

Design and Implementation of a Triangle Energy Adaptive Thresholding Scheme for Discrete Wavelet Packet Based Wideband Spectrum Sensing in Cognitive Radio

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ABSTRACT

Cognitive radio (CR) technology addresses spectrum scarcity, but requires both speed and accuracy to be effective. Noise uncertainty often compromises sensing accuracy, while wideband sensing creates significant computational overhead that limits speed. To address these challenges, this paper introduces Triangle Energy Adaptive Thresholding (TREAT) for Discrete Wavelet Packet Transform (DWPT)-based wideband spectrum sensing. TREAT leverages the energy derived from the triangular structure of the DWPT tree to compute adaptive thresholds for sub-band channels at the terminal nodes. Performance evaluations demonstrate that TREAT reduces computational complexity by an average of 50%, resulting in faster decision times compared to conventional schemes. Furthermore, TREAT improves channel discovery by identifying 28 vacant sub-band channels compared to 26 for the reference method. In terms of sensing accuracy across the -10 dB to 10 dB SNR range, TREAT achieves a cumulative accuracy of 87.5% (17.5% mean average), outperforming the reference scheme's 81.25% cumulative accuracy (16.25% mean).

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INTRODUCTION

The electromagnetic spectrum is the means by which all wireless devices and services operate. However, like any other natural resource, it is not infinite. The recent increase in demand for high data rate in communication and multimedia systems and devices has depleted much of the available electromagnetic spectrum, giving rise to a scarcity in radio spectrum (Cisco, 2015). The problem of spectrum scarcity has further been exacerbated by the spectrum allocation pattern by regulatory agencies, which is inefficient because the level of utilization of such spectrum by the primary allottees indicates gross underutilization at certain time intervals, thus resulting in wastage (Ashish & Soo, Y, 2014; Honggui, 2015).

To mitigate the effect of spectrum scarcity, a well-known solution proposed in literature is the cognitive radio (CR) technology, which can be described as a smart radio technology, built with the capacity to sense its radio environment and also be able to decide when and how to make spectrum utilization when such spectrum become available i.e. when the radio spectrum is not being used by the primary user. To achieve its functionality, CR performs three basic tasks as shown in Figure 1 (Haykin, 2005). These tasks include radio analysis which deals with detection of spectrum holes for spectrum sensing and estimation of the radio environment interference temperature. Channel state estimation and predictive modeling deals with the estimation of channel state information, and prediction of channel capacity. The transmit-power control and spectrum

management task deals with the efficient management of available spectrum (Haykin, 2005).

Various thresholding techniques have been proposed in literature; the authors in (Liu et al., 2017) proposed a threshold-setting algorithm for energy detection scheme which maximizes spectrum utilization; this was realized through the derivation and analysis of a closed form expression for the adaptive threshold. Using a scheme called Constant Threshold Range, the authors in (Bhawna & Kachan, 2014) proposed a thresholding technique for energy detection which seeks to reduce the trade-off between probability of false alarm and probability of miss-detection. Taking the variance of samples and the number of samples for a given sub-band channel, the author in (Donoho, 1995) developed an adaptive threshold for a wavelet system, which can be directly applied to wavelet-based spectrum sensing. This paper focuses on spectrum sensing in the radio scene analysis state. This was achieved by developing an adaptive threshold based on the tree structure of the discrete wavelet packet transform (DWPT) as shown in Figure 2. Accurate channel sensing in cognitive radio depends very much on the strength of the thresholding technique. Naturally, due to uncertainty in noise level, fixed thresholding technique is not feasible. Therefore, many sensing techniques generally adopt one type of adaptive technique or the other. To achieve fast and accurate spectrum sensing, a CR must have a good and optimal thresholding technique. The thresholding techniques are usually implemented as algorithms in a CR determine if a frequency spectrum is occupied or not.

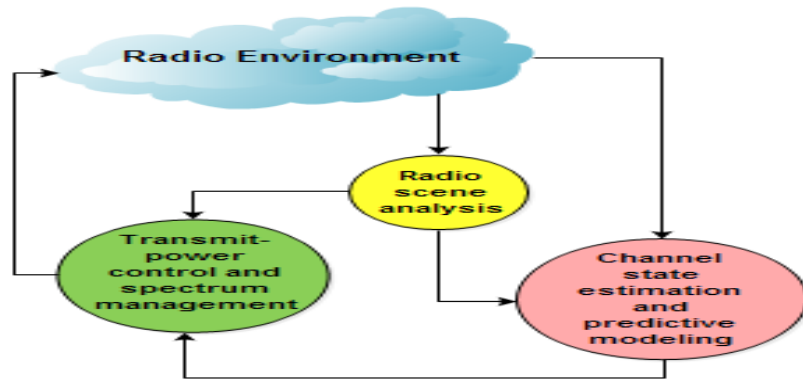


Figure 1: Tasks performed by a cognitive radio

The proposed scheme in this work presents a thresholding technique for discrete wavelet packet transform (DWPT) spectrum sensing based on the tree structure derivable from it. The adaptive threshold will explore Euclidean distance geometry and the dynamic energy possessed by parent-child node relationship that is inherent in the DWPT tree. The

consequence of this will be that the adaptive threshold will enable spectrum sensing that is fast, accurate, and energy efficient. The paper will also present the implementation of adaptive threshold in hardware so as verify its performance and application with real data.

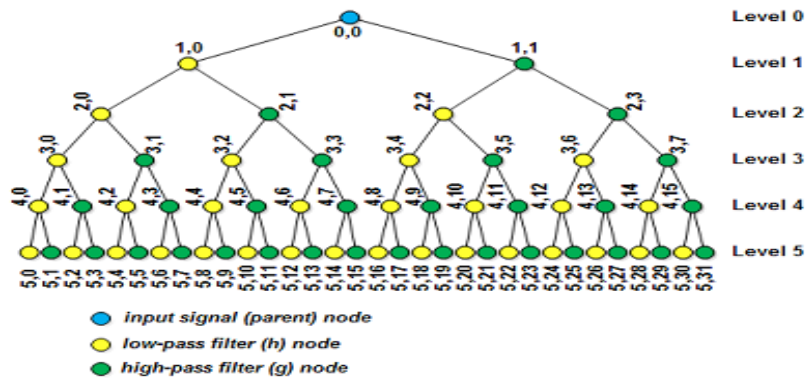


Figure 2: DWPT tree with five levels of decomposition

The implementation will involve the use of two platforms: the Arduino platform, and LabVIEW. The mathematical function which implements the DWPT tree presented in Figure 2 will be implemented on the Arduino platform, while the developed adaptive threshold will be implemented in LabVIEW. The output of the Arduino platform will be interfaced to LabVIEW through serial communication. This is to allow for performance measurement of the proposed system.

The rest of the paper is organized as follows: section 2 will review the DWPT with respect to signal decomposition and analysis. In section 3, presents derivation and expression for the energy possessed by the geometric structure of a DWPT tree. Section 4 deals with the geometry of a DWPT and derivation of the adaptive threshold. In section, the method by which the implementation will be achieved is presented. The performance of the derived adaptive threshold is tested in section 5, alongside a comparison with another threshold. In section 6, we verify the implementation of the adaptive threshold using the necessary platforms and procedures. Finally, we draw a conclusion in section 7.

MATERIALS AND METHODS

This section presents the materials and methods that were used in achieving the objectives of this work. The first step is the analysis of signal decomposition by a DWPT; this is a necessary step because it forms the foundational basis on which the adaptive thresholding scheme will be derived.

DWPT Signal Decomposition Analysis

The DWPT tree as shown in Figure 2, decomposes an incoming signal at each node by splitting it into two subspaces $W_{n,j}$ which has the property of orthogonality, and is expressed mathematically as (Nikookar, 2013):

$$W_{n,j} = W_{2n,j-1} \oplus W_{2n+1,j-1} \quad (1)$$

Where n is a nonnegative integer, j is the decomposition level, and $\oplus$ is orthogonal addition. The wavelet packet coefficients

$\xi_{l+1}^{2p}[n]$ are generated using the scaling filter, and the coefficients $\xi_{l+1}^{2p+1}[n]$ are generated using the wavelet filter. The coefficients are expressed as (Nikookar, 2013):

$$\xi_{l+1}^{2p}[n] = \sqrt{2} \sum_k h[k] \xi_l^{2p}[2n-k], n=0,1,\dots,N-1 \quad (2)$$

$$\xi_{l+1}^{2p+1}[n] = \sqrt{2} \sum_k g[k] \xi_l^{2p}[2n-k], n=0,1,2,\dots,N-1 \quad (3)$$

Where $h[k]$ is the low-pass filter, $g[k]$ is the high-pass filter, and p is the position at level l . For the signal in each sub-band channel, the energy is calculated as (Ruch, D & Patrick, J, 2009; Wei et al., 2014; Zhinjin et al., 2012):

$$E = \frac{1}{T} \int_0^T \left[\sum_{j \geq j_0} \sum_k c_{j,k} \phi_{j,k}(t) + d_{j,k} \psi_{j,k} \right]^2 dt \quad (4)$$

$$E = \frac{1}{T} \sum_{j \geq j_0} \sum_k (c_{j,k}^2 + d_{j,k}^2) \quad (5)$$

Where $c_{j,k}$ is scaling function coefficient, $d_{j,k}$ is the wavelet function coefficient. Having looked at the DWPT tree and how it decomposes a signal, we will in the next section explore the dynamic energy in this tree structure and derive an adaptive threshold for it.

DWPT Geometric Structure Energy

To derive an expression for the energy in the geometry of the tree structure of DWPT as shown in Figure 2, we view the relationship between the parent nodes and child nodes from a triangular perspective in which each parent node and the two

corresponding child nodes form a triangle with vertices XYZ as shown in Figure 3, where X is the parent node, and Y and Z are the two child nodes respectively.

For a DWPT, the distance, $\mathbf{e}$, between X and Y is a vector whose length is determined by the components of the vector which are the coefficients in the subband channel. This is mathematically expressed as (Itskov, 2009; Owen & Corrado, n.d.; Robert et al., 2003):

$$\|XY\|_2 = \|\mathbf{e}\|_2 = \sqrt{e_1^2 + e_2^2 + \dots + e_n^2} \quad (6)$$

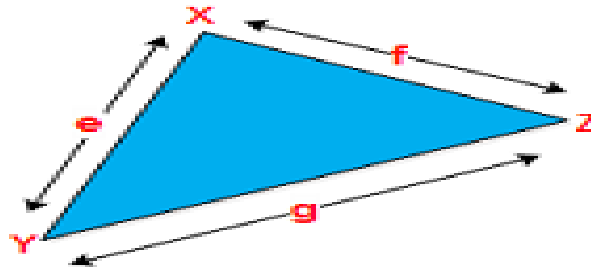


Figure 3: Parent-Child nodes triangle with vertices XYZ

Substituting the scaling and wavelet functions coefficients in (5) for the subband channel represented by $\|XY\|_2$ yields:

$$\|XY\|_2 = \sqrt{(c_{j_1,k_1} + d_{j_1,k_1})_{XY}^2 + (c_{j_2,k_2} + d_{j_2,k_2})_{XY}^2 + \dots + (c_{j_n,k_n} + d_{j_n,k_n})_{XY}^2} \quad (7)$$

Also,

$$\|XZ\|_2 = \|\mathbf{f}\|_2 = \sqrt{f_1^2 + f_2^2 + \dots + f_n^2} \quad (8)$$

Similar substitution of the scaling and wavelet functions in (8) yields:

$$\|XZ\|_2 = \sqrt{(c_{j_1,k_1} + d_{j_1,k_1})_{XZ}^2 + (c_{j_2,k_2} + d_{j_2,k_2})_{XZ}^2 + \dots + (c_{j_n,k_n} + d_{j_n,k_n})_{XZ}^2} \quad (9)$$

The vector $\mathbf{g}$ is obtained by computing the Euclidean distance between vectors $\|XY\|_2 = \|\mathbf{e}\|_2$ and $\|XZ\|_2 = \|\mathbf{f}\|_2$. This is given by (Boyd & Vandenberghe, 2009; Cooperstein, 2015; Meyer, C, 2000; Sohail & Saber, 2009):

$$\mathbf{g}(\mathbf{e}, \mathbf{f}) = \left[(\mathbf{e} - \mathbf{f})^T (\mathbf{e} - \mathbf{f}) \right]^{\frac{1}{2}} = \left[\begin{matrix} e_1 - f_1 & e_2 - f_2 & \dots & e_n - f_n \end{matrix} \right] \begin{bmatrix} e_1 - f_1 \\ e_2 - f_2 \\ \vdots \\ e_n - f_n \end{bmatrix} \quad (10)$$

$$\mathbf{g}(\mathbf{e}, \mathbf{f}) = \left[(e_1 - f_1)^2 + (e_2 - f_2)^2 + \dots + (e_n - f_n)^2 \right]^{\frac{1}{2}} \quad (11)$$

Expressing (11) in the form of (6) or (8) yields:

$$\mathbf{g}(\mathbf{e}, \mathbf{f}) = \sqrt{(e_1 - f_1)^2 + (e_2 - f_2)^2 + \dots + (e_n - f_n)^2} \quad (12)$$

Substitution of the scaling and wavelet functions into (12) yields:

$$\mathbf{g}(\mathbf{e}, \mathbf{f}) = \|\mathbf{g}\|_2 = \sqrt{\left[(c_{j_1,k_1} + d_{j_1,k_1})_{XY} - (c_{j_1,k_1} + d_{j_1,k_1})_{XZ} \right]^2 + \left[(c_{j_2,k_2} + d_{j_2,k_2})_{XY} - (c_{j_2,k_2} + d_{j_2,k_2})_{XZ} \right]^2 + \dots + \left[(c_{j_n,k_n} + d_{j_n,k_n})_{XY} - (c_{j_n,k_n} + d_{j_n,k_n})_{XZ} \right]^2} \quad (13)$$

A geometric analysis of Figure 2 shows that the triangular relationship in Figure 3 exists between adjacent levels i.e. between parent node level and child nodes level. These relationships are shown Figure 4.

Let Δ represent any of the triangle in Figure 4, and let θ_j denote the angle at the j^{th} vertex of Δ , and l_j denote the opposite edge of the j^{th} vertex of Δ with length determined by either (7), (9), or (13). Also, let A denote twice the area of Δ . The energy possessed by Δ is given by (Clark et al., 2012):

$$E_\theta(\Delta) = \frac{w}{A} \sum_{i=1}^3 \|l_i\|^2 \quad (14)$$

where $w = 1/\sqrt{3}$ and A is obtained using the Cayley-Menger determinant as (Dominique & Fofou, 2004; Karl & Andre, 2009; Manfred & Harold, 1986):

$$-16A^2 = \begin{vmatrix} 0 & a & b & c \\ a & 0 & c & b \\ b & c & 0 & a \\ c & b & a & 0 \end{vmatrix} = \begin{vmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & c^2 & b^2 \\ 1 & c^2 & 0 & a^2 \\ 1 & b^2 & a^2 & 0 \end{vmatrix} \quad (15)$$

In (15), a, b, and c are determined using (7), (9), and (13).

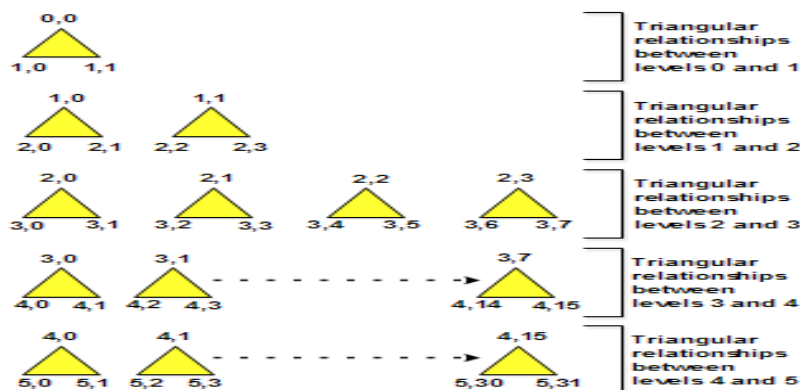


Figure 4: Triangular relationship between node levels in DWPT tree

According to (Zhinjin et al., 2012), the threshold (which we call referred scheme in this paper) for a subband channel in the DWPT tree shown in Figure 2 can be computed using:

$$\lambda_{i+1,2j} = \frac{\lambda_{i,j} + \alpha E_{i+1,2j}}{2} \quad (16)$$

$$\lambda_{i+1,2j+1} = \frac{\lambda_{i,j} + \alpha E_{i+1,2j+1}}{2} \quad (17)$$

Where $(j=0,1,\dots,2^i-1)$ is the number of channels at the $(i+1)$ th level of decomposition, $\lambda_{i,j}$ is the threshold associated with the parent node, $\lambda_{i+1,2j}$ and $\lambda_{i+1,2j+1}$ are the thresholds associated with the two child nodes emanating from the same parent node at the $(i+1)$ th level of DWPT decomposition. $E_{i+1,2j}$ And $E_{i+1,2j+1}$ are the energies associated with the two child nodes at the $(i+1)$ th level of decomposition, while α is a tuning factor which makes the received energy have a profound effect on the adaptive threshold if it tends to 1. It should be noted that there are 63 nodes in the DWPT tree shown in Figure 2, and starting at level-1, the expressions in (16) and (17) will together require 62 computations to accurately determine the thresholds for all the subband channels at level-5 decomposition. It can be seen that as the level of decomposition increases, the number of computations will increase exponentially using (16) and (17). This increase will definitely have undesirable effects on the speed of the spectrum sensing using this approach.

However, the energy possessed by each triangle in Figure 4 can be substituted into (16) and (17) to compute the threshold for the two child nodes in the triangle in one step (which we call proposed scheme in this paper). This effectively reduces (16) and (17) into a single equation which is expressed as:

$$\lambda_{i+1,2j}, \lambda_{i+1,2j+1} = \frac{\alpha E_{\theta}(\square X_{i,j} Y_{i+1,2j} Z_{i+1,2j+1})}{2} \quad (18)$$

Where $\square X_{i,j} Y_{i+1,2j} Z_{i+1,2j+1}$ is the triangle with vertices $X_{i,j}$ (parent node), $Y_{i+1,2j}$ (first child node), and $Z_{i+1,2j+1}$ (second child

node). This reduces by half the total number of computations required to compute the thresholds for all the subband channels. Substituting (14) into (18) yields:

$$\lambda_{i+1,2j}, \lambda_{i+1,2j+1} = \frac{\alpha \frac{w}{A_{\square X_{i,j} Y_{i+1,2j} Z_{i+1,2j+1}}} \sum_{i=1}^3 \|l_i\|^2}{2} \quad (19)$$

Where l_i is computed using the expression in (7), (9), and (13). The expression in (19) called triangle energy adaptive threshold (TREAT) will yield the adaptive threshold for the two child nodes at the $(i+1)$, $(2j, 2j+1)$ th level of decomposition.

As stated in section 1, the DWPT function stated in (2) and (3) will be implemented on the Arduino platform, while the adaptive threshold derived in (19) will be implemented in LabVIEW. We present the implementation methodology in the next section.

Implementation Methodology

To implement the DWPT function of Figure 2 in hardware, the expression in (2) and (3) has to be factored into lifting steps. According to (Daubechies & Sweldens, 1998), (2) and (3) can be factored into lifting steps for a Db4 wavelet as follows:

$$\left. \begin{aligned} s_{j+1}^{(1)}[n] &= s_j[2n] + \sqrt{3}s_j[2n+1] \\ d_{j+1}^{(1)}[n] &= s_j[2n+1] + \frac{1}{4}\sqrt{3}s_{j+1}^{(1)}[n] - \frac{1}{4}(\sqrt{3}-2)s_{j+1}^{(1)}[n-1] \\ s_{j+1}^{(2)}[n] &= s_{j+1}^{(1)}[n] - d_{j+1}^{(1)}[n+1] \\ s_{j+1}[n] &= \frac{\sqrt{3}-1}{\sqrt{2}}s_{j+1}^{(2)}[n] \\ d_{j+1}[n] &= \frac{\sqrt{3}+1}{\sqrt{2}}d_{j+1}^{(1)}[n] \end{aligned} \right\} \quad (20)$$

Where $s_{j+1}^{(1)}[n]$ is the updated value at the next iteration (H filter output of Figure 2), and $d_{j+1}^{(1)}[n]$ is the predicted value at the next iteration (G filter output in Figure 2). Based on the lifting steps in, the implementation will have the hardware architecture shown in Figure 5.

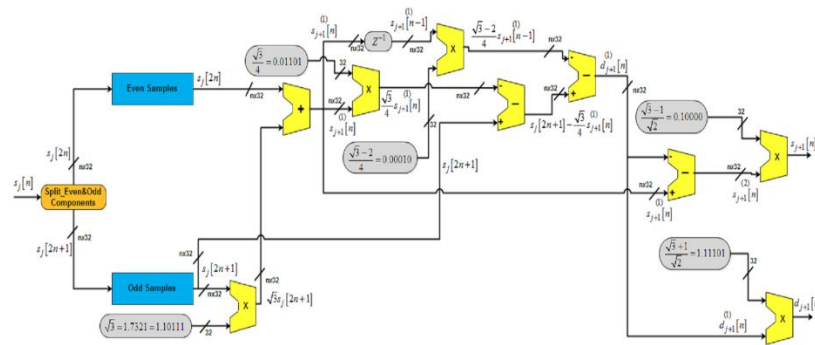


Figure 5: Implementation hardware architecture of DWPT based on lifting steps

The architecture shown in Figure 5 will be coded using the Arduino IDE (sketch) with the ATMEGA2560 microcontroller as the target device. The output of the DWPT from the microcontroller will be fed to LabVIEW via serial communication from where TREAT will perform spectrum sensing. Figure 6 shows the conceptual diagram of the complete system design. The Hilbert transform in Figure 6 is

to enhance the frequency edges in the sub-band signals coming from the DWPT. This is necessary in order to make the edge detection better in spectrum sensing. The reader is referred to our earlier work i.e. (Dibal et al., 2018) for the mathematical derivation and further information on the combination of DWPT and Hilbert transform for enhanced sub-band frequency edge detection.

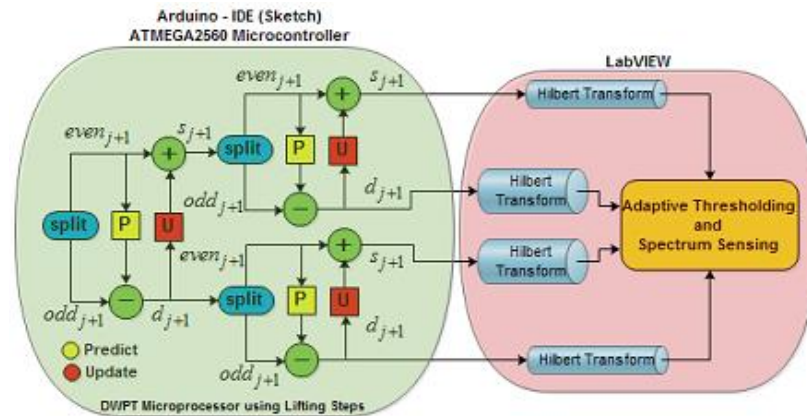


Figure 6: Conceptual diagram for DWPT microprocessor with adaptive thresholding

Design Simulation

To perform simulation for the design in Section 2.2, the relationship in (Nikookar, 2013) i.e. 2^l , this work determine the number of sub-band channels when decomposed to level

l . For 5 levels of decomposition, we obtain 32 sub-band channels. The experiment involves a composite input signal having different amplitudes and frequencies as described in Table 1. The simulation of the power spectrum density (PSD) of the input signal at SNR of -10dB is shown in Figure 7.

Table 1: Input Signal Parameters

	Amplitude	Frequency (MHz)
Signal 1	1.3	15
Signal 2	1.7	40
Signal 3	2.0	67
Signal 4	1.8	81

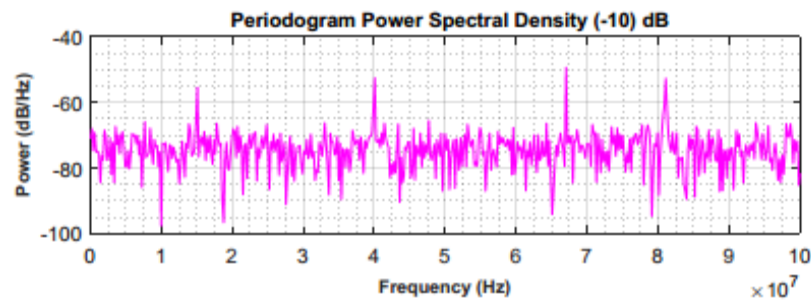


Figure 7: Power Spectrum Density of Input Signal at -10dB

At -10dB, the distribution profile of the coefficients in each sub-band channel is shown in Figure 8, where the sub-band channels with low energy have low coefficient profile, while those with high energy have high coefficient profile. A close inspection of Figure 8 reveals that at -10dB, sub-band

channels 6, 18, and 29 have low energy due to their coefficient profile. This assertion is further corroborated in Figure 9, where the energy in each sub-band channel computed using (5) is shown.

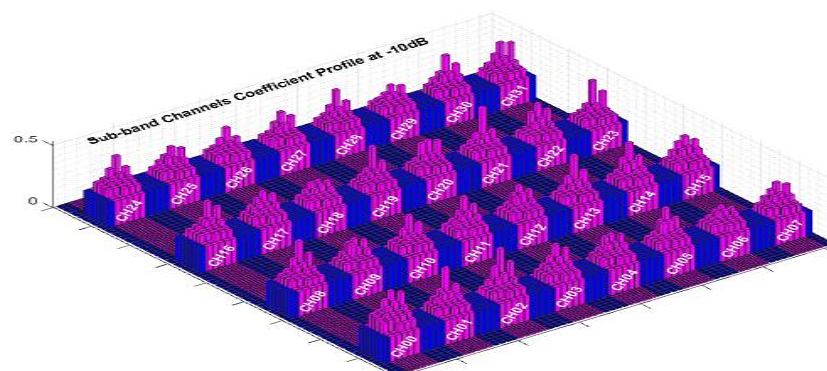


Figure 8: Sub-band channels coefficient profile at -10dB

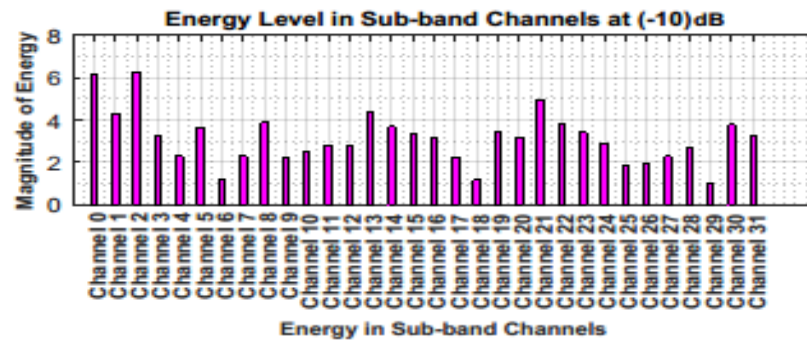


Figure 9: Sub-band channels energy at -10dB

Performing the simulation at -5dB and comparing the results with that of -10dB, shows that there was a false alarm in sub-band channel 26 when the SNR value was -10dB; this is

shown in Figure 10. Similarly, the simulation of the proposed scheme is again tested side-by-side with the referred scheme at 0dB and 5dB and shown in Figure 11.

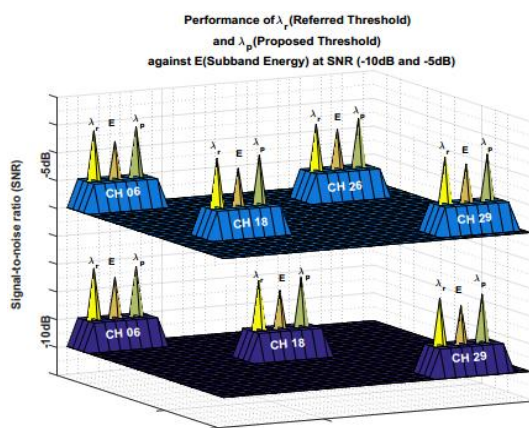


Figure 10: Performance of proposed and referred schemes at -10dB and -5dB (only vacant sub-band channels are shown)

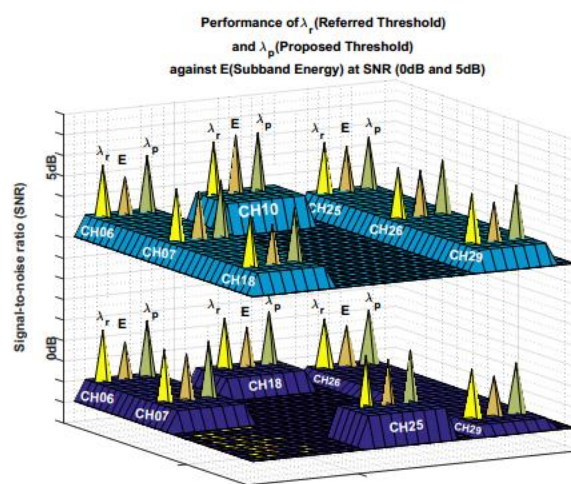


Figure 11: Performance of proposed and referred schemes at 0dB and 5dB (only vacant sub-band channels are shown)

RESULTS AND DISCUSSION

This section is divided into two – the first presents the analysis and discussions for the results obtained from the simulation performed in this paper. The second section similarly presents the analysis and discussions for the results obtained from the hardware implementation performed in this paper.

Simulation Results and Discussion

In this paper, the thresholding scheme defined in (16) and (17) referred scheme was adopted, and TREAT as defined in (19)

as the proposed scheme. The performance of the result at signal-to-noise ratio of -10dB reveals that both the proposed and referred schemes identified sub-band channels 6, 18 and 29 as UNOCCUPIED; this is shown in Figure 12. This is possible because the energies in sub-band channels 6, 18, and 29 at -10dB were lower than the respective adaptive thresholds (both proposed and referred) for those channels. From the sub-band channels coefficient and energy profiles in Figures 8 and 9, the result in Figure 10 was not unexpected.

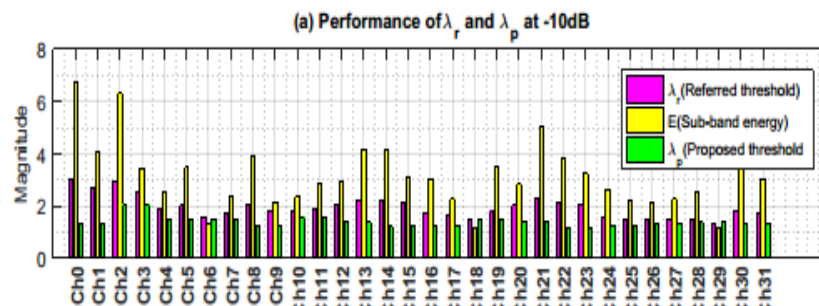


Figure 12: Performance of proposed and referred thresholding scheme at -10dB

The false alarm occurred at -10dB because at low SNR value, the noise competes with the signal in strength; hence, a

detection technique can easily classify a noisy channel as OCCUPIED (which is a false alarm). However, as the SNR

value increases, the signal strength increases, thus making a detection technique more accurate in detection and classification of sub-band channels.

However, in Figure 11, sub-band channels 7 and 25 were classified as UNOCCUPIED at 0dB by TREAT and the referred scheme; this indicates a false alarm in these sub-band channels at -10dB and -5dB as shown in Figure 10. However, at 5dB, the proposed scheme classified sub-band channel 10

as UNOCCUPIED while the referred scheme classified the same sub-band channel as OCCUPIED. It can be seen that there was a case of miss-detection by the referred scheme, while the proposed scheme correctly classified the sub-band channel as UNOCCUPIED.

Table 2 shows the performance comparison between the proposed scheme (TREAT), and the referred scheme from -10dB to 10dB at interval of 5 values.

Table 2: Performance Comparison of Proposed and Referred Thresholding Schemes

S/N	Signal-to-noise ratio (dB)	Vacant sub-band channels (Proposed Scheme)	Total vacant sub-band channels (Proposed Scheme)	Percentage ratio (%) – Proposed Scheme	Vacant sub-band channels (Referred Scheme)	Total vacant sub-band channels (Referred Scheme)	Percentage ratio (%) – Referred Scheme
1	-10	6,18, 29	3	9.3750	6,18, 29	3	9.3750
2	-5	6, 18, 26, 29	4	12.500	6, 18, 26, 29	4	12.500
3	0	6, 7, 18, 25, 26, 29	6	18.750	6, 7, 18, 25, 26, 29	6	18.750
4	5	6, 7, 10, 18, 25, 26, 29	7	21.875	6, 7, 18, 25, 26, 29	6	18.750
5	10	4, 6, 7, 10, 18, 25, 26, 29	8	25.000	6, 7, 9, 18, 25, 26, 29	7	21.875

The analysis of Table 2 indicates that the proposed scheme showed better detection accuracy than the referred scheme in the sense that fewer miss-detections were observed in the proposed scheme. Secondly from 4, it can be seen that for the level of performance in Table 2, the proposed scheme is faster and more resource-friendly because for the five levels of decomposition considered in this paper, only decomposition levels 4 and 5 are needed for the proposed scheme, while decomposition levels 1 to 5 are needed in the referred scheme. By implication, the referred scheme will require a much higher number of data points i.e. 3437 data points for

thresholding than the proposed scheme which has 1664 data points. This assertion is shown in Figure 13. For a cognitive radio, the fewer number of data points will translate to fewer computations, thus yielding better energy savings and longer battery life. Moreover, the high number of data points in the referred scheme in Figure 13 implies that a longer decision time is required by an adaptive threshold built on that scheme, whereas the proposed scheme will require a shorter decision time. Figure 14 shows the performance gains of the proposed scheme in terms of both speed and decision time.

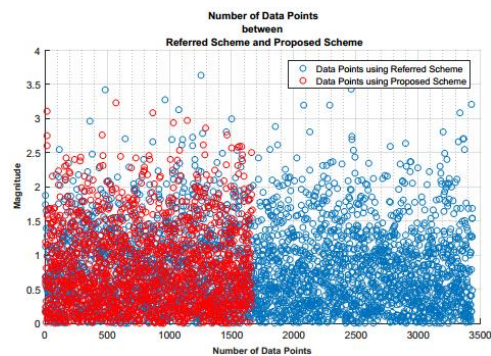


Figure 13: Number of data points for computing threshold in proposed and referred scheme

Hardware Implementation Results and Discussion

Owing to memory constraint of the target device (ATMEGA2560 microcontroller), the tree structure in Figure 2 will be implemented for level 3 decomposition for the lifting steps in (20). Using the lifting steps in (20), the result for coding DWPT in the Arduino Integrated Development Environment (IDE) called sketch with the target device as ATMEGA2560 is shown in Figure 15 after compilation, verification, and HEX file generation; the workflow for this process is shown in Figure 16.

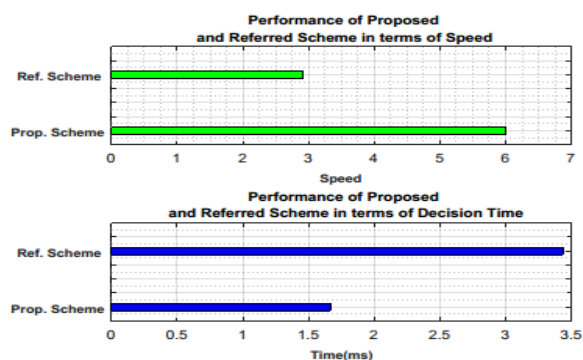


Figure 14: Performance of proposed and referred schemes in terms of computation speed and decision time

The result from the second stage in the implementation of the design in LabVIEW is shown in Figure 20 where a LabVIEW virtual instrument (VI) was designed for the acquisition of data from the DWPT implemented on the ATMEGA2560 microcontroller using serial communication. The settings for the serial communication are shown in Table 3, with the corresponding implementation result is shown in Figure 17, and the acquired data in Figure 18.

Table 3: Parameter Settings for Serial Communication

Serial Communication Parameters	Setting
Baud Rate	9600
Data Bits	8
Parity	None
Stop Bits	10
Flow Control	None



Figure 15: Design coding, compilation, and verification using sketch

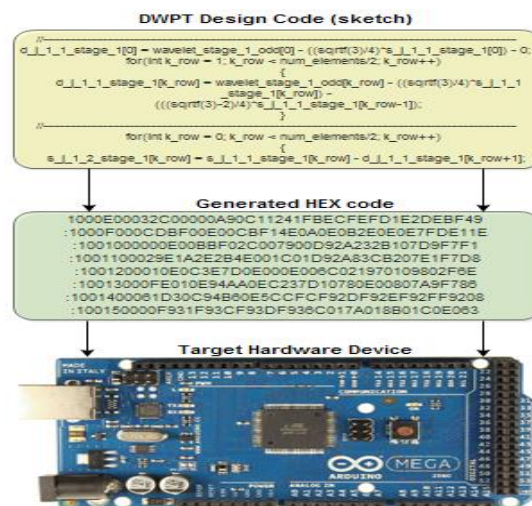


Figure 16: Process flow for HEX file generation and firmware embedding

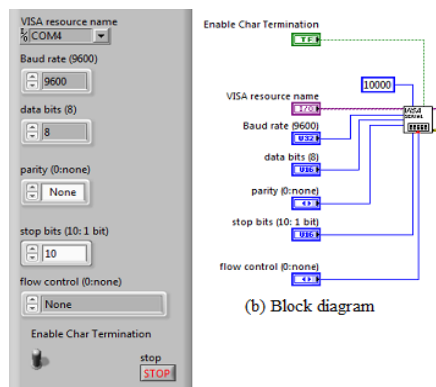


Figure 17: LabVIEW implementation of serial communication settings

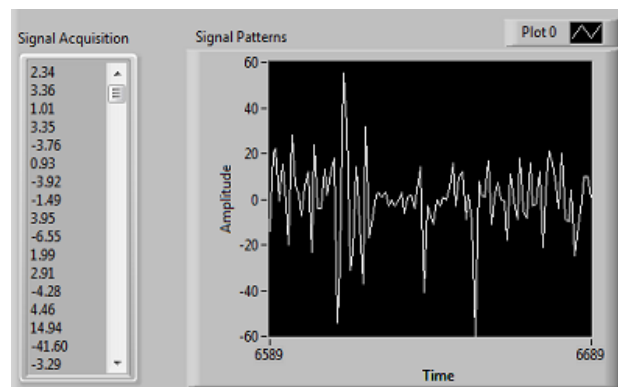


Figure 18: Signal acquisition in LabVIEW using serial communication

The acquired signal in Figure 18 is sorted according to each subband channel and then passed through a Hilbert transformer for reasons stated in section 4. Figure 19 shows an example of this where a partial view of the signals at -10dB

in subband channel 0 of the DWPT is acquired by LabVIEW alongside the application of the Hilbert transform for reasons just stated.

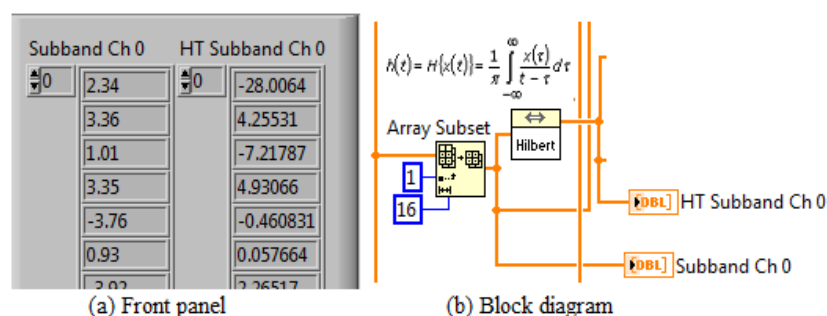


Figure 19: Partial view of subband channel 0 data acquisition with Hilbert transform

Using the derived threshold in (19), the adaptive threshold is computed from the acquired signals for adjacent subband channels in the triangles between levels 2 and 3 (only 3 levels of decomposition are considered in implementation due to device resource constraints). As an example, for the triangle with vertices $X=2,0$ $Y=3,0$ and $Z=3,1$ in Figure 4, the computation of the adaptive threshold at -10dB alongside the

energy in the respective subband channels defined by (5) is shown in Figure 20. The parameters $\|e\|$, $\|f\|$, $\|g\|$ are the distances between vertices XY, XZ, and YZ respectively, as shown in Figure 3 and defined by (7), (9), and (13) respectively.

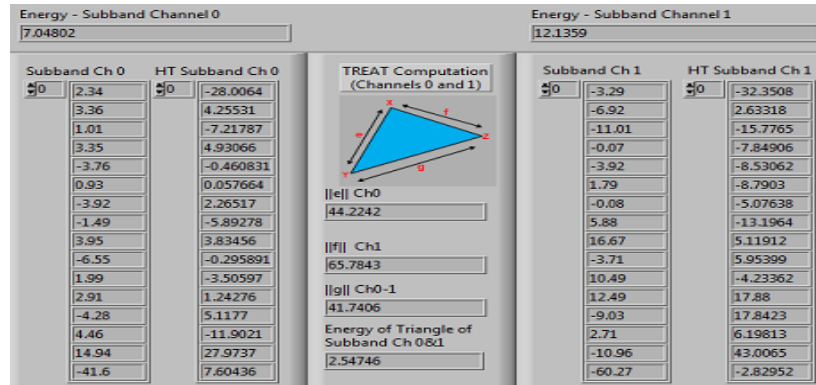


Figure 20: Computation of adaptive threshold and subband energies at -10dB

After successful data acquisition and computation of all the necessary parameters, we perform spectrum sensing for the

signal at -10dB 0dB, and 10dB. The results are shown in Figures 21, 22, and 23 respectively.

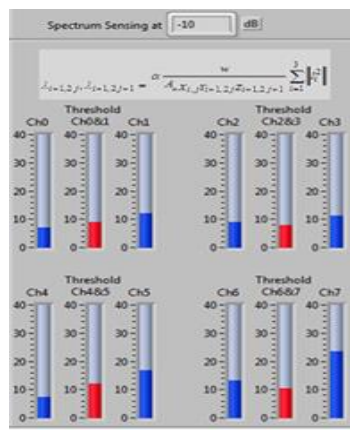


Figure 21: Front panel – Spectrum sensing at -10 dB

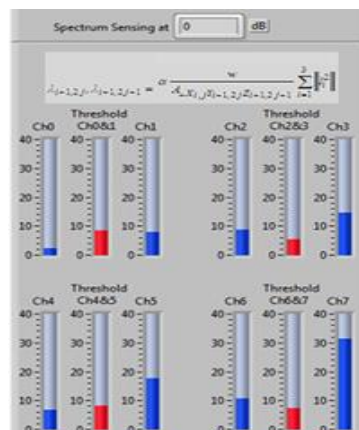


Figure 22: Front panel – Spectrum sensing at 0 dB

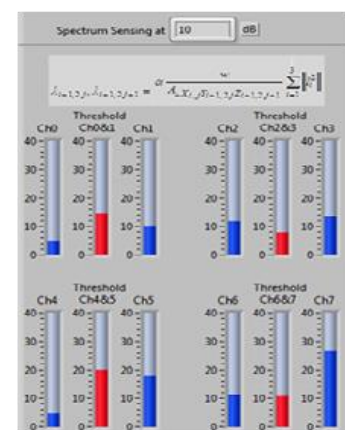


Figure 23: Front panel – Spectrum sensing at 10 dB

In Figure 21, it can be seen that at -10dB, subband channels 0 and 4 were identified as UNOCCUPIED channels. This is because the threshold values for those channels are greater than the energy in the channels. In Figure 22, it can be seen that the spectrum sensing performed at 0dB classifies subband channels 0, 1, and 4 as UNOCCUPIED channels. This means that there was false alarm in subband channel 1 when the SNR value was -10dB. The false alarm occurred at -10dB because at low SNR value, the noise competes with the signal in strength; hence, a detection technique can easily classify a noisy channel as OCCUPIED (which is a false alarm). However, as the SNR value increases, the signal strength increases, thus making a detection technique more accurate in detection and classification of sub-band channels. Performing spectrum sensing at 10dB as shown in Figure 23 shows the classification of subband channels 0, 1, 4, 5 as UNOCCUPIED. Another case of false alarm in subband channel 5 when the SNR value was -10dB and 0dB was observed. From the results obtained in Figures 15 to 23, it can be seen that the hardware implementation of the DWPT and the proposed adaptive threshold was successful.

CONCLUSION

This paper successfully engineered and deployed a geometric energy adaptive thresholding technique to enhance DWPT-based wideband spectrum sensing. By evaluating the local energy configuration inside the triangular sub-structures of the DWPT tree using Euclidean geometry, the proposed algorithm updates decision boundaries dynamically. The system architecture was physically implemented using an Arduino ATMEGA2560 for executing wavelet lifting step decompositions, integrated with a LabVIEW platform that handles real-time adaptive thresholding logic. Comparative evaluations proved that the proposed framework delivers notable enhancements across key performance metrics, including sensing speed, signal accuracy, decision latency, and data point capacities. Successful hardware-in-the-loop telemetry confirmed that the LabVIEW module effectively processes and maps the spectrum states derived from the embedded Arduino microcontroller, demonstrating a viable asset for physical cognitive radio deployments. Future work will focus on transitioning the embedded DWPT lifting steps from the 8-bit microcontroller to a dedicated Field-

Programmable Gate Array (FPGA) architecture to enable ultra-low latency, parallelized wideband processing. Additionally, the authors plan to integrate machine learning classifiers within the LabVIEW framework to dynamically optimize the tuning coefficients under fast-fading channel conditions and severe primary user emulation attacks.

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