Adaptive Spectrum Sensing in Cognitive Radio Networks

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ABSTRACT
The available radio spectrum is not used efficiently, therefore a new technology called Cognitive Radio (CR) is used to increase the spectrum utilization. The objective of CR is to use the available spectrum efficiently without any interference to the Primary Users (PUs). Spectrum sensing plays an essential part in cognitive radio networks inorder to obtain spectrum awareness. Energy detection, matched filter detection, cyclostationary detection etc are the most commonly used techniques for spectrum sensing.This paper proposes an Adaptive spectrum sensing technique in which a particular sensing method from matched filter detection, Energy detection or Wavelet based detection is chosen according to the information available and SNR of the received signal. This paper also investigates the performance of both Eigen value and Wavelet based sensing in low SNR regions.

Keywords
Cognitive Radio, Spectrum sensing, Energy detection, Eigen value, Wavelet, Matched filter

1. INTRODUCTION
Cognitive radio is a new method for executing radio communications which takes into consideration more efficient use of spectrum [1]. It senses the spectral environment over a range of frequency bands and exploits the temporally abandoned bands for opportunistic wireless transmissions. Since a CR is operating as a secondary user (SU) which does not have any primary rights to preassigned frequency bands, it is essential for it to dynamically identify the presence of primary users. Hence, they need to make use of effective and efficient spectrum sensing techniques that make sure the Quality of Services (QoS) for PUs and exploiting all dynamic opportunities.

According to Federal Communication Commission (FCC) report on spectrum utilization, many licensed bands are unoccupied and not used. FCC also reveals that in thickly populated urban areas the spectrum utilization barely ever crossed 35% at any given time [2].

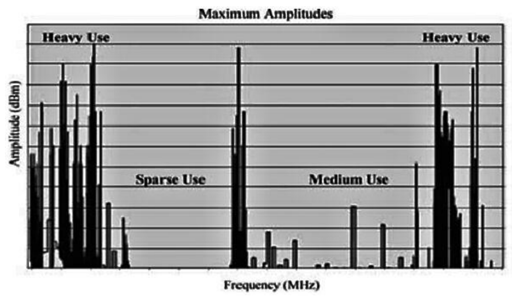

Figure 1 : Frequency Spectrum Utilization

Figure 1 shows that some frequency bands are occupied heavily, some are moderately occupied and remaining bands are not occupied at all [3]. Hence CR is used to solve the spectrum utilization problem. Inorder for CR to solve this problem, it requires efficient spectrum sensing schemes. The traditional spectrum sensing schemes available are energy detection, eigen value detection and matched filtering. But each technique has its own merits as well as disadvantages. Therefore a single sensing technique cannot perform well in a varying radio environment. Thus we aim to propose an adaptive spectrum scheme which switches between different spectrum sensing schemes based on a set value of threshold.

Initially energy detection is used for high SNR regions and eigen value detection for low SNR regions. But since wavelet detection outperforms eigen value detection in low SNR regions, an adaptive scheme replacing eigen value detection with wavelet detection is also proposed. In both cases matched filtering is used if the prior information regarding primary user is available.

Rest of the paper is organized as follows. Section 2 gives a generalized view of spectrum sensing and its classification. Section 3 gives the flowchart of the proposed scheme as well as detailed explanation of sensing methods used. Section 4 gives the results of the proposed scheme simulated in MATLAB 2014 and Section 5 concludes the paper.

2. SPECTRUM SENSING IN COGNITIVE RADIO

The process by which the unused part of the licensed spectrum called spectrum holes or white spaces are identified is called spectrum sensing. The spectrum hole concept is shown in figure 2 [4].

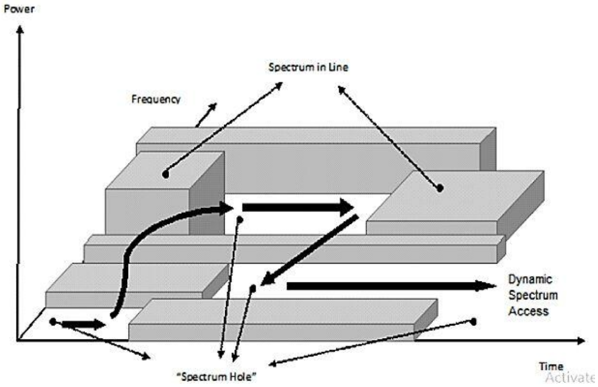

Figure 2 : Spectrum hole concept

General model of spectrum sensing is shown in figure 3. The output T after spectrum sensing is compared with a threshold value inorder to make a decision regarding the presence or absence of PU [5].

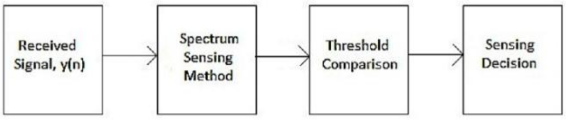

Figure 3 : General model of spectrum sensing

Generally the spectrum sensing techniques can be classified as transmitter detection and cooperative detection. In transmitter detection only one SU is involved in making a decision whereas in cooperative detection multiple SUs coordinate together to make a decision. Figure 4 shows the classification of spectrum sensing techniques [6].

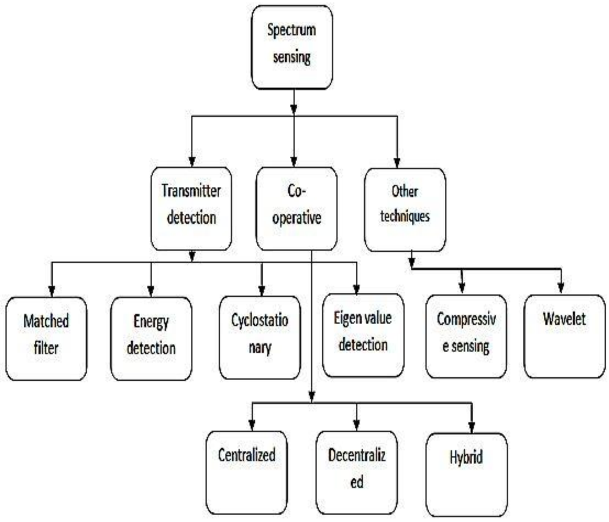

Figure 4 : Classification of spectrum sensing

In this paper, only transmitter detection methods like energy detection, matched filtering and eigen value detection are used for adaptive spectrum sensing. Since wavelet detection performs well under noise, an adaptive scheme replacing eigen value with wavelet detection is also experimented.

3. METHODOLOGY

Radio environment is changing constantly. Every sensing technique has its own pros and cons. Some of them work well under low Signal to Noise Ratio (SNR) condition while some at high SNR. So a single sensing technique cannot adapt to the changing environment and thus facilitates the need for improved spectrum sensing schemes. In this paper we propose an Adaptive Spectrum Sensing Technique in which it adapts the sensing method according to the frequently changing wireless environment and the available information. The flowchart for the adaptive spectrum sensing technique is given in figure 5 [7].

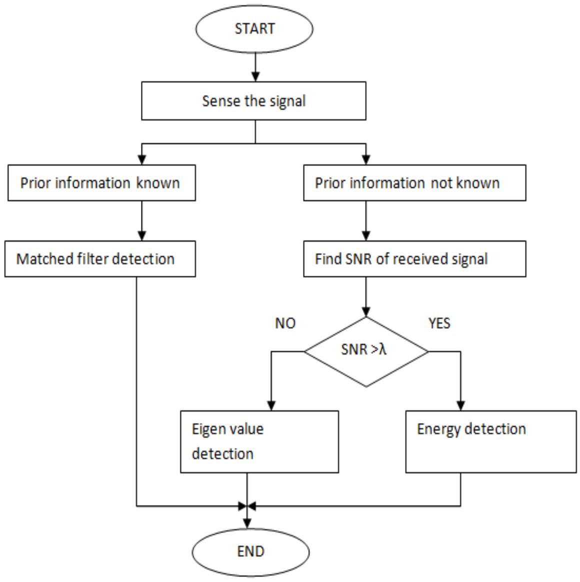

Figure 5: Flowchart of adaptive spectrum sensing

If the SU has prior information about PU, then directly apply matched filter detection. If no information is available, then estimate the SNR of received PU signal. If it is greater than λ then use energy detection else use eigen value detection. We have chosen a λ of 2 dB.

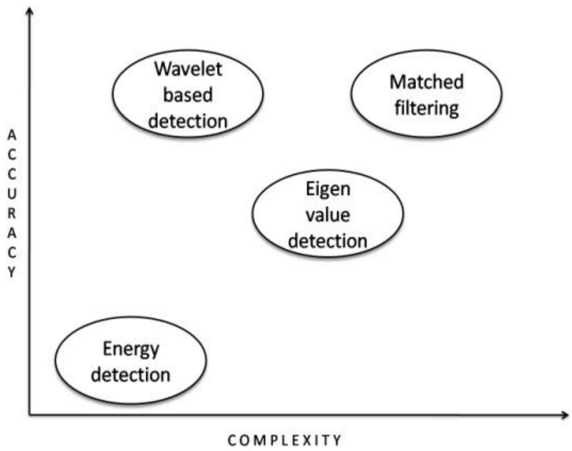

Figure 6 : Plot of Accuracy vs Complexity for different Sensing Methods

From figure 6 it is clear that wavelet has higher accuracy and reduced complexity compared to eigen value based detection [8]. The effect of noise on wavelet based sensing technique is dramatically reduced. Hence eigen value is been replaced by wavelet based technique and further results were studied. Figure 7 shows the modified flowchart.

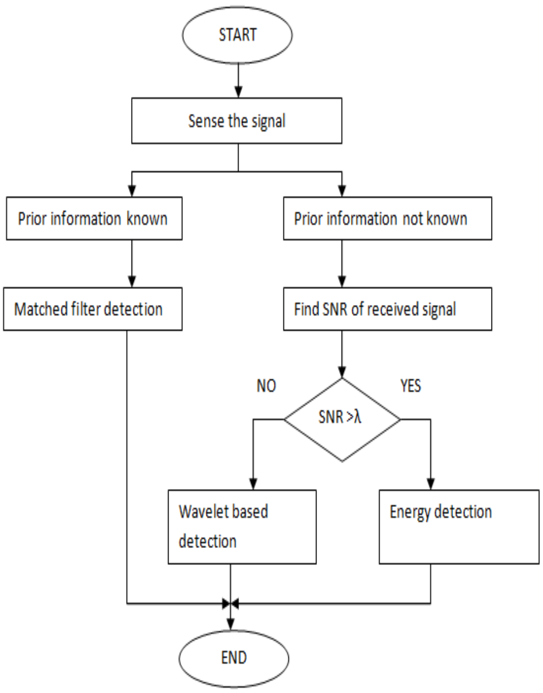

Figure 7: Modified flowchart for adaptive spectrum sensing

3.1 ADAPTIVE SENSING WHEN PRIOR KNOWLEDGE IS AVAILABLE

When the prior information about PU is known, the optimum method to be used is matched filter detection [9]. It uses information like modulation type, frequency, pulse shaping, bandwidth etc [10]. Figure 8 shows the block diagram of matched filter detection.

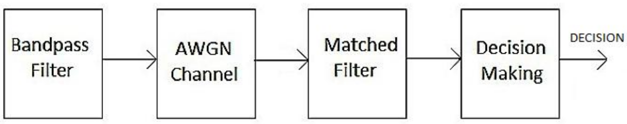

Figure 8: Block diagram of matched filter detection

In matched filter, the known signal is correlated with the unknown signal or the received signal. If there is a certain degree of matching between the two i.e if it is greater than the threshold then PU is present else PU is absent.

$$R = \sum_{K} Y[K]\, X[K]^*$$

Where Y[K] is the received signal and X[K] is the known signal.

$$R > \gamma \quad H1: \quad \text{PU is present}$$
$$R < \gamma \quad H0: \quad \text{PU is absent}$$

Where γ is the threshold of matching. H0 indicates PU is absent and H1 indicates PU is present.

The probability of detection Pd and probability of false alarm Pfa are two test statistics for CR. Pd is the probability to correctly detect the PU and Pfa is the probability that the detector makes a decision of H1 when the right decision was exactly H0. Pd and Pfa for matched filter is given as below.

$$Pd = Q\left(\frac{\gamma - \varepsilon}{\sqrt{\varepsilon\sigma_n^2}}\right)$$

$$Pfa = Q\left(\frac{\gamma}{\sqrt{\varepsilon\sigma_n^2}}\right)$$

Where σ_n^2 is the variance of noise and Q is the q-function defined as

$$Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^{\infty} e^{\frac{\gamma^2}{2}}\, d\tau$$

$$\varepsilon = \sum_{K} (X[K])^2$$

The number of samples required for the matched filter can be chosen as:

$$K = [Q^{-1}(Pfa) - Q^{-1}(Pd)]^2 SNR^{-1}$$

Where Pd and Pfa are the probability of detection and probability of false alarm respectively

3.2 ADAPTIVE SENSING WHEN PRIOR KNOWLEDGE IS NOT AVAILABLE

When prior information is not available about PU, it can either use eigen value detection or energy detection depending on the estimated SNR. The threshold value of SNR set is λ. If SNR > λ , then it uses energy detection else it uses eigen value detection. The hypothesis test for both the methods is given as follows [11]:

$$Y(n) = W(n) \qquad \text{H0: PU is absent}$$

$$Y(n) = W(n) + X(n) \qquad \text{H1:PU is present}$$

Where *Y(n)* is the received signal, *X(n)* is the PU signal and *W(n)* is the Additive White Gaussian Noise (AWGN).

3.2.1 *ENERGY DETECTION*

It is the most commonly used spectrum sensing technique because of its simplicity [12]. The block diagram of energy detector is given in figure 9.

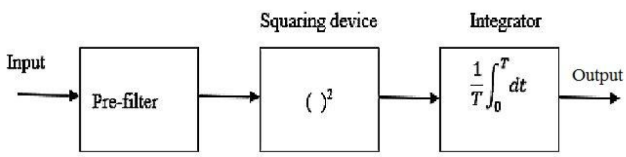

Figure 9 : Block diagram of energy detection

As shown in figure 9, first the received signal is passed through a pre-filter which is basically a band pass filter inorder to remove the unwanted frequencies. It is then squared and integrated over a time interval T. Finally the output of energy detector would be the energy of the received signal which is compared with a threshold to make decision about the PU [13].

One difficulty with the energy detector is the choice of the threshold since it is highly susceptible to background noise and interference. Also, it cannot distinguish between noise signal and PU signal and hence cannot work in low SNR regions because of which we use it in high SNR regions [14].

The test statistic of energy detector is given as:

$$R = \sum_{K} (Y[K])^2$$

Where Y[K] is the received signal.

$$R > \gamma \quad H1: \quad \text{PU is present}$$
$$R < \gamma \quad H0: \quad \text{PU is absent}$$

Where γis the threshold of noise power. If energy of signal greater than this threshold, then PU is present and vice versa.

The threshold γ is given by:

$$\gamma = Q^{-1}(Pfa)\sqrt{2K\sigma_n^4} + K\sigma_n^2$$

Where Pfa, and Pd, are given by:

$$Pfa = Q\left[\frac{\gamma - K\sigma_n^2}{\sqrt{2K\sigma_n^4}}\right]$$

$$Pd = \left[\frac{\gamma - K(\sigma_n^2 + |h|^2\sigma_s^2}{\sqrt{2K(|h|^2\sigma_s^2 + \sigma_n^2)^2}}\right]$$

Where σ_s^2 and σ_n^2 are the average received signal power and noise power respectively.

3.2.2 EIGEN VALUE DETECTION

Since energy detection cannot perform well in low SNR regions, we go for eigen value detection when estimated SNR is low i.e. SNR < λ .

The type of eigen value detection we use here is called Maximum-Minimum Eigen value (MME) method. In MME method, first of all the sample covariance matrix of the received signal is calculated and its eigen values are found. The ratio of maximum to minimum eigen value is compared with a threshold to make a decision regarding PU [15].

Sample covariance matrix is a matrix whose elements in i, j position is the covariance between the i^{th} and j^{th} elements of a random vector. Sample covariance matrix of received signal Y is given by:

$$R_Y = \frac{1}{N}(YY^T)$$

The threshold for the comparison of ratio of maximum-minimum eigen value can be expressed as:

$$T = \frac{\left(\sqrt{Ns} + \sqrt{L}\right)^2}{\left(\sqrt{Ns} - \sqrt{L}\right)^2}\left(1 + \frac{\left(\sqrt{Ns} + \sqrt{L}\right)^{-2/3}}{(NsL)^{-1/6}} F_1^{-1}(1 - Pfa)\right)$$

Since this method needs to calculate the covariance matrix and its eigen values, the complexity involved is high. Hence inorder to reduce complexity, we propose a wavelet based detection instead of eigen value detection.

3.3 ADAPTIVE SENSING USING WAVELET DETECTION INSTEAD OF EIGEN VALUE DETECTION

The two radio sources present at each location of spectrum sensing are PU and white noise. Even though presence and absence of PU user vary with time, White noise exists for sure. We also assume that each SU has the ability to measure the radio waves and make the appropriate decision . For a given location, let the SU receive the signal wave x(t), t =1,...,n after sampling with n number of discrete measurements.

Wavelet transformation algorithm is to be applied in determining whether the original received wave from antenna holds signals or not ie H1 or H0. For this we use an algorithm called WATRAB [16].

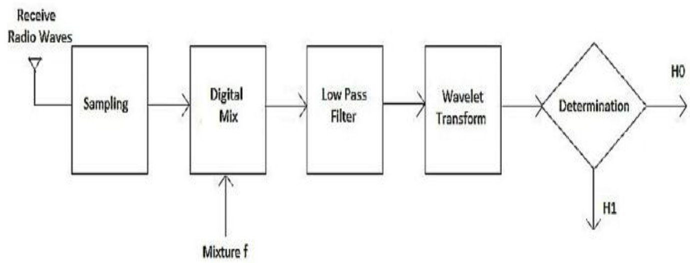

Figure 10 : General architecture of WATRAB

Here, we use a mixer and a combination of low pass filters and daubechies db4 wavelet transform is then applied. The signals remains nearly unaffected after the transform, whereas noises are intensely affected. For the input X(t), t=1,...,n, obtained after sampling we have the following:

$$X(t) = a1(t)\cos(2\pi f t) + a2(t)\sin(2\pi f t)$$

Here a1 and a2 are the baseband signals. Use the mixture as

$$Y(t) = X(t)\cos(2\pi f' t)$$

where f' is the frequency of the mixture. After passing through low pass filter, Y(t) becomes

$$Y(t) = a1(t)\cos\left(2\pi t(f - f')\right) + a2(t)\sin(2\pi t(f - f'))$$

The above observations clearly says that by carefully selecting f' a simple LPF is allowed to function as a BPF in wavelet transform based spectrum sensing [17].

4. RESULTS AND DISCUSSION

Here, the simulation results of different sensing algorithms are presented and their performance is evaluated on the basis of Pd, Pfa and SNR. Also the comparison between eigen value detection and wavelet detection is also given. Then we have presented the adaptive spectrum sensing scheme to adapt the sensing method according to the varying radio environment and the available information.

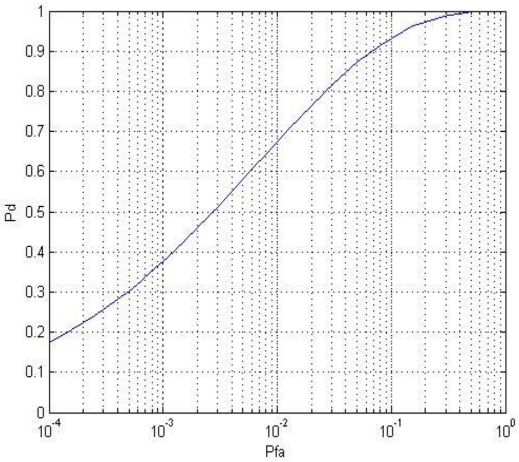

Figure 11 : Pd vs Pfa for matched filter detection

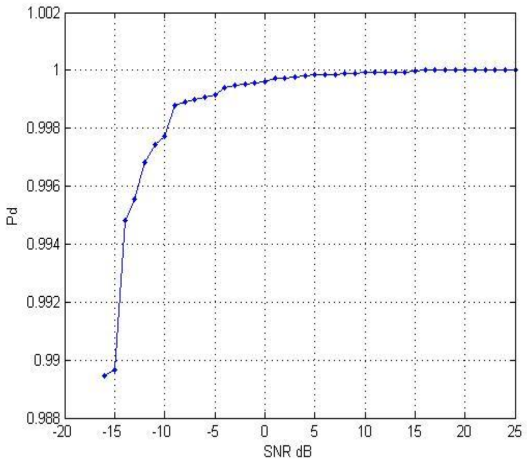

Figure 12 : Pd vs SNR for matched filter detection

Figure 11 is plotted for a SNR of 2dB, and figure 12 is plotted for a Pfa of 0.1. It can be seen from figure 11 that as Pd increases Pfa also increases and figure 12 shows that there is a high probability of detection even for very low values of SNR.

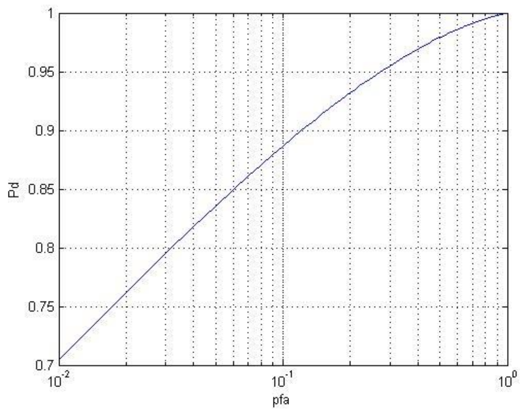

Figure 13 : Pd vs Pfa for energy detection

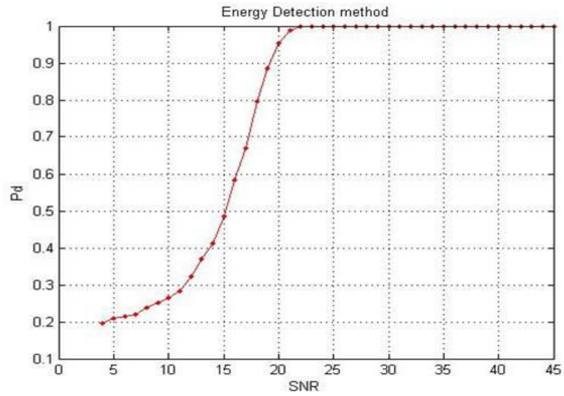

Figure 14 : Pd vs SNR for energy detection

Figure 13 is plotted for a SNR of 2dB and figure 14 is plotted for a Pfa of 0.1. As Pd increases Pfa also increases in energy detection as shown in figure 13. From figure 14 it is clear that Pd is high only for high SNR values

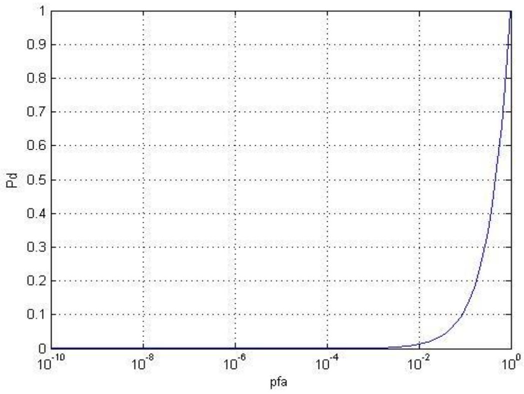

Figure 15 : Pd vs Pfa for eigen value detection

Figure 15 is plotted for a SNR of 2 dB. It is observed that Pd approaches one for Pfa greater than 0.01.

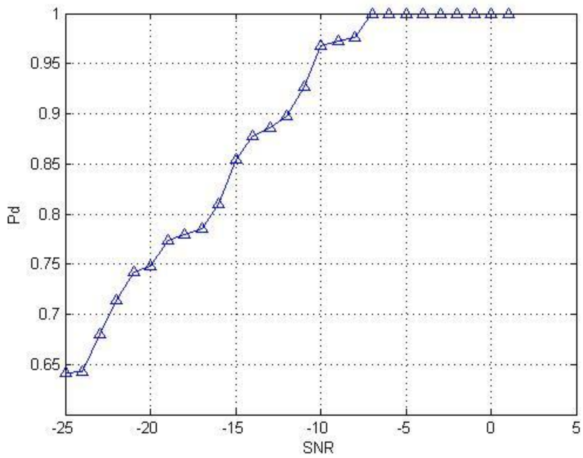

Figure 16 : Pd vs SNR for eigen value detection

Figure 16 is plotted for a Pfa of 0.1. It can be seen that Pd is high even for low values of SNR.

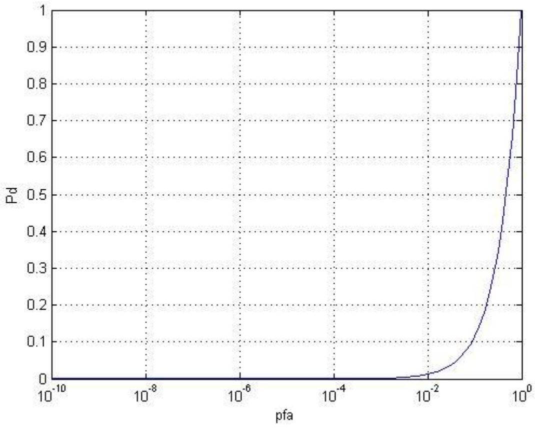

Figure 17 : Pd vs Pfa for wavelet detection

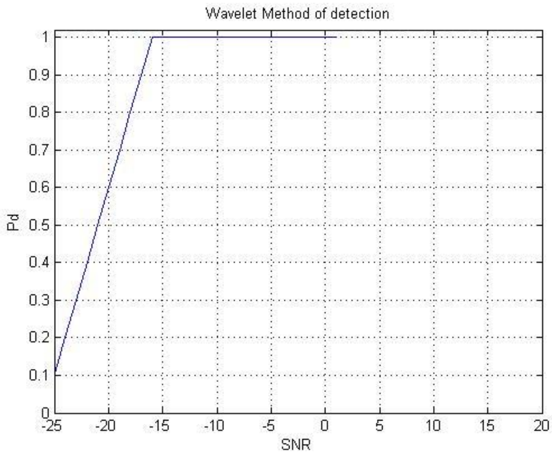

Figure 18 : Pd vs SNR for wavelet detection

Figure 17 is plotted for a SNR of 2 dB and figure 18 is plotted for a Pfa of 0.1. Figure 17 is similar to figure 15.

From figure 18 it is clear that wavelet detection provides higher Pd for low SNR regions than eigen value detection. Figure 19 shows the comparison between eigen value detection and wavelet detection.

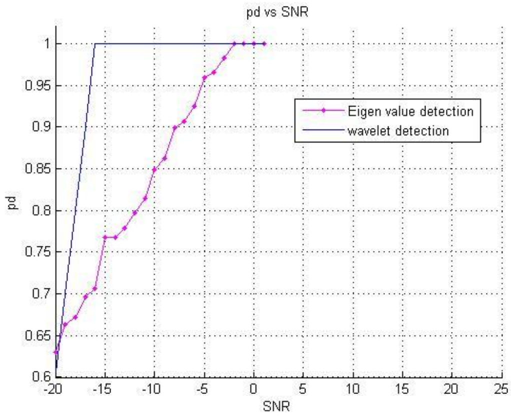

Figure 19 : Comparison of eigen value detection and wavelet detection

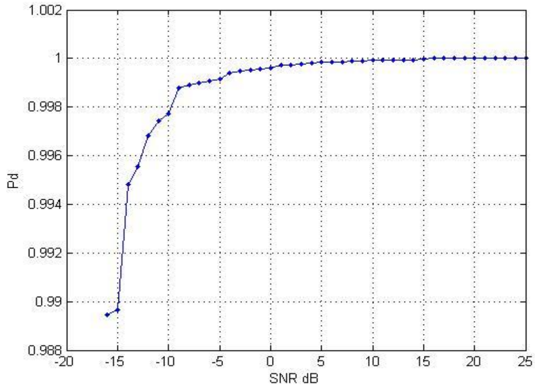

Figure 20 : Adaptive sensing with prior knowledge available (matched filter)

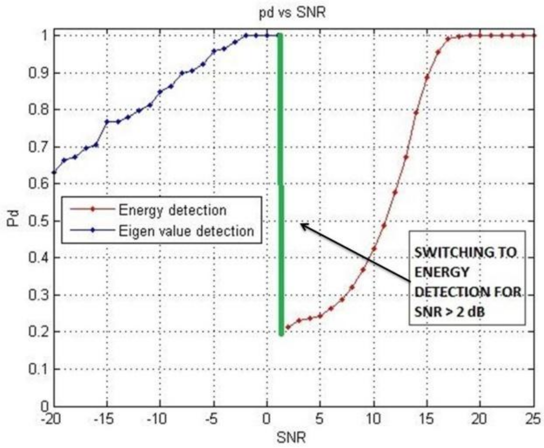

Figure 21 : Adaptive sensing without prior knowledge

Figure 20 and 21 shows the plot of adaptive sensing. When prior information is available, it uses matched filter detection. If prior knowledge is not available, it switches between eigen value detection (for SNR < 2dB) and energy detection (for SNR > 2dB) as shown in figure 21. Also, since wavelet detection has higher accuracy and lesser complexity than eigen value detection, an adaptive sensing replacing eigen value with wavelet is proposed and shown in figure 22.

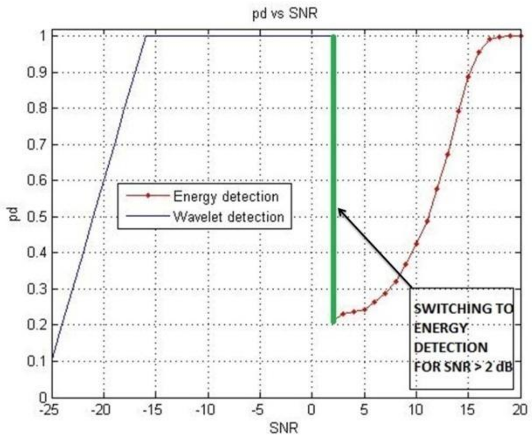

Figure 22 : Adaptive sensing without prior knowledge (using wavelet detection)

When prior information is available, it uses matched filter detection as shown in figure 20. If prior knowledge is not available, it switches between wavelet detection (for SNR <

2dB) and energy detection (for SNR > 2dB) as shown in figure 22.

5. CONCLUSION

An adaptive spectrum sensing technique has been implemented and all the four transmitter detection techniques Energy detection, Matched filter detection, Eigen value detection and Wavelet based detection technique have been simulated using MATLAB and the results of all the four techniques have been analyzed. When prior information about the primary user signal is available matched filter technique is applied. Energy detection is the simplest technique but its detection performance is high only after a certain value of SNR.Wavelet based detection technique is experimented replacing Eigen value detection and the results shows that wavelet detection provides high accuracy than eigen value detection in low SNR regions.

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