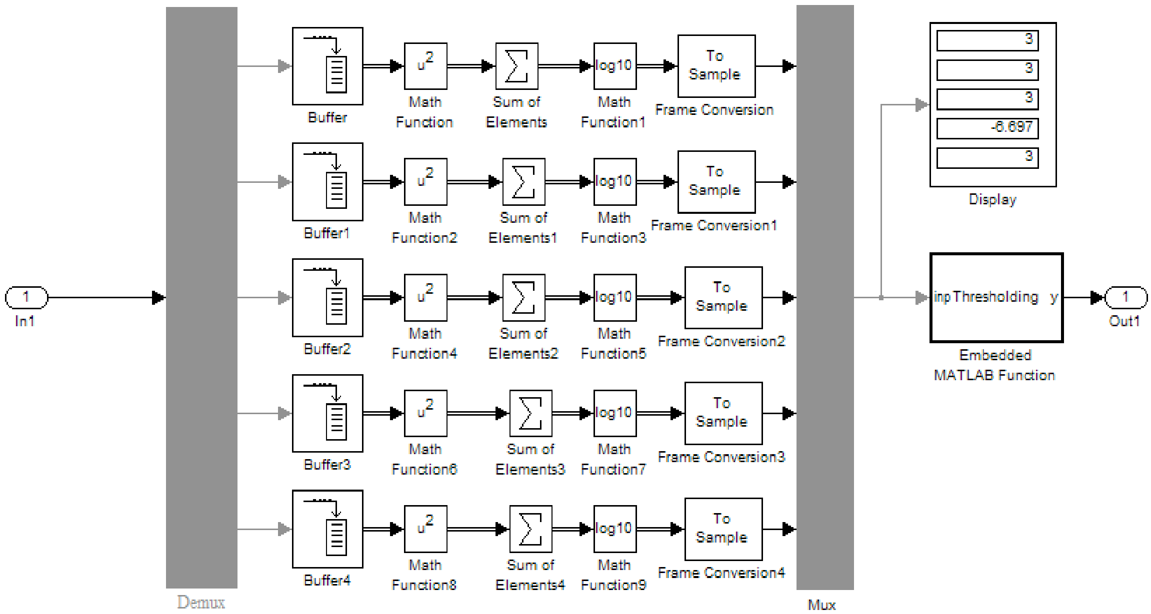

Figure 2: Inner blocks of Spectrum Sensing using Energy detection subsystem

As one can see in figure 2, the multiplexed signal coming from the previous subsystem is initially de-multiplexed and separated into five channels. The output of de-multiplexer will provide back the five channels which now contain FM signals which are added with the Gaussian noise.

One method to calculate the energy of a signal is to take N samples of the signal, then square it, integrate the values over N samples and finally take the log. Now if this value goes above a certain threshold we say that the signal exists and else it does not. This process will be done in the next block i.e. an embedded MATLAB function. In this case we have assumed N as 10000. The other method to calculate the energy is by taking the square of FFT coefficients of the signal and then adding all these squared coefficients values together. The end result will actually be the energy of the signal.

3. Eigen Value based spectrum sensing (Max-Min Method)

In this method, the basic requirement is the generation of covariance matrix from the channel samples. Then the ratio of the maximum Eigen value to the minimum Eigen value of the covariance matrix is found out and compared with a pre-calculated threshold. If the Eigen value is found greater than the threshold, the existence of the signal from the primary user is confirmed and else it would symbolize the non existence of the signal in the channel. The limiting law of the largest Eigen value distribution (Tracy-Wisdom distribution) is utilized to set a decision threshold. This is better than energy detection because it has an idea about the noise content of a channel, which comes useful in case of low SNR signals [5]. l

Here the signal is oversampled or multiple receiver antennas are used. This is done to obtain information about the noise information also. Thus sample covariance matrix of the received signal contains the signal and noise information, respectively. Based on random matrix theories (RMT), this information is quantized and then used for signal detection. The threshold and the probability of false alarm are also found by using the RMT [4]. Eigen value based detection method overcomes the noise uncertainty difficulty while keeps the advantages of the energy detection. The method can be used for various signal detection without knowledge of the signal, the channel and noise power.

The covariance matrix is obtained differently when signal is oversampling and when multiple receivers antennas. If multiple receivers antennas are used each antenna collects N samples during the sensing time. The K base stations will collaborate in a way that they together form the received data matrix using all the samples collected [8].

The covariance matrix R is obtained as, $\mathrm{R} = \mathrm{YY}^H$. The elements of matrix i.e. y_i^j denotes the j$^{\text{th}}$ sample from the i$^{\text{th}}$ antenna and the sample values H denotes the Hermitian operator. Now we need to find out the largest and smallest Eigen value λ_1 and λ_N of this covariance matrix.

In case of oversampling, let's assume $x(n), n = 0,1,...,MN_s - 1,$ be the received signal samples, which is oversampled with oversampling factor M [9]. The procedure for generating the covariance matrix in this case is stated below.

Step 1: Compute the sample covariance matrix [9]

$$\mathbf{R}(N_s) = \frac{1}{N_s}\sum_{n=0}^{N_s-1}\mathbf{y}(n)\mathbf{y}^H(n) \tag{6}$$

Where

$$\mathbf{y}(n) = [\mathbf{x}(n)^T \quad \mathbf{x}(n-1)^T \quad ... \quad \mathbf{x}(n-L+1)^T]^T,\ n = 0,\ 1,...$$
$$\mathbf{x}(n) = [x_1(n) \quad x_2(n) \quad ... \quad x_M(n)]^T,\ n = 0,\ 1,...$$
$$x_i(n) = x(nM + i - 1), i = 1,2,...,M;\ n = 0,\ 1,...,N_s - 1$$

Step 2: Compute the threshold [9]: Since we have no information on the signal, it is difficult to set the threshold based on the Pd. Hence, usually we choose the threshold based on the P_F .I.e.

$$\gamma = \frac{(\sqrt{N_s}+\sqrt{ML})^2}{(\sqrt{N_s}-\sqrt{ML})^2}\left(1+\frac{(\sqrt{N_s}+\sqrt{ML})^{-2/3}}{(N_sML)^{1/6}}F_1^{-1}(1-P_F)\right) \tag{7}$$

where F_1 is the Tracy-Wisdom distribution of order 1 [4] and P_0 is the required probability of false alarm.

Step 3: Compute the maximum Eigen value and minimum Eigen value of the matrix $\mathbf{R}(N_s)$ and denote them as λ_{max} and λ_{min}, respectively.

Step 4: Determine the presence of the signal based on the Eigen values and the threshold; if $\frac{\lambda_{\text{max}}}{\lambda_{\text{min}}} > \gamma$, signal exists; otherwise, signal is assumed to be not existing..

The primary user signal generation part in this case the same as in the case of energy detection spectrum sensing. The "Spectrum sensing using Eigen values" subsystem receives the primary user signals are then de-multiplexed and directed into five channels as shown in figure 3. For each channels these samples are utilized to generate a covariance matrix. The whole Eigen-value based detection algorithm including the generation of covariance matrix is implemented through the embedded function block i.e." EigVal" function. At the right end of figure 3, one can see the Threshold function block which makes the final decision in this case i.e. whether the spectrum is utilized or not. The Eigen value ratios for each of the channels are displayed in the 'display' block shown at the top right corner of figure 3. The steps in the generation of covariance matrix, the threshold calculation and the algorithm logic are explained in detail in the beginning of this section.

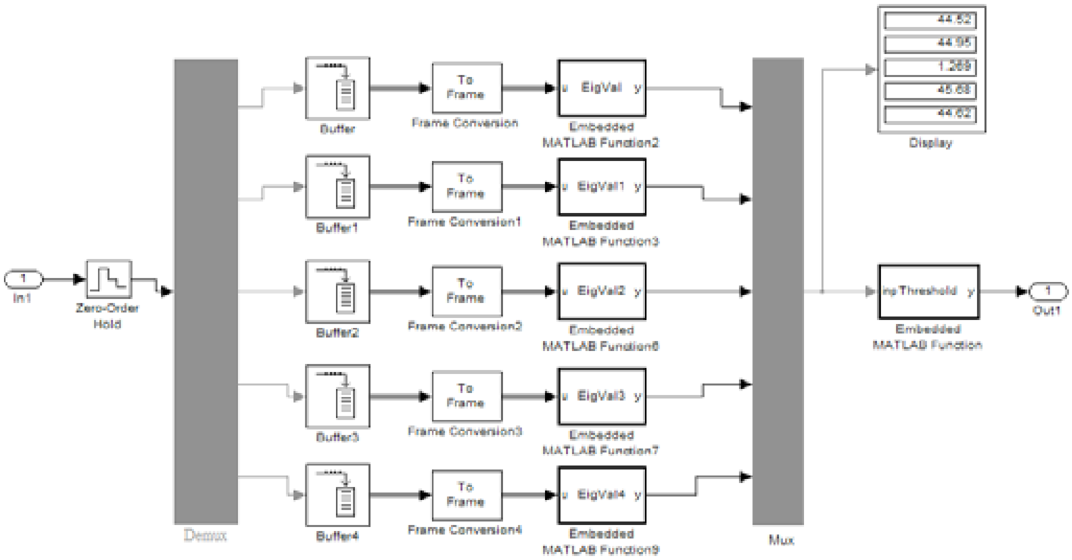

Figure 3: Inner blocks of Eigen value based Spectrum Sensing subsystem

The threshold values will vary according to the false detection probability. The ROC curves can be drawn here by plotting the probability of detection by varying the probability of false detection. (When we vary the probability of false alarm the threshold also gets varied as per equation 7, which in turn changed the probability of detection).

4. Correlation based Spectrum Sensing

For good spectrum sensing, we can exploit any properties that exist in signal that are not present in the noise. One such property is the autocorrelation of the signal samples. The autocorrelation function of bandpass noise is a modulated ‘sinc’ function whose envelope has its first zero crossing at 1/W, where W is the bandwidth of the noise (as well as the sensing bandwidth). However, the envelope of the autocorrelation function of the signal will deviate from a ‘sinc’, depending on the transmit symbol rate, modulation, and pulse shaping. When correlation is present in this signal, the first zero crossing of the autocorrelation will happen at a larger time lag than that of the noise.

To detect the deviation of the received waveform from noise, the envelope of the empirical autocorrelation function of the received signal is integrated up to its first null τ = 1/W and this value is used as a decision statistic to test the hypothesis that a primary user is present, which exploits both the energy and autocorrelation of the received samples [10].

In signal processing, given a signal s(t), the continuous autocorrelation $R_f(\tau)$ is the continuous cross-correlation of f(t) with itself, at lag τ, and is defined as:

$$\mathrm{R}_f(\tau) = \int_{-\infty}^{\infty} s(t) s^*(t-\tau) dt \tag{8}$$

where s* represents the complex conjugate. For a real function, s* = s An Autocorrelation Function is one which is obtained by obtained by plotting the autocorrelation values that is obtained for various lags. An autocorrelation value close to one says that the signal is more correlated and if the value is close to zero we say that the signal is least correlated. In spectrum sensing noise is a factor which greatly affects the quality of sensing. And it is a fact that the signal affected by white Gaussian noise is difficult to be interpreted.

In case of the random noise, it is a fact that the correlation will be very small or negative even for the first lag. I.e. there will not be any similarity between two adjutant samples. But it is not the case with periodic signals; they will have good correlation with the adjacent samples. The figure 4(a) shows the autocorrelation of a noisy signal. Here one can see that the autocorrelation becomes negative right after the first lag. But if you see figure 4(b) one can see that the autocorrelation becomes negative only after the 30^{th} lag..

Here, as in the case of 'Energy Detection' the 'primary user' subsystem will generate five signals each FM modulated using a different carrier. These signals are multiplexed and transmitted through the Gaussian channel to the spectrum sensing block (subsystem) i.e. the 'spectrum sensing using correlation/lag detection' block. This block will sense the spectrum through the above mentioned method and give out the index of the band for which the spectrum is absent. The secondary block will modulate its message using a carrier frequency which is not being utilized by the primary user

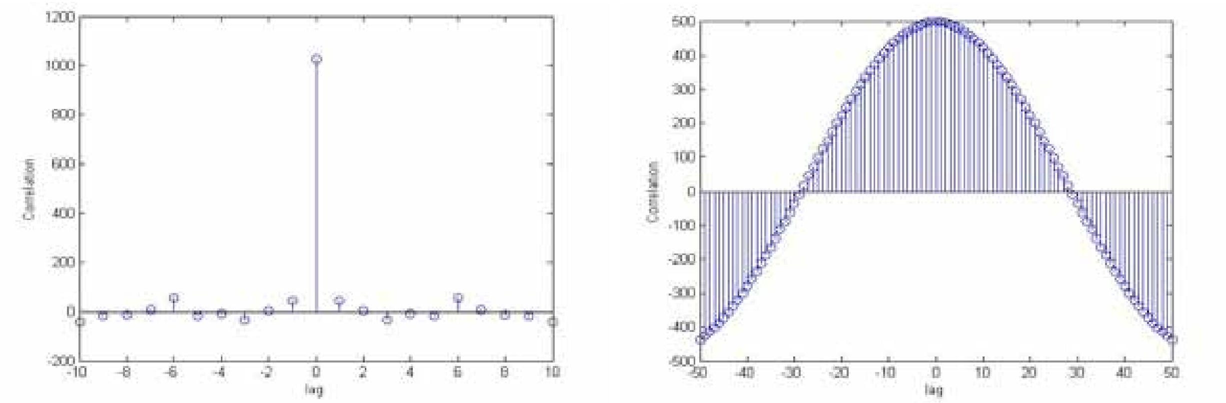

Figure 4: (a) Autocorrelation of noise (b) Autocorrelation of Sin signal (500Hz)

Here the primary signals are generated in the same way, as mentioned in the case of Energy detection. In the 'Spectrum Sensing using Lag Detection subsystem, the autocorrelation based spectrum sensing logic is implemented. This inner block of this sub-system is shown in figure 5. Usually To detect the deviation of the received waveform from noise, the envelope of the empirical autocorrelation function of the received signal is integrated up to its first null = 1/W and this value is used as a decision statistic to test the hypothesis that a primary user is present, which exploits both the energy and autocorrelation of the received samples.

We have used a slightly modified logic in this case. Here we need to just detect the first-lag of the autocorrelation function for sensing the spectrum. We can see that even for very weak signal we can see that the first lag remains as a prominent feature which says about the existence of signal in the band. In our case we have stopped the primary transmission at 100MHz. Thus noise is the only signal which is transmitted and it is fact that the first lag for noise will be a negative value or a value close to zero. Here the correlation value for third channel is 0.02061, which is close to 0.

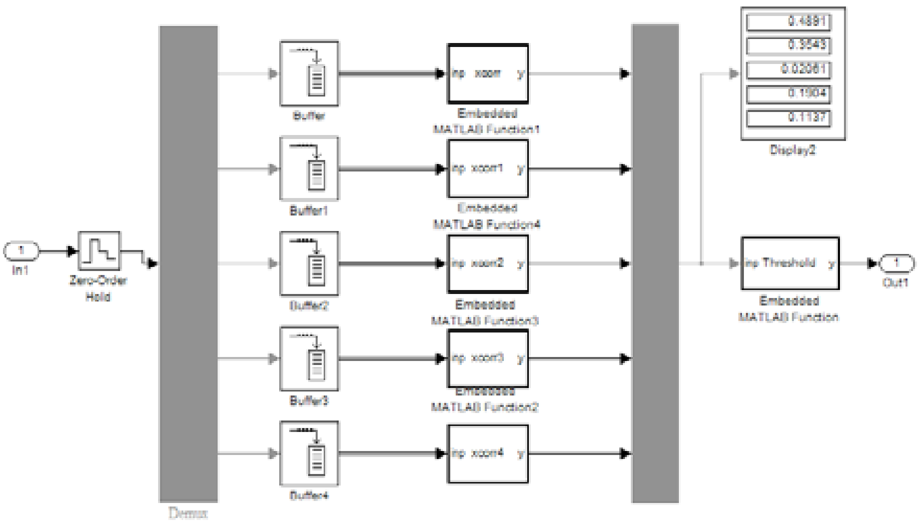

Figure 5: Inner blocks of Correlation detection spectrum sensing subsystem

5. SVD based Spectrum Sensing

In SVD based spectrum sensing, the Singular Valued Decomposition of the matrix (Hankel matrix), formed from the incoming signal samples is taken to and its Eigen values are found out. This is different from normal Eigen value spectrum sensing in the sense that, the Eigen values that we obtain through SVD decomposition is different from the one we obtain through normal Eigen value calculation.

Apart from the Eigen value decomposition method that we saw, here, the ratio of maximum to the minimum Eigen values or ratio of 2nd largest Eigen value to the 3rd largest Eigen value can be compared with a preset threshold to serve the signal detection. We consider a CR network with N samples utilized to perform spectrum sensing at the ith CR user. Here Eigen value based spectrum sensing algorithm is used to sense the spectrum since it has the advantage of detecting any unknown signals; also it is tolerant against channel noise.

The response of the system in different time intervals is used to construct the below data matrix (Hankel matrix). Thus for a time series r(n) with n = 1,2,…,N, commonly, we can construct a Hankel matrix with M = N – L + 1 rows and L columns illustrated as follows,

$$R = \begin{bmatrix} r(1) & r(2) & .... & r(L) \\ r(2) & r(3) & .... & r(L+1) \\ . & . & . & . \\ r(N-L+1) & r(N-L+2) & .... & r(N) \end{bmatrix}_{(N-L+1)\,\mathrm{x}\,\mathrm{L}}$$

Where L is the smoothing factor and N is the number of samples [12].

This matrix can be factorized as $R = U\sum V^T$ where U and V are two unitary matrices and $\sum$ is a diagonal matrix which is formed by the Eigen values of R. The received signal r(n) includes only AWGN contribution such that its singular values are similar and close to zero. When a primary user signal is present whose power is higher than a threshold, there will exist two dominant singular values to represent this primary user signal. In this paper the prediction of primary user is predicted if the ratio of second largest singular value λ_2 to the third largest singular value λ_3 is greater than a threshold γ.

$$\frac{\lambda_2}{\lambda_3} \geq \gamma \tag{9}$$

Selection of Threshold (γ)

$$\gamma = \sqrt{\frac{N\left(\delta_{M,L-2}F_1^{-1}\left(\sqrt{1+c_{M,L}-p_f}\right)+\mu_{M,L-2}\right)}{\sigma_u^2\left(\sqrt{N}+\sqrt{ML}\right)^2}} \tag{10}$$

Where

$$\delta_{ML} = \left(\sqrt{M-1}+\sqrt{L}\right)\left(\frac{1}{\sqrt{M-1}}+\frac{1}{\sqrt{L}}\right)^{\frac{1}{3}} \tag{11}$$

$$\mu_{ML} = \left(\sqrt{M-1}+\sqrt{L}\right)^2 \tag{12}$$

Where N is the number of samples, M is the smoothing factor, F^{-1} is the distribution function of Tracy-Widom distribution of order, p_f is the probability of false detection and $C_{M,L}$ is an empirical constant.

Speaking about the advantages of SVD based spectrum sensing algorithm, it performs better in the low signal-to-noise ratio (SNR) environment. The algorithm is suitable for blind spectrum sensing where the properties of the signal to be detected are unknown. This is also the advantage of the algorithm since any signal would interfere and subsequently affect the quality of service (QoS). But the computational complexity of SVD-based detector is medium compared to the energy detector.

Here the primary signals are generated in the same way, as mentioned in the case of Energy detection. The inner blocks of the subsystem named ‘Spectrum Sensing using SVD’ are shown in figure 6. The Henkel matrix is first formed using samples values flowing through each channels and SVD decomposition is done for each channel (The output of the SVD decomposition consist of three matrices U, $\sum$and V^T). This is done using embedded MATLAB coding block. This diagonal value of the $\sum$matrix, which is the Eigen value arranged in descending order, is then extracted out and the ratio between the second and the third Eigen values are found out. If this ratio exceeds the selected threshold then it is confirmed that the channel under analysis is utilized by the primary user else the secondary signals are transmitted.

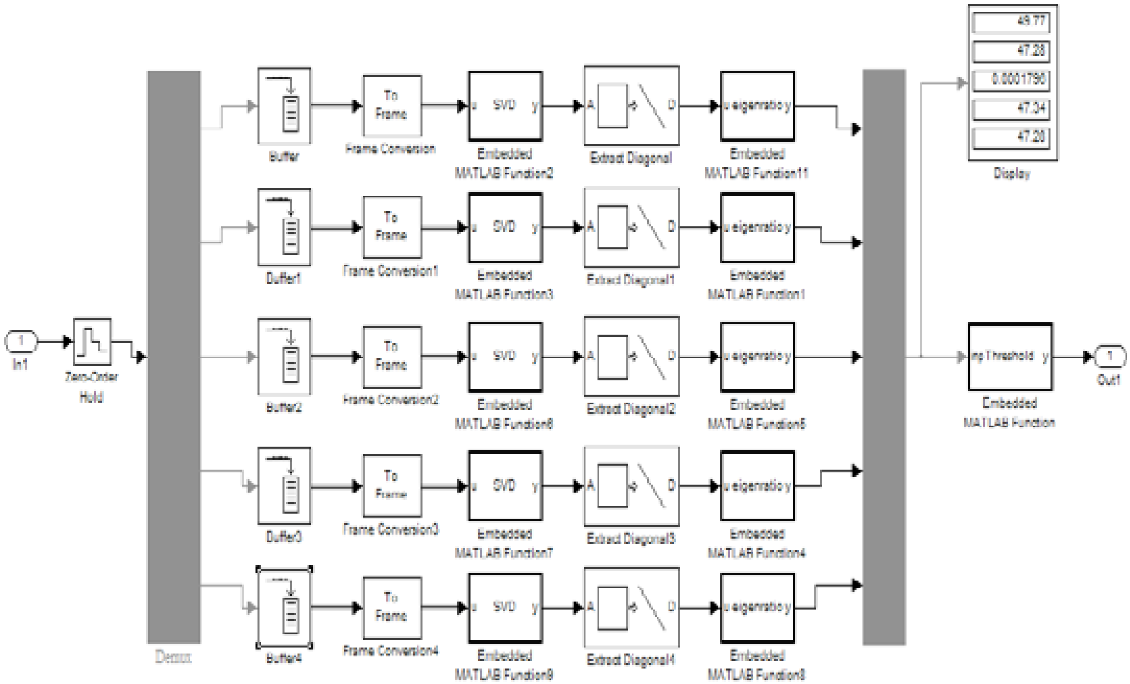

Figure 6: Inner blocks of spectrum sensing using SVD subsystem

The ROC curves can be drawn here by plotting the probability of detection by varying the probability of false detection. (When we vary the probability of false alarm the threshold also gets varied as per equation 10, which in turn changed the probability of detection).

6. Conclusion

Different spectrum sensing algorithms respond differently at different SNR’s. In the paper, simulink models for four of the major spectrum sensing algorithms i.e. Energy detection method, Correlation detection method, Eigen value based detection method and SVD based detection were developed. The paper also explains about the advantages and disadvantages of the discussed spectrum sensing methodologies.

Also the SNR against Probability of detection plots is obtained for the above said spectrum sensing methodologies. The probability of false alarm considered here is 0.8 for all the algorithms. One can easily do a performance analysis of the selected four algorithms from figure 7.

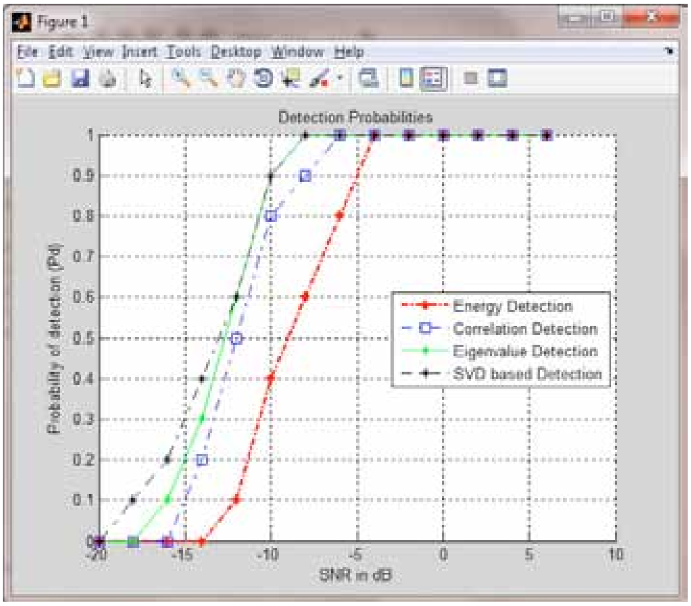

Figure 7: Detection probabilities

References

[1] Jun Ma, Geoffrey Ye Li, Biing Hwang (Fred) Juang, “Signal Processing in Cognitive Radio”, Fellow IEEE.

[2] Danijela Cabric, Shridhar Mubaraq Mishra, Robert W.Brodersen, “Implementation Issues in Spectrum Sensing for Cognitive Radios”, Berkeley Wireless Research Center, University of California, Berkeley

[3] “E3 White Paper,”Spectrum Sensing”, November 2009,
https://www.ict-e3.eu/project/white_papers/E3_White_Paper_Sensing.pdf

[4] H. Urkowitz, “Energy detection of unknown deterministic signals,” *Proceedings of the IEEE*, vol. 55, no. 4, pp. 523–531, 1967.

[5] F. F. Digham, M. S. Alouini, and M. K. Simon, “On the energy detection of unknown signals over fading channels,” IEEE Transactions on Communications, vol. 55, no. 1, pp. 21–24, 2007.

[6] A. Sahai, N. Hoven, R. Tandra, “Some Fundamental Limits on Cognitive Radio”, *Proc. of Allerton Conference*, Monticello, Oct 2004.

[7] Tevfik Y¨ucek and H¨useyin Arslan, “A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications”, *IEEE Communication Surveys & Tutorials*, Vol. 11, No. 1, First Quarter 2009.

[8] Lu Wei and Olav Tirkkonen, “Cooperative Spectrum Sensing of OFDM Signals Using Largest Eigen value Distributions”, Department of Communications and Networking, Helsinki University of Technology (TKK).

[9] Yonghong Zeng and Ying-Chang Liang, “Maximum-Minimum Eigen value Detection For Cognitive Radio”, Institute for Infocomm Research, Singapore.

[10] R. K. Sharma and J. W. Wallace, “A Novel Correlation Sum Method For Cognitive Radio Spectrum”, Department of Electrical Engineering, Jacobs University.

[11] Takeshi Ikuma and Mort Naraghi-Pour, “A Comparison of Three Classes of Spectrum Sensing Techniques”, Department of Electrical and Computer Engineering Louisiana State University.

[12] Shaoyi Xu, Yanlei Shang, Haiming Wang, “SVD based Sensing of a Wireless Microphone Signal in Cognitive Radio Networks”, School of Telecommunication Engineering, *BUPT*, Beijing 100876, China.

[13] R.Gandhiraj, Silpa.S.Prasad, K.P.Soman, “Multi-User Spectrum Sensing Based on Multitaper Method for Cognitive Environments”, *International Journal of Computer Applications*, Foundation of Computer Science, New York, USA.

[14] R.Gandhiraj, Aravind.H, K.P.Soman, “A Novel approach to Spectrum Sensing”, *Third National conference on Recent Trends in Communication, Computation and Signal Processing*, March 1-2, 2011.

[15] R.Gandhiraj, Silpa.S.Prasad, K.P.Soman, “Efficient Spectral estimation with Slepian tapers in Cognitive Environment: A review”, *Second National conference on Recent Trends in Communication, Computation and Signal Processing*, March 26-27, 2010.

[16] Silpa S. Prasad, R. Gandhiraj, K.P.Soman "Cognitive Radio as a Background for Spectrum Sensing - A Review", *National Conference on Recent Innovation in Technology 2010 (NCRIT 2010)*, organized by Rajiv Gandhi Institute of Technology (Govt. Engineering College), Kottayam, Kerala, March 04-06, 2010.