Performance Evaluation of the Energy Detection Using Vmd and Discrete Wavelet Transform For Cognitive Radio

Poorva Kanungo[1] Sanjay Chouhan2 Rupesh Yadav[3]
[1,2,3]Department of Electronics and communication Engineering

Abstract— The cognitive radio is one of the novel concepts from conventional exclusive spectrum assignment to dynamic spectrum assign. They provide the spectrum for efficient and sufficient utilization of the radio electromagnetic resources. Researches are focuses on the cooperative spectrum sensing technique to increase reliability of the spectrum for cooperative spectrum sensing technique are very difficult to tolerate with both individual node of the wireless network for the short time. In this paper proposes the energy detection method for spectrums sensing on the basis of estimated SNR, it is calculated in advance for available network. The proposed method in which is also analysis performance of the signal to noise ratio (SNR) and the Decision Accuracy using different wavelet family.

Key words: Cognitive radio (CR), Spectrum Sensing, Energy detection (ED), Discrete Wavelet Transform (DWT)

I. INTRODUCTION

The cognitive radio based systems and channel is a revolutionary new concept in wireless communication system. Such systems are built on the novel software defined radio architecture and have powerful signal processing capabilities to sense spectrum underutilization or spectral holes. In the cognitive abilities the embedded system processor emulate the human brain through continuously studying the radio sense through an aggregation of external radio stimuli provided the end devices. In these network can thus dynamically allocate spectrum method to multiple user thereby sensing network congestion. The coupled together with cutting edge wireless technology such as orthogonal frequency division multiplexer they can meet the growing wireless broadband network demand of billions of users worldwide by efficiency utilizing spectrum resources in wireless network technique, which are scarce and expensive.

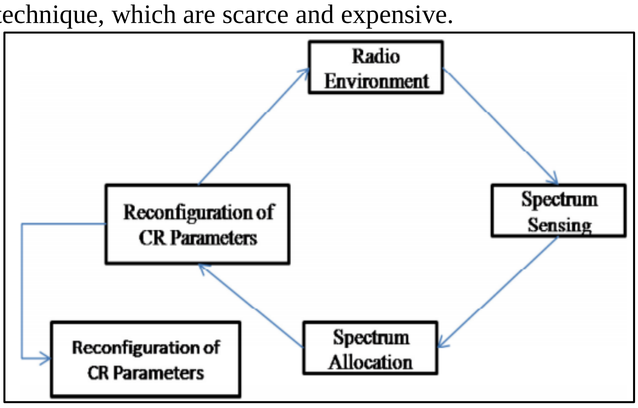

Fig. 1: Cognitive Radio system

The priority users of priority in using the spectrum scheme; SUs need to constantly perform real time monitoring of the licensed spectrum in which can be used. The method used for sensing the Primary User presence is called spectrum sensing (SS). There are several sensing method such as feature detection, energy detection, matched filter, cyclostationary central cooperative sensing and distributive cooperative sensing method. In spectrum sensing the SU constantly senses/checks the transmission network for the presence of the primary signals in the channel. After sensing the spectrum the cognitive radios allocate the spectrum to the SUs and the SUs need to reconfigure themselves in order to use the newly allocated spectrum method. The block diagram of cognitive radio cycle is shown in fig. 1.

The method of the detecting the availability of the primary user (PU) in a radio spectrum environment is called the spectrum sensing .There several method of the spectrum sensing technique such as matched filter detection, energy detection, cyclostationary feature detection. Energy detection is the more robust technique with the low computationally complexity. In the energy detector is used to find the frequency spectrum is vacant or not. In these paper are analysis Performance of the wavelet transform based energy detector spectrum sensing and its comparison for different types of wavelet family.

II. SPECTRUM SENSING

Spectrum sensing refers to the task of estimating the radio channel parameters such as transmission network characteristics, power availability, noise level, interference level, spectrum availability, etc. the spectrum sensing is mainly done in the frequency and time domain. It can also be done in code and phase domains as well.

The unlicensed users or SUs need to continuously monitor the spectrum for the presence of the licensed users or primary user. If the primary user is absent for a particular time, the SU can use that spectrum for transmission scheme till the primary user reappears. Once the primary user reappears, the SU should yield that spectrum for the primary user and should shift to some other unused spectrum. This implies that the SUs should continuously monitor the entire spectrum for an opportunity to use a channel that is not being used by the primary user. This technique of continuously monitoring the spectrum is called spectrum sensing. The optimizing the spectrum usage being the main aim of cognitive radio, makes spectrum sensing the most basic and important process for cognitive radio. The unused spectrums may be available in two cases either a temporal unused spectrum or a spatial unused spectrum. The spectrum sensing performance however is affected by noise uncertainty, shadowing and multipath fading. The major spectrum sensing techniques that have been developed in the past decade are discussed in this section. The sensing techniques can be classified into two major types: Local spectrum sensing in which SU makes an independent decision regarding the presence of the primary user (PU) and the cooperative spectrum sensing in which a group of SUs decide on the presence of the primary user.

Before diving into the spectrum sensing techniques we introduce the hypothesis test, based on which the performances of the techniques are tested. The hypothesis model is as follows:

$$H0: y(t) = n(t)$$
$$H0: y(t) = h * (t) + n(t)$$

Where y(t) is the received signal, x(t) is the primary user signal, n(t) is additive white Gaussian noise and h is the channel gain of the primary user. The hypothesis H0 is a null hypothesis which means that there is no primary signal present whereas H1 indicates the presence of the primary signal. The summary of all the spectrum sensing techniques discussed in the following sections is given in table 1 at the end of the section.

A. *Spectrum Sensing Energy Detection (ED)*

Energy Detection (ED) is one of the most basic sensing schemes. It is the signal detection mechanism using an energy detector to specify the presence or absence of signal in the band. The Neyman-Pearson (NP) lemma is the most often used approach in energy detection techniques. It increases the probability of detection (Pd) for a given probability of false alarm (Pfa). The optimal if both the signal and the noise are Gaussian, and the noise variance is perfectly known. Performance degrades rapidly when there is uncertainty in the noise power value and is also incapable to differentiate between signals from different systems and between these signals and noise. Its advantage lies in its simplicity and not requiring prior knowledge of the primary users (PU) signal making it best suited for fast spectrum. The energy detection process can be made in the time domain or frequency domain through a FFT block. The advantage of the frequency domain testing lies in the flexibility the FFT can provide by trading temporal resolution for frequency resolution. In this means that a narrowband signal's bandwidth and central frequency can be estimated without requiring a very flexible pre-filter.

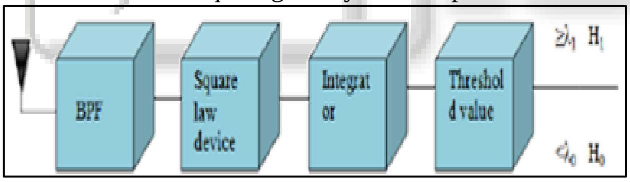

Fig. 2: Block Diagram of the Energy Detector

The ED test statistics can be defined as follows:

$$T^{ED} = \frac{1}{N}\sum_{n=0}^{N-1} y[n]^2 = \frac{1}{N}\sum_{l=0}^{L-1}\sum_{k=0}^{N_{fft}-1} Y_k(l)^2 \gtrless \gamma \quad (1)$$

Where Nf f t is the size of the Fast Furious Transform employed using FFT-based detection and L the number of samples used in the average of each FFT output bin (N= L.N f f t). Since Y[n]2 has a central chi-square distribution under H0 and non-central chi-square distribution under H1, the probabilities of false alarm and detection becomes.

$$P_{fa} = P(T_i^{ED} > \gamma | H_0) = \frac{\Gamma\left(N \frac{\gamma}{2\sigma_n^2}\right)}{\Gamma(N)} = P\left(N . \frac{\gamma}{2\sigma_n^2}\right)$$

$$P_d = P(T_i^{ED} > \gamma | H_0) = Q_L\left(\sqrt{\frac{\mu}{\sigma_n^2}} . \sqrt{\frac{\gamma}{\sigma_n^2}} .\right) \quad (2)$$

Where Γ(.,.) is the lower incomplete gamma function, Γ(.) the complete gamma function, p(.,.) the regularized gamma function and QL(.) is the generalized Marcum-Q function. From 4.2 it can be inferred that defining a threshold based on the probability of false alarm requires perfect knowledge of noise power (σ_n^2). Considering the central limit theorem for a desired Pd and Pf a , the number of required samples can be approximated by the equation:

$$\mathbf{N = 2[Q - 1(\,Pfa\,) - Q - 1(\,Pd\,)(1 + SNR)]2\,SNR - 2} \quad \mathbf{(3)}$$

III. DISCRETE WAVELET TRANSFORM

The DWT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions, called scaling functions and wavelet functions, which are associated with low pass and high pass filters, respectively. The decomposition of the signal into different frequency bands is simply obtained by successive high pass and low pass filtering of the time domain signal. The original signal x[n] is first passed through a half band high pass filter g[n] and a low pass filter h[n]. After the filtering, half of the samples can be eliminated according to the Nyquist's rule, since the signal now has a highest frequency of π/2 radians instead of π. The signal can therefore be subsampled by 2, simply by discarding every other sample. This constitutes one level of decomposition and can mathematically be expressed as follows:

$$y_{high}[k] = \sum_n x[n] . g[2k - n] \quad (4)$$
$$y_{low}[k] = \sum_n x[n] . h[2k - n] \quad (5)$$

where yhigh[k] and ylow[k] are the outputs of the high pass and low pass filters respectively, after sub sampling by 2. This decomposition halves the time resolution since only half the number of samples now characterizes the entire signal.

At every level, the filtering and subsampling will result in half the number of samples (and hence half the time resolution) and half the frequency band spanned (and hence doubles the frequency resolution). Figure illustrates this procedure, where V2 is the original signal to be decomposed, H[z] and G[z] are low pass and high pass filters respectively.

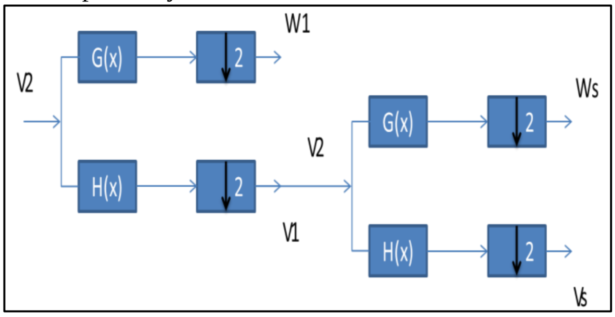

Fig. 3: Two level decomposition

IV. VARIATIONAL MODE DECOMPOSITION

VMD is a newly-developed time-frequency analysis method for adaptive signal decomposition, which can decompose a multicomponent signal into a number of band-limited IMFs (BLIMFs) through an iteration solving process of a special variational model. The mathematical model of VMD is as follows. An original signal x ptq can be decomposed into a limited number of sub-signals uk that have different center frequencies ωk and limited bandwidths. First, the one-sided spectrum of uk is obtained by the Hilbert transform:

$$\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)$$

Then, the spectrum of each mode is transferred into the baseband by frequency mixing:

$$\left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-j\omega_k t}$$

Next, the bandwidth of each mode can be estimated by calculating the L2-norm of the demodulated signal. Finally, VMD is built as a constrained variational model

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-j\omega_k t} \right\|_2^2 \right\} \; s.t. \; \sum_k u_k = x$$

To obtain the optimal solution of the above variational model, the quadratic penalty factor α and the Lagrange multiplier λ are imported into VMD. By turning the constrained problem into an under-constrained problem.

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-j\omega_k t} \right\|_2^2 + \left\| x(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), x(t) - \sum_k u_k(t) \right\rangle$$

Based on this, tuku , tωku , λ are updated alternately by iterations using the alternative direction method of multipliers [7]. In addition, the BLIMFs, which are found in tuku, are decomposed from the original signal. The flow diagram of the VMD algorithm is shown in Figure 4.

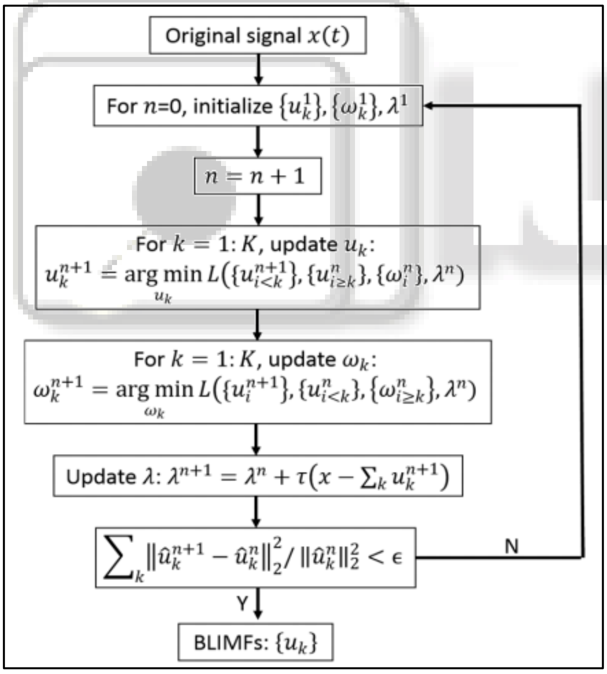

Fig. 4:1 Flow diagram of the variational mode decomposition (VMD) algorithm

V. RESULTS

A simulation is performed to verify the effectiveness of the proposed method. The Energy Detection using Discrete Wavelet Transform for Cognitive radio. Spectrum-sensing cognitive radio is used to detect channels in the radio frequency spectrum. Spectrum sensing is a fundamental requirement in cognitive radio network. Many signal detection techniques can be used in spectrum sensing so as to enhance the detection probability.

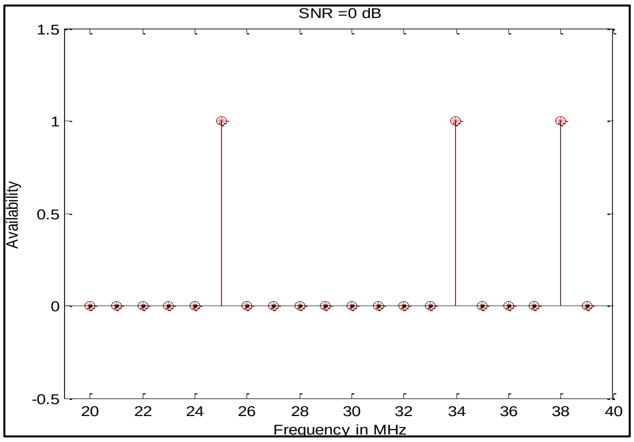

Fig. 5: Performance of Availability with FFT

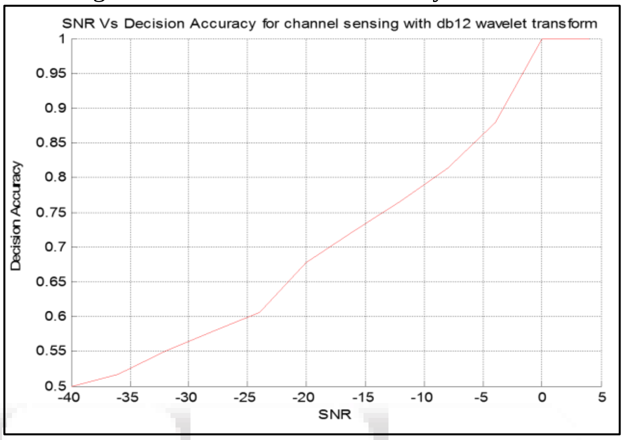

Fig. 6: Performance of SNR Vs Division Accuracy with Wavelet Transform

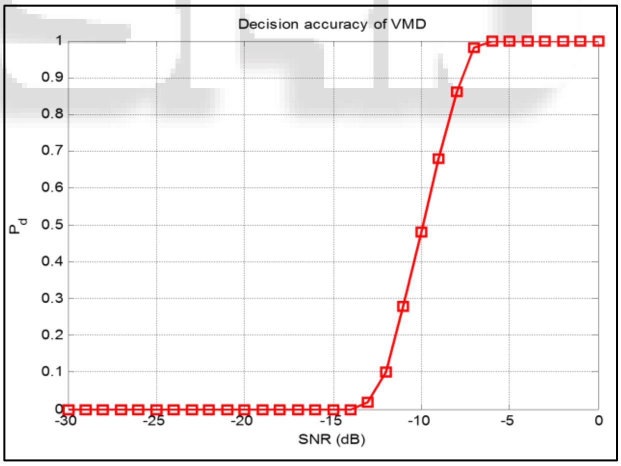

Fig. 7: Performance of SNR Vs Pd with VDM

VI. CONCLUSIONS

In this paper proposed method VMD and discrete wavelet transform based on energy detection method in Cognitive radio. Also comparison through various value of SNR in terms of the Availability of Free spectrum and signal to noise ratio. It is an efficient perspective method to classify the spectrum which improves the performance of the energy detector by measuring the PSD for various SNR and calculated threshold value. However threshold which can accurately detect the Probability of the Detection of the received signal using different types of wavelet family.

REFERENCES

[1] S.V.R.K. rao, G.singh, "Wavelet based spectrum sensing techniques in cognitive radio", international conference on modeling optimization computing, 2012.
[2] Shiann-Shiun Jeng, Jia-Ming Chen, Hong-Zong Lin and Chen-Wan Tsung, "Wavelet-Based Spectrum Sensing for Cognitive Radios using Hilbert Transform", World Academy of Science, Engineering and Technology, Vol:5 2011.
[3] Ms. Shrutika S. Sawant, "Wavelet Packet Transform Based Energy Detector for Spectrum Sensing", International Journal of Emerging Technology and Advanced Engineering, Volume 2, Issue 3, March 2012.
[4] Arti Gupta ME, "Performance Evaluation of the Energy detection Using different Wavelet family for Spectrum Sensing in Cognitive radio", Volume 3, Issue 4, April 2014.
[5] Karthik Divakaran, Naveen Manikandan P, "Wavelet based spectrum sensing techniques for cognitive radio", International Journal of Computer Science & Information Technology (IJCSIT), Vol 3, No 2, April 2011.
[6] Zhi Tian, "A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios", 1-4244-0381-2/06/$20.00 ©2006 IEEE.
[7] Soman K P, Prabaharan Poornachandran, "Recursive Variational Mode Decomposition Algorithm for Real Time Power Signal Decomposition", Elsevier Procedia Technology 21, 2015.

