PERFORMANCE ANALYSIS OF WAVELET PACKET TRANSFORM BASED ENERGY DETECTOR IN COGNITIVE RADIO

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ABSTRACT

Rapid development of new and ever expanding wireless applications and services, spectrum resources are facing huge demands. Currently, spectrum allotment is done by giving each new service with its own fixed frequency block. As more and more technologies are moving towards fully wireless, demand for spectrum is enhancing. In this context, a new technology, cognitive radio (CR) has been come out to solve this spectrum scarcity problem. The most important function of cognitive radio is spectrum sensing which requires more accuracy & low complexity. There are various methods of spectrum sensing. In this paper we analyze the performance of energy detector spectrum sensing algorithm based on wavelet packet transform (WPT) in cognitive radio.

***Keywords*:** Additive White Gaussian Noise (AWGN), Cognitive radio (CR), Energy detection (ED), Wavelet Packet Transform (WPT), Wavelet Packet Energy Detection (WPED).

INTRODUCTION

Cognitive Radio (CR) is a system/model for wireless communication. It is built on software defined radio which an emerging technology providing a platform for flexible radio systems, multiservice, multi-standard, multiband, reconfigurable and reprogrammable by software for Personal Communication Services (PCS). It uses the methodology of sensing and learning from the environment and adapting to statistical variations in real time. The Cognitive Radio is an emerging technology, for the efficient use of the limited spectrum available [1]. The concept was first originated by Defense Advance Research Products Agency (DARPA) scientist, Dr. Joseph Mitola and the result of that concept is IEEE 802.22, which is a standard aimed at using cognitive radio for Wireless Regional Area Network (WRAN) using white spaces in the TV frequency spectrum while assuring that no harmful interference is caused to the incumbent operation, i.e., digital TV and analog TV broadcasting, and low power licensed devices [2]. As an intelligent spectrum sharing technology, CR has ability to opportunistically adapt behavior of secondary user (SU) to reuse or share the same spectrum allocated to primary user (PU), according to sensing environment, and learning about application requirements [3]. IEEE 802.22 is going on establishing the standard of CR technology. This standard is based on the scenario that unlicensed (or CR) users communicate using idle or unused licensed frequency bands without interfering with licensed users [10].

According to cognitive cycle cognitive radio performs three functions such as spectrum sensing, spectrum analysis & spectrum decision making. Out of that the most important function of CR is spectrum sensing i.e. to find out spectrum holes or the white spaces. Many methods have been proposed to detect whether PU is on, such as energy detection (ED), matched filtering detection (MFD) and cyclostationary feature detection (CFD). Energy detection is the most widely used method of spectrum sensing due to its low computational and implementation complexity [4]. Matched filtering is known as the optimum method in additive white Gaussian noise (AWGN) channel, it needs to know the exact information of PU [5]. Cyclo-stationary detection (CSD) can detect the PU signal which has cyclostationary period feature. This detection also requires partial information about PU [5] [6]. Spectrum sensing techniques based on the fast Fourier transform (FFT) are easy to implement to find energy level. This is applicable only for low frequency. It may be disadvantage of this technique. In this paper, we address the energy detection technique using wavelet packet transform under the background of uncertain AWGN. We analyze performance of an energy detection algorithm on the basis of wavelet packet transform and estimated noise power and signal power for spectrum sensing.

The remainder of this paper is organized as follows. Section II briefly describes the wavelet analysis and power measurement. Section III, the wavelet packet transform based energy detection algorithm is presented. It explains how to realize efficient energy detection under noise unknown. Section IV discusses the results of the simulations and, finally the conclusions are given in Section V.

Wavelet analysis and power measurements

Discrete Wavelet Transform (DWT)

DWT is designed from the multi-resolution analysis that decomposes the given signal space into a approximate space, V, and detail spaces, W, as shown in (1).

$$V_{j+1} = W_j \oplus V_j = W_j \oplus W_{j-1} \oplus V_{j-1} \qquad (1)$$

Where W_j is the orthogonal complement of V_j in V_{j+1} and $\oplus$ represents the orthogonal sum of two subspaces. Two space, V_j and W_j are constructed by orthonormal scaling functions, $\varphi_{j,k}$, and orthonormal wavelet functions, $\psi_{j,k}$, respectively. Scaling function, $\varphi_{j,k}$, and wavelet function, $\psi_{j,k}$, are obtained as

$$\phi_{j,k}(t) = 2^{j/2}\phi(2^j t - k) = \sum_i h_{i-2k}\phi_{j+1}k(t) \qquad (2)$$

$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k) = \sum_i g_{i-2k}\phi_{j+1}k(t)$ With high-pass filter, $g_{i-2k} = \langle \psi_{j,k}, \phi_{j+1,l} \rangle$ and low-pass filter, $h_{i-2k} = \langle \phi_{j,k}, \phi_{j+1,l} \rangle$ $\langle\rangle$ means inner product. Using these functions, DWT of a given signal, *f*, provides scaling coefficients and wavelet coefficients. The scaling coefficient at the j^{th} level k^{th} time is computed by

$$C_{j,k} = \langle f, \phi_{j,k} \rangle = \sum_i h^*_{i-2k} \langle f, \phi_{j+1,l} \rangle = \sum_i h^*_{i-2k} C_{j+1,l} \tag{3}$$

The wavelet coefficient at the *j*th level and *k*th time is

$$d_{j,k} = \langle f, \psi_{j,k} \rangle = \sum_i g^*_{i-2k} \langle f, \phi_{j+1,l} \rangle = \sum_l g^*_{l-2k} C_{j+1,l} \tag{4}$$

Fig. 1 and 2 show 2-level analysis part of the DWT and its frequency separation property.

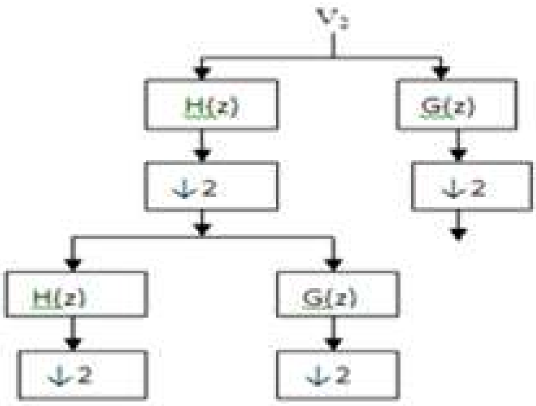

Fig.1. 2-level analysis part of DWT

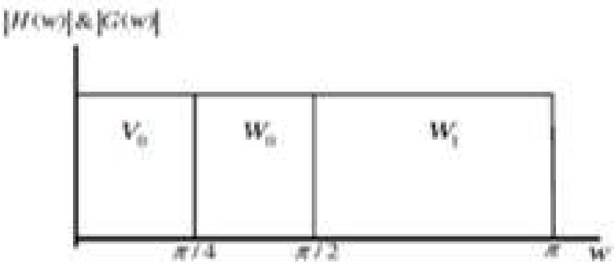

Fig.2. Frequency separation of 2-level analysis part of DWT

Wavelet Packet Transform (WPT)

The difference between DWT and WPT just lies in the decomposition of detail space. WPT decomposes not only the approximation space but also the detail space. This means that it can separate frequency band uniformly. Fig. 3 and 4 represent 2-level analysis part of the WPT and its frequency separation property.

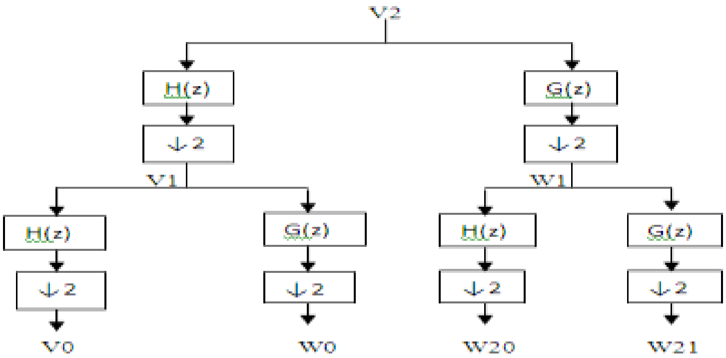

Fig.3. 2-level analysis part of WPT

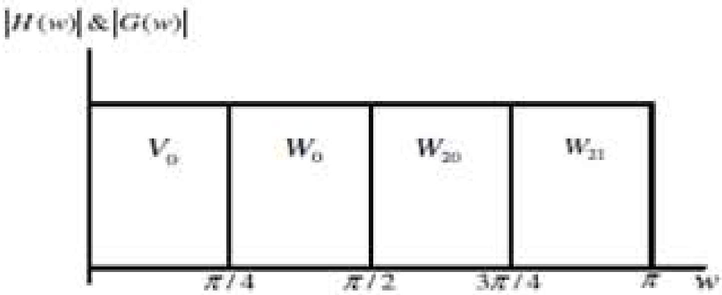

Fig.4. Frequency separation of 2-level analysis part of WPT

Energy detection algorithm

The model for energy detection based on wavelet packet transform is described in Fig.5

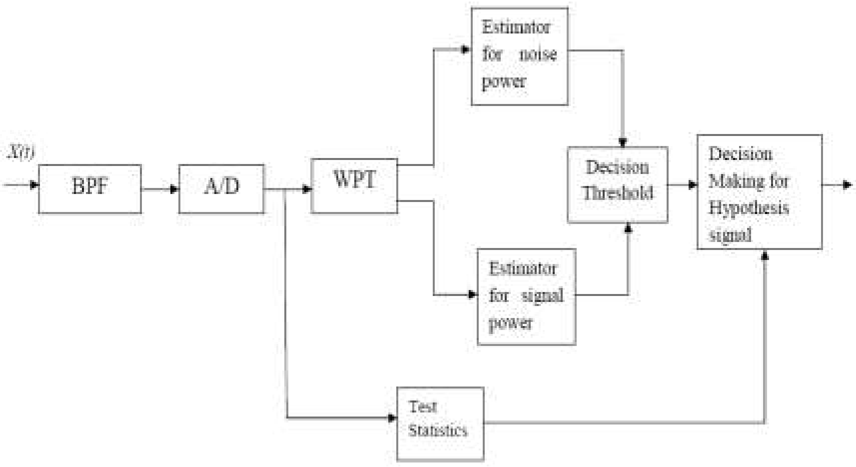

Fig.5 Block diagram of Energy Detection Model based on WPT

From the center frequency *fc* of band pass filter (BPF) removes the out of band signals & selects the bandwidth of interest *W*. After this signal is converted into digital & we get digital signal $x(n)$ which is given by,

$$x(n)= s(n)+ w(n) \quad n = 0,1,\ldots, N-1. \tag{8}$$

Where, $s(n)$ is the Primary User (PU) signal with zero mean and variance of σ_s^2 & $w(n)$ is Additive White Gaussian Noise (AWGN) with zero mean and variance of σ_w^2.

If there is no transmission by PU, $s(n) = 0$. Then hypothesis can be tested as,

$$H_0: \ x(n)=w(n,) \quad n=0,1,\ldots\ldots N-1; \tag{9}$$

If there is transmission by PU, $s(n) \neq 0$. Then hypothesis can be tested as,

$$H_1: \ x(n)=s(n)+w(n,) \quad n=0,1,\ldots..N-1; \tag{10}$$

Digital signal $x(n)$ will be processed separately by four step which described as follows.
Step 1: $x(n)$ is sent to Wavelet Packet transform (WPT) to estimate current noise power (σ_w^{*2}) and signal power (σ_s^{*2}).
Step 2: By calculating the energy of $x(n)$ we get the test statistic *(X),*

$$X = \sum_{n=0}^{N-1} |x(n)|^2 \tag{11}$$

The test statistic X is a random variable whose probability density function (PDF) is chi-square distributed. When N is sufficiently large, we can approximate the PDF using Gaussian distribution according to the central limitation theorem [8]

$$H_0 \ \square \qquad {}^{2}_{w}, 2N\sigma_w^4) \tag{12}$$

$$H_0 \ \square \qquad {}^{2}_{s} + \sigma_w^2), 2(N\sigma_s^2 + \sigma_w^2)^2) \tag{13}$$

Referred to constant false alarm rate (CFAR) principle [9], we have probability of false alarm *PF* as follows,

$$P_f = P(X > \gamma H_0)$$
$$= Q\left[\frac{\gamma - N\sigma_w^2}{\sigma_w^2\sqrt{2N}}\right] \tag{14}$$

$$P_D = P(X > \gamma H_1)$$
$$= Q\left[\frac{\gamma - N(\sigma_s^2 + \sigma_w^2)}{(\sigma_s^2 + \sigma_w^2)\sqrt{2N}}\right] \tag{15}$$

Where $Q(a) = \frac{1}{2} erfc(\frac{a}{\sqrt{2}})$, *erfc(.)* is the complementary error function, γ is the decision threshold,

$$\gamma = N\sigma_w^2 + \sqrt{2N}\sigma_w^2 Q^{-1}(P_F) \qquad (16)$$

Replace the exact noise variance in (16) with the estimated noise σ_w^{*2} in step 1, we can get,

$$\gamma^* = N\sigma_w^{*2} + \sqrt{2N}\sigma_w^{*2} Q^{-1}(P_F) \qquad (17)$$

Put σ_w^{*2}, σ_s^{*2} & γ^* into (15), we get

$$P_D = \frac{1}{2} erfc\left(\frac{\gamma^* - N(\sigma_s^2 + \sigma_w^2)}{2(\sigma_s^{*2} + \sigma_w^{*2})\sqrt{N}} \right) \qquad (18)$$

If $X > \gamma^*$, we can make a decision that the channel is occupied by one PU or more. Otherwise, the channel is vacant, and SUs could make use of the channel at this moment.

Simulations and analysis

In this section, we give some simulations of WPED algorithm proposed in this paper. Simulation uses the three stage wavelet packet decomposition with db5 as wavelet filter and chooses BPSK as PU signal. Experiments are performed under AWGN channel and SNR is changed from -10 dB to 0 dB. The results of three groups are given below.

i. The sampling frequency is 1000Hz and the sample number N is 500. The probability of false alarm Pf is set to 0.01. Due to using the WPT to estimate noise power, the performance of proposed WPED with uncertain noise is almost as perfect as the ED with noise certain known, as shown in Fig.6. It means that the proposed WPED is robust to uncertain noise. Hence WPT is quite a robust method for CR applications when the noise is unknown.

ii. The sampling frequency is 1000Hz and the sample number N is 500. The probability of false alarm Pf is set to 0.1, 0.01, and 0.001 respectively. Higher the Pf is the performance of WPED method raises evidently with the increase of probability of false alarm.

iii. The sampling frequency is 1000Hz and the sample number N is 500. The probability of false alarm Pf is set to 0.01. Simulation compares three stage wavelet packet decomposition with two stage wavelet packet decomposition. It is described in fig.8. The simulation results show that the performance of WPED method rises evidently with the increase of level of decomposition.

iv. Hypothesis test - From simulation if signal power (X) is greater than threshold then we can make decision that channel is occupied by PU, otherwise channel is vacant. Table 1 gives information about presence of PU.

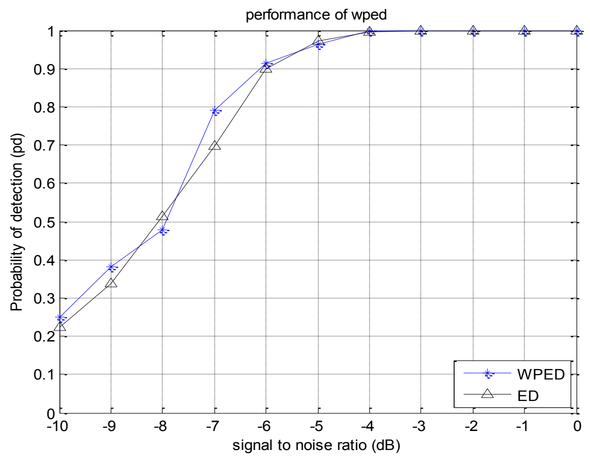

Fig.6. Comparison of performance of proposed WPED and ED

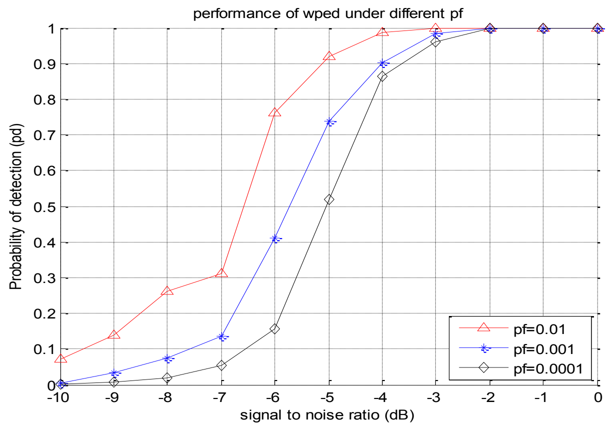

Fig.7. Performance of proposed WPED under different probabilities of false alarm

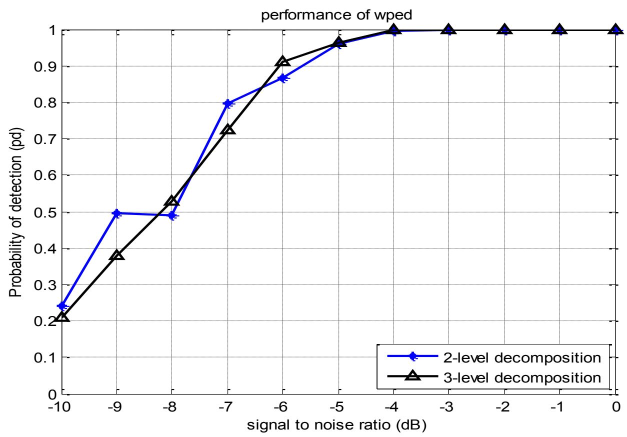

Fig.8. Performance of proposed WPED under different levels of wavelet packet transforms

Table 1. Hypothesis test

Sr. No.	SNR(dB)	Hypothesis Test
1.	-10	PU is absent
2.	-9	PU is absent
3.	-8	PU is absent
4.	-7	PU is absent
5.	-6	PU is absent
6.	-5	PU is absent
7.	-4	PU is present
8.	-3	PU is present
9.	-2	PU is present
10.	-1	PU is present
11.	0	PU is present

CONCLUSION

Energy Detection spectrum sensing using Wavelet Packet Transform (WPED) method outperforms the traditional energy detection method when the noise was unknown which is the real scenario. We get the estimated noise power, signal power and decision threshold by Wavelet Packet Transform (WPT) method more exactly. Performance of WPED rises as stages of decomposition rises.

Hence it is quite a robust method for spectrum sensing in Cognitive Radio when information about PU is unknown.

REFERENCES

1. Federal Communications Commission,"Spectrum Policy Task Force Report," ET Docket No. 02-135, November. 2002.
2. IEEE 802 LAN/MAN Standards Committee 802.22 WG on WRANs (Wireless Regional Area Networks).
3. Q. Zhang, A. B. J. Kokkeler and G. J. M. Smit, "A Reconfigurable Radio Architecture for Cognitive Radio in Emergency Networks," The 9th European Conference on Wireless Technology, vol.1, 2006, p p.35-38.
4. S. Ciftci and M. Torlak, "A Comparison of Energy Detectability Models for Spectrum Sensing", in Proceedings of IEEE "GLOBECOM" 2008, pp. 1-5.
5. P. D. Sutton, K. E. Nolan and Linda E. Doyle, "Cyclostationary Signatures in Practical Cognitive Radio Applications," IEEE Journal on selected areas in communications, vol. 26, no. 1, January 2008, pp.13-24.
6. W. A. Gardner, "Exploitation of spectral redundancy in cyclostationary signals," *IEEE Signal Process. Mag.*, vol. 8, no. 2, pp. 14–36, Apr. 1991.

7. Weon-Ki Yoon and Michael J. Devaney,"Power Measurement Using the Wavelet Transform" *IEEE Transactions on Instrumentation and Measurement,* vol. 47, no. 5, October 1998

8. J. G.Proakis, "Digital Communications", 4th Edition, McGraw-Hill, 2001.

9. E. Peh and Y. Liang, "Optimization of Cooperative Sensing in Cognitive Radio Networks", in Proceedings of WCNC2007, pp.27-32.

10. C.Cordeiro & Kiran Challapali," IEEE 802.22: An Introduction to the first wireless standards based on Cognitive Radio.