Adaptive Threshold for Energy Detector Based on Discrete Wavelet Packet Transform

Zhijin Qin
Beijing University of Posts and Telecommunications
Queen Mary University of London
Beijing, China
qinzhijin@gmail.com

Nan Wang, Yue Gao and Laurie Cuthbert
Electronic Engineering and Computer Science
Queen Mary University of London
London, UK
{nanw}{ yue.gao}{laurie.cuthbert}@eecs.qmul.ac.uk

Abstract—**One promising approach to achieving high precision and low complexity in a cognitive radio system is the energy detector based on the Discrete Wavelet Packet Transform (DWPT). However, the thresholds used in previous spectrum detection algorithms are fixed values determined by false alarm probability and sample points. When the Signal to Noise Ratio (SNR) is lower than 5dB, an energy detector with fixed threshold may falsely determine some unoccupied sub-channels as occupied. In this paper, a threshold adapter adopting adaptive threshold is proposed to increase the detection sensitivity, meanwhile, reduce the computational complexity. Simulation results are presented to demonstrate the effectiveness of this algorithm.**

Keywords- spectrum sensing, discrete wavelet packet transform, fixed threshold, adaptive threshold

I. INTRODUCTION

With advanced developments in wireless communication services, efficient use of spectrum is becoming more significant. Cognitive radio was proposed to address this issue by fully making use of radio resources [1]. It can sense the environment and serve target users without causing interference to primary users [2]. Spectrum sensing is the first step in detecting the surrounding spectrum environment in a cognitive radio system. There are several kinds of techniques used for spectrum detection, such as matched filter detection, energy detection, and cyclostationary feature detection. Energy detection is the most common scheme of spectrum sensing with low computational complexity [3]. Cyclostationary feature detection is used to detect the primary users by calculating the cyclostationary features of target signals. It is more precise than energy detector, but requires higher computational complexity.

To obtain high precision with low computational complexity, a two-stage sensing architecture has been proposed by the IEEE 802.22 working group [4]. At the first stage, the energy detector is used to determine whether the spectrum is occupied or not. At the second stage, the feature detector is used to determine whether these unoccupied spectrum are occupied by weak signals. Youngwoo Youn *et al* [5] used an energy detector to obtain the energy of each sub-channel, and then it was compared with a fixed threshold to determine whether the channel is occupied by primary users or not. In their later work, a double threshold is used, and the channels can be classified into three states: the assured occupied channel (black), the unassured channel (gray), and the assured unoccupied channel (white) [6]. The energy detector will only transfer the unassured channels to the feature detector at the second stage. As a result, the number of channels to be processed at the second stage was reduced, and the computational complexity was decreased as well.

The performance of the energy detector is mainly dependent on channel environments such as noise, interference, shadowing and multipath fading [7]. Thus, setting a proper threshold for the energy detector is the key to obtaining higher sensitivity. Spectrum sensing with a fixed threshold works well when the SNR is high; however, when channel environment becomes poor, for instance, the SNR becomes lower, the energy of each channel increases as a function of noise increasing. If the threshold stays the same as the value when the SNR is high, the energy of each channel will become much higher than it. As a result, some unoccupied sub-channels will be determined as occupied, which makes secondary users lose chances to access these white channels.

II. Energy Detector Based on Discrete Wavelet Packet Transform

The concept of DWPT and the model of energy detector are introduced in this section.

A. Discrete Wavelet Packet Transform

With DWPT, a signal can be represented as

$$f(t)=\sum_{j\geq j_0}\sum_{k}(c_{j,k}\varphi_{j,k}(t)+d_{j,k}\psi_{j,k}(t)) \qquad (1)$$

where $c_{j,k}$ and $d_{j,k}$ are scaling and wavelet coefficients respectively. $\varphi_{j,k}(t)$ and $\psi_{j,k}(t)$ are wavelet bases. $\varphi_{j,k}(t)$ is scaling function describing approximation of a signal, and $\psi_{j,k}(t)$ is wavelet function describing detailed space of a signal. Energy of signals can be measured as follows: [8]

$$E=\frac{1}{T}\int_0^T[\sum_{j\geq j_0}\sum_{k}c_{j,k}\varphi_{j,k}(t)+d_{j,k}\psi_{j,k}(t)]^2\,dt \qquad (2)$$

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$$= \frac{1}{T} \sum_{j \ge j_0} \sum_k (c_{j,k}{}^2 + d_{j,k}{}^2)$$

B. Energy Detector

The procedure for the energy detector based on DWPT is described as follows:

1) perform n levels DWPT to the received signals;
2) calculate the energy of each sub-channel;
3) compare it with the fixed threshold and classify sub-channels as occupied or unoccupied.

The fixed threshold (λ) is determined by the false alarm probability (P_f) and the number of sample points (N). It can be calculated as follows:

$$\lambda = Q^{-1}(P_f)\sqrt{2N} + N \quad (3)$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp(-\frac{u^2}{2}) du$.

III. PROPOSED ALGORITHM

In order to classify spectrum of interest more precisely and reduce computational complexity, a new algorithm is proposed in this section. In the new algorithm, the threshold adapter is used to obtain an adaptive threshold during the process of classifying the spectrum of interest.

The procedure of the proposed algorithm is shown in Figure 1 and described as follows:

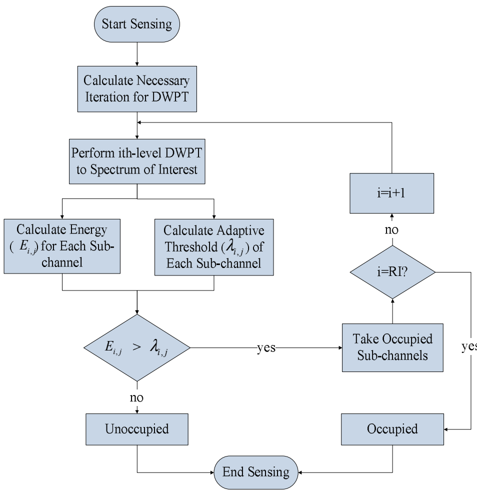


Figure 1. Procedure of Proposed Algorithm

- Compute the necessary iteration RI for DWPT as $RI = \log_2(B_s / B_d)$. B_s refers to the spectrum of interest and B_d to the bandwidth of each sub-channel.
- Perform *ith*-level DWPT decomposition (the initial value of i equals to 1).
- Calculate the energy of each channel, and compare it with the threshold. If the energy is lower than the threshold, the related channels are determined as unoccupied. Then the channel will not be processed in the next level DWPT decomposition. If the energy is higher than the threshold, it will be processed in the next level DWPT decomposition. Here, the threshold is determined by the threshold adapter. In the first level DWPT decomposition, fixed threshold is applied and calculated by (3). The adaptive threshold will be used for the further level DWPT decomposition.
- Steps 2 and 3 are repeated until the necessary iteration (*RI*) levels.

When doing *(i+1)th*-level DWPT decomposition to the spectrum of interest, the adaptive threshold ($\lambda_{i+1,j}$) for channel j can be calculated by

$$\lambda_{i+1,2j} = \frac{\lambda_{i,j} + \alpha \cdot E_{i+1,2j}}{2} \quad (4)$$

$$\lambda_{i+1,2j-1} = \frac{\lambda_{i,j} + \alpha \cdot E_{i+1,2j-1}}{2} \quad (5)$$

where i, j are index. $E_{i+1,2j}$ is the energy of channel $2j$ in the spectrum of interest after *(i+1)th*-level DWPT decomposition. Channel j is one of the sub-channels when doing *ith*-level DWPT decomposition to the spectrum of interest. Channels $2j-1$ and $2j$ are the further divisions of channel j after *(i+1)th*-level DWPT decomposition. $\lambda_{i,j}$, $\lambda_{i,2j-1}$ and $\lambda_{i,2j}$ are thresholds for channel j , channel $2j-1$ and channel $2j$ respectively. α (0<α<1) is the parameter to determine the adaptive threshold.

In (4) and (5), when α tends to 1, the adaptive threshold is affected largely by the energy of the received signals. When α tends to 0, the threshold for each sub-channel after the *(i+1)th*-level DWPT decomposition tends to be half of the threshold after the *ith*-level DWPT decomposition. It is also similar to the fixed threshold of sub-channels after the *(i+1)th*-level DWPT decomposition.

IV. SIMULATION ENVIRONMENT AND RESULTS

In the simulation process, we assumed that 16 sub-channels are present in the spectrum of interest (64 MHz) and the bandwidth for each sub-channel is 4 MHz. So the 4-level DWPT decomposition is applied. Since the down-sampling is required at each level of DWPT decomposition, the order of wavelet packets in higher frequency and lower frequency is exchanged at every level DWPT decomposition. Therefore, these wavelet packets will not be sorted from low frequency to high frequency. The frequency range of each wavelet packet is shown in following table.

TABLE I. FREQUENCY RANGE OF EACH WAVELET PACKET

Packet number	Frequency range (MHz)	Packet number	Frequency range (MHz)
(4, 0)	(0, 4)	(4,1)	(4, 8)
(4,2)	(12, 16)	(4,3)	(8, 12)

(4,4)	(28, 32)	(4,5)	(24,28)
(4,6)	(16, 20)	(4,7)	(20, 24)
(4,8)	(60, 64)	(4, 9)	(56, 60)
(4,10)	(48, 52)	(4,11)	(52, 56)
(4,12)	(32, 36)	(4,13)	(36, 40)
(4,14)	(44, 48)	(4,15)	(40, 44)

The false alarm probability is set to be 0.01. The primary users are assumed as 3 MHz bandpass signals, and there are three channels are occupied by primary users. In the simulation process, the centre frequencies of the three primary users are fixed as f = 9, 27, 45 MHz, respectively. Therefore, the energy of sub-channel 3 (8 MHz, 12 MHz), 7 (24 MHz, 28 MHz), 12 (44 MHz, 48 MHz) is anticipated to be higher than other channels after 4 levels DWPT decomposition.

As assumed, there is no primary user in sub-channel 2. However, when SNR=5dB, sub-channel 2 will be falsely determined as occupied by the fixed threshold. This is shown in Figure 2. This will lead the secondary users losing the chance to access the spectrum from 4 MHz to 8MHz. When SNR is lower than 5 dB, the false alarm probability will increase. While when SNR is higher than 5dB, the fixed threshold can be used to accurately determine whether the channel is occupied or not.

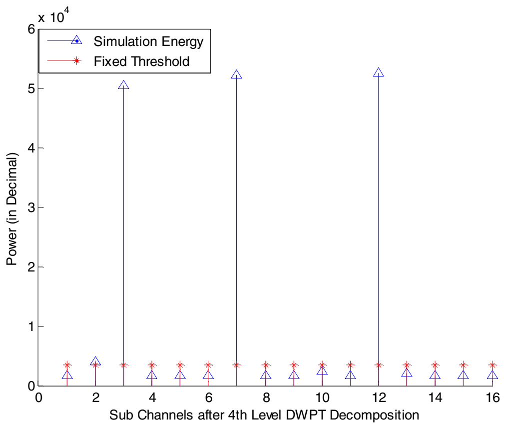


Figure 2. Energy of Sub-channels, SNR=5dB

Then we adopt the adaptive threshold to detect the primary users in the spectrum of interest. Set the SNR of received signals as -17dB, and take α=0.45, 0.50, 0.55. Before calculating the energy of each sub-channel, the wavelet packets are re-ordered from low frequency to high frequency. After performing the *4-th* level DWPT decomposition, the energy of each sub-channel is shown in Figure 3 to Figure 5.

In Figure 3, it shows the fixed threshold is much lower than the simulation energy of each sub-channel. However, when the threshold adapter is adopted, the new threshold will be enlarged. But the thresholds in all sub-channels are still lower than the simulation energy. Therefore, the case of α=0.45 cannot improve the performance. In Figure 4, when α=0.50, the detection sensitivity has been improved because the adaptive threshold of each sub-channel has been further enlarged and sub-channels without primary users can be detected as unoccupied. In Figure 5, taking α=0.55, the adaptive threshold become higher than the energy of sub-channels 3 and 7. As a result, these two channels will be determined as unoccupied even though primary users exist in them. As a result, secondary users can access to these channels, which would lead to harmful interference to the primary users.

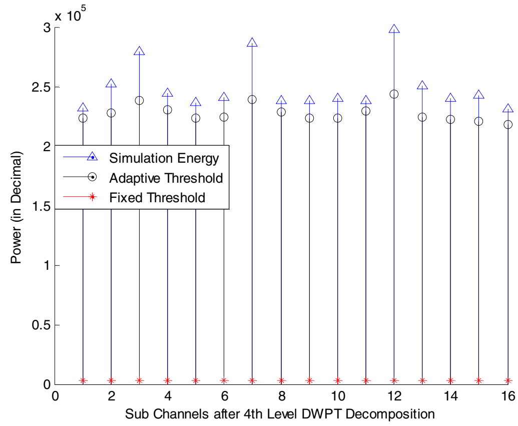


Figure 3. Energy of Sub-channels, α=0.45, SNR=-17dB

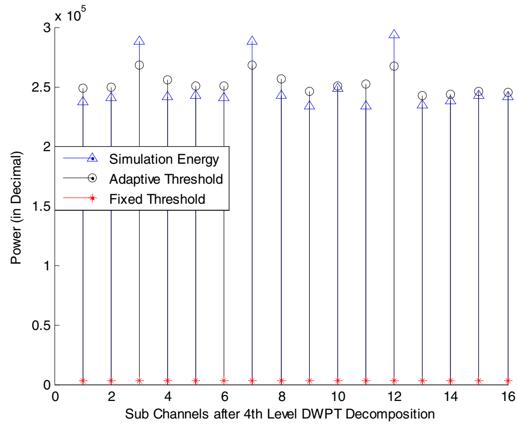


Figure 4. Energy of Sub-channels, α=0.50, SNR=-17dB

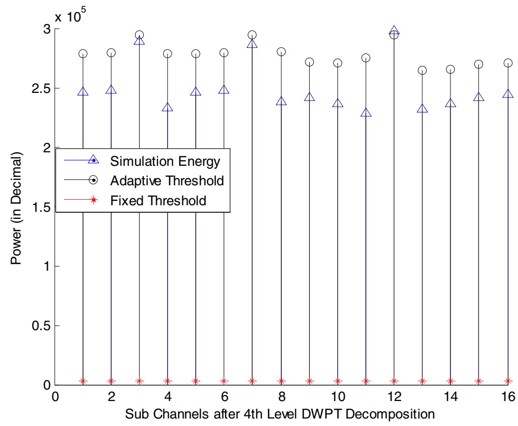


Figure 5. Energy of Sub-channels, α=0.55, SNR=-17dB

When α=0.53, the energy of sub-channel 3, 7, 12 is higher than the adaptive threshold, as shown in Figure 6. If we keep α increasing, the energy of the three sub-channels will be lower than the adaptive threshold. As a result, these channels will be falsely determined as unoccupied. Therefore, the proper range for α is from 0.5 to 0.53.

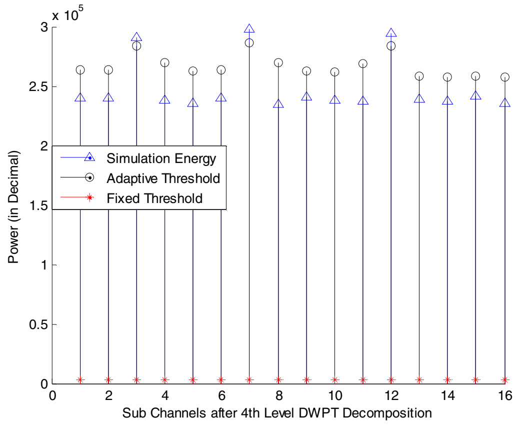
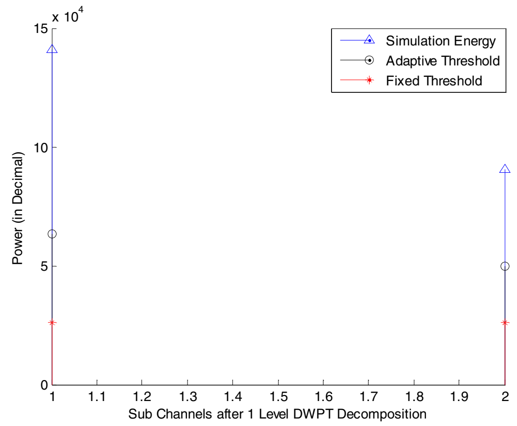


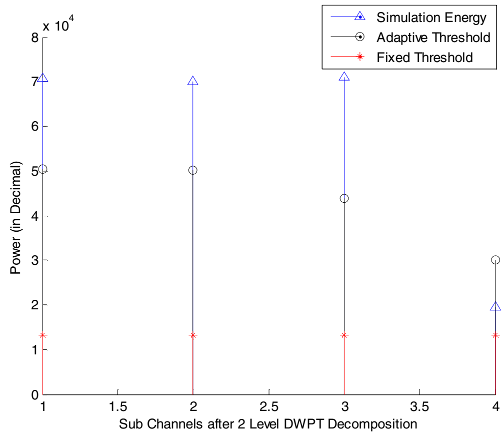
Figure 6. Energy of Sub-channels, α=0.53, SNR=-17dB

Finding out the unoccupied channel as early as possible can reduce the computational complexity as the occupied channel will not be processed in the further level DWPT decomposition. Thus, the threshold should be as large as possible. So the optimal value of α is 0.53.

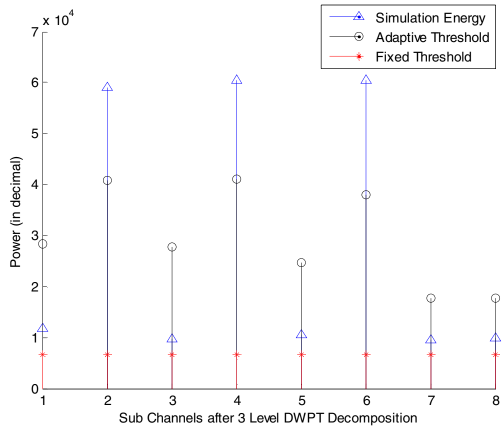
In the case of α=0.53 and SNR= 0dB, the *4th*-level DWPT decomposition of the received signals is shown in Figure 7. After the *2nd*-level DWPT decomposition, the energy of sub-channel 4 (48MHz, 64MHz) is higher than the fixed threshold. So, if the fixed threshold is used, sub-channel 4 is determined as occupied and should be processed at the *3rd*-level DWPT decomposition. If the adaptive threshold is applied, the energy of sub-channel 4 becomes lower than the threshold. So it will be determined as unoccupied and will not be processed at the next level DWPT decomposition. Hence, the computational complexity of the sensing algorithm is reduced and secondary users can access the spectrum between 48 MHz and 64 MHz.



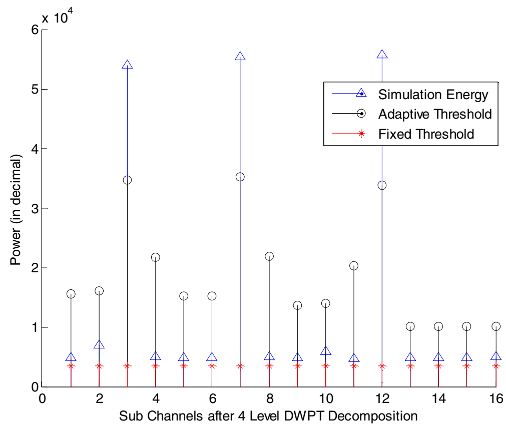
(a)



(b)



(c)



(d)

Figure 7. Energy of Sub-channels, α=0.53, SNR=0dB (a) 1st Level DWPT Decomposition (b) *2nd* Level DWPT Decomposition (c) *3rd* Level DWPT Decomposition (d) *4th* Level DWPT Decomposition

V. CONCLUSTIONS

In this paper, we proposed a threshold adapter to get an adaptive threshold for an energy detector based on DWPT. The threshold of a channel changes adaptively as a function of the energy of that channel. It is an efficient perspective to classifying spectrum as it can improve performance of the energy detector when the SNR is low. Based on the simulation results, the fixed threshold cannot detect primary users accurately when the SNR is lower than 5 dB. However, the threshold adapter can accurately detect out the primary users when the SNR is -17 dB. Therefore, a 22 dB gain of detection sensitivity has been obtained. In addition, once a spectrum has been detected as unoccupied at a lower level DWPT decomposition, it does not need to be processed in the next. This will reduce the computational complexity.

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