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Wavelet-based spectrum sensing with improved thresholding for enhanced detection in cognitive radio networks

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ABSTRACT

Cognitive radio (CR) technology is an adaptive, intelligent radio and network technology that can automatically detect available channels in a wireless spectrum. Spectrum sensing is the most important component in CR due to its ability to sense and recognize parameters related to the radio channel characteristics. However, there are some spectrums that are not used known as spectrum holes. It is challenging to accurately identify these spectrum holes, especially when employing traditional energy detection techniques, which suffer from incorrect threshold selection at low signal-to-noise ratio (SNR) levels. This work suggests a wavelet-based spectrum sensing technique in conjunction with an enhanced thresholding method to improve detection accuracy and decrease noise to overcome this constraint. MATLAB simulations are used for evaluating three threshold functions: hard, soft, and improved. The results indicate that the improved threshold achieves superior denoising performance and a higher detection probability compared to the traditional energy detection method. In this study, the energy detection technique was also implemented for comparison with the wavelet-based approach. The findings reveal that wavelet-based sensing consistently provides a higher detection probability (P_{DET}), demonstrating its effectiveness and reliability for cognitive radio (CR) application.

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1. INTRODUCTION

Spectrum refers to the range of invisible radio frequencies through which wireless signals travel. These signals can enable the user to communicate with other users through mobile devices, look up directions to a location, and perform all other functions. Nowadays, the spectrum resources are in high demand due to the rapid expansion of wireless applications and services. With the growing adoption of Internet of Things (IoT), significant growth in connected devices is expected soon [1], [2]. A larger spectrum bandwidth is required to accommodate the increasing number of wireless devices. However, the accessible spectrum is a limited resource. According to the existing spectrum allocation chart, it is quite difficult to secure open spectrum to handle impending amounts of wireless devices and mobile data traffic [3]-[5].

Furthermore, the exponential rise in wireless users and the constant demand for faster data speeds are also elements that influence the RF spectrum. From that, most of the frequency spectrum has been utilized.

To overcome the impending spectrum crunch issue, the concept of cognitive radio has been introduced. Generally, there are two main users in cognitive radio (CR), which are primary users (PU) known as licensed users and secondary users (SU) act as unlicensed users. The basic concept in CR is to identify if the PU is using the bandwidth that has been allocated to them. The SU will identify the available unused spectrum, which is known as a spectrum hole for their own use. A spectrum hole is a licensed bandwidth that has not been unused for some time, typically in a specific location. The SU strategically makes use of frequency gaps to optimize spectrum utilization. If the SU detects the presence of a PU in the spectrum band, it will immediately stop using that band and switch to another one that is accessible to prevent interfering with the PU [6], [7]. Therefore, spectrum sensing is required in CRs to identify whether a frequency band is vacant.

Spectrum sensing has been a significant element in CR due to the shadowing, fading, and time-varying natures of wireless channels [8]. The challenge occurs in choosing the best method of spectrum sensing to detect and identify all the spectrum holes in surroundings. One of the spectrums sensing techniques that is used to identify the spectrum hole is the energy detection method. However, this method is ineffective due to it being difficult to choose a decision threshold. In addition, it also gives low accuracy in detection of spectrum holes, especially at low signal-to-noise ratio (SNR) [9], [10]. Based on the previous research from [9], [11], [12] the detection of spectrum holes is less accurate at a low signal-to-noise ratio (SNR) level and affects the performance of the spectrum sensing. To overcome this problem, wavelet-based sensing will be used as it can give good performance when detecting spectrum holes at high SNR values and can be able to determine the signal's wavelet transform [10].

Improving spectrum sensing reliability under varying noise and SNR conditions has led to the use of double threshold and dynamic threshold techniques. The double threshold method applies two decision levels to reduce false alarms and missed detections [13], [14], while dynamic thresholding adjusts the threshold automatically according to noise or channel changes to maintain accuracy. Recent studies have combined these methods in hybrid frameworks to improve detection at low SNR [8]-[10]. For example, Raghavendra and Manjunatha [15] developed a hybrid eigenvalue–energy detection model using double thresholding with meta-heuristic optimization, and Du and Wang [16] introduced an adaptive double-threshold scheme for vehicular networks. These methods demonstrate how adaptive thresholding can improve overall sensing performance in cognitive radio systems and overcome the shortcomings of traditional energy detection.

Despite the advancements in adaptive thresholding techniques, signal distortion and noise contamination remain major challenges that can degrade the accuracy of spectrum sensing, particularly during signal transmission. In cognitive radio systems, transmitted signals are often easily affected by noise, making it difficult for the receiver to accurately decode the information. Moreover, the high-frequency components of some signals contain not only noise but also important data, making it impractical to simply filter out the high-frequency region [17]. To address this, signal denoising techniques such as thresholding are commonly applied to separate noise from useful information. Thresholding is widely used because it is computationally simple and effective; however, its performance strongly depends on proper threshold selection [18].

This project proposed implementing the hard threshold, soft threshold, and improved threshold function to overcome this issue. By executing those methods in this project, the best threshold for detection can be chosen to improve denoising performance and increase the accuracy of threshold estimation. From that, the performance efficiency of the wavelet-based detection can also be determined in terms of the probability of detection, P_{DET}. The algorithm of wavelet detection in this project is formulated at a frequency of 2.4 GHz by using the MATLAB software.

2. METHODS

This project is conducted throughout the simulation using the MATLAB software. The USRP N210 hardware was used to analyze the measured data signal from [19], [20]. This data contains around 74320 samples of amplitudes with respect to frequency in the Wi-Fi range between 2.43 GHz and 2.445 GHz. The general phases involved in this work are shown in Figure 1. This work will focus on Phase 2 until Phase 4, since Phase 1 has been done in [19].

2.1. Wavelet-based detection method

Figure 2 displays the illustration of the system model for wavelet-based sensing. From this system model, the continuous wavelet transform (CWT) of the signal is computed to determine the power spectral density in the wavelet-based sensing. By that, the spectrum occupancy can be determined by comparing the threshold with the edge.

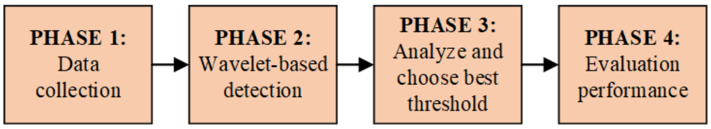

Figure 1. Phase of development and evaluation of wavelet detection

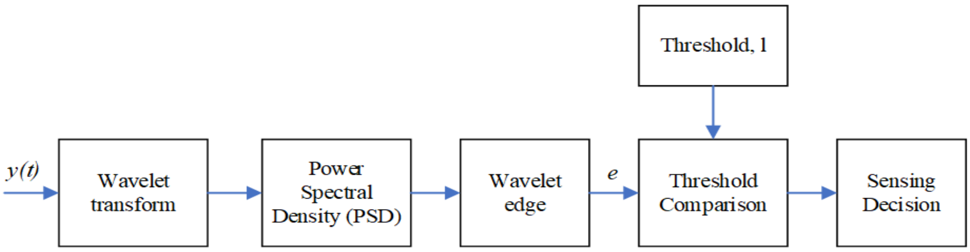

Figure 2. System model for wavelet-based sensing [18], [20]

2.1.1. Measure signal (*y*)

The *string* function is used to convert the string value, that containing measured data signal of 74320 samples with the frequency range of 2.43 GHz to 2.445 GHz, into an integer value. The data must be converted from Giga to integer since big data sets can be in the form of large files that take a long time to analyze or do not fit into the RAM that is available.

2.1.2. Wavelet transform

The mother wavelet $\psi(t)\epsilon L^2(R)$ is used in analyzing the function in wavelet transform. This function meets the allowable situation $C_w = \int_R^- |\psi(w)|^2 |w|^{-1} dw < +\infty$, where $\psi(w)$ is the Fourier transform of $\psi(t)$. In the CWT, the translation and dilation parameters, *a* and *b*, respectively, vary continuously. Therefore, CWT uses shifted and scaled copies of $\psi(t)$ [21]:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) \tag{1}$$

where $a, b \in R;\ a \neq 0$. Hence, CWT is defined as:

$$W_f(a,b) = \frac{1}{\sqrt{|a|}} \int f(t) \overline{\psi\left(\frac{t-b}{a}\right) dt} \tag{2}$$

2.1.3. Power spectral density

Before proceeding with part of the power spectral density, the inverse fast fourier transform (IFFT) needs to be done first. The IFFT can be seen as a transformation of a time domain signal into a frequency domain signal, where the magnitude and phase of the signal is preserved in the signal after transformation. Hence, the IFFT is one of the most important steps in power spectrum analysis. The sampling frequency, *fs*, that will be used for this project is 2.5 GHz, which is the maximum frequency. The sample time of this signal will be expressed with the (1) [22]. The sampling for the signal is important as the data of the signal consists of high-frequency components to prevent the loss of the information of the signal.

$$Sample\ time, t = \frac{1}{fs} \tag{3}$$

The power spectral density (PSD) is intended for utilization with continuous spectra. The integral of the PSD over a given frequency range is used to calculate the average power in the signal across that frequency range. The peaks in this spectrum, unlike the mean-squared spectrum, do not signify power at a particular frequency. In the absence of noise, the normalized power spectral density (PSD) for each subband is defined as [23]:

$$\int_{F_{i-1}}^{F_i} S_i(f)df = F_i - F_{i-1} \quad (4)$$

The observed signal *r(t)* for power spectral density is measured as follows:

$$S_r(f) \sum_{i=1}^{N} a_i^2 S_i(f) + S_w(f) \quad (5)$$

where a_i^2 is the PSD within i-th subband and $S_w(f)$ is the PSD's noise. Then, the PSD inside each subband is estimated after identifying $\{F_i\}_{n=1}^{N-1}$:

$$B_i = \frac{1}{F_i - F_{i-1}} \int_{F_{i-1}}^{F_i} S_r(f)df \quad (6)$$

2.1.4. Wavelet edge

Since the density of the power of any signal is represented by a single spike at the desired frequency, the wavelet edge is used to make judgments about sensing. The complexity of edge detection in a frequency-dependent image can be comparable to that of wideband spectrum sensing.

The smoothing function, *Φ(f)* is a continuous differentiable wavelet with a compact support, *m* vanishing moments, and *m* times. Based on the Lipschitz exponent, which measures the local regularity signal of importance, the strictly positive number *m* is chosen as in [24]. The representation of *(f)* dilation by scale factor *s* is given as [25]:

$$\Phi s(f) = 1s\Phi(fs) \quad (7)$$

when applied to dyadic scales, *s* takes values from powers of 2, as in *s* = *2j* where j = 1,2,3 and 4. The continuous wavelet transform (CWT) of *Sr(f)* is given in (5) where * denotes convolution *(f)* [25]:

$$WsSr(f) = Sr * \Phi s(f) \quad (8)$$

where $WsSr(f)$ is a representation of the correlation between the values of $Sr(f)$ for one scale and the dilated wavelet function [23]. By using the CWT, the first order and second order derivatives of $WsSr(f)$ smoothed by the scaled wavelet *Φs(f)* can be represented in (9) and (10) respectively [25]:

$$W_s^1 S_r(f) = s\frac{d}{df}(S_r * \Phi_s)(f) \quad (9)$$

$$W_s^2 S_r(f) = s^2\frac{d^2}{df^2}(S_r * \Phi_s)(f) \quad (10)$$

In fixed scales, the local maxima of wavelet modulus $W_s^1 S_r(f)$ which refers to *f*, correspond to zero-crossings of $W_s^2 S_r(f)$ and to inflection points for $S_r(f)$ [23]:

$$\widehat{F_n} = max\{|W_s^1 S_r(f)|\} \quad (11)$$

$$\widehat{F_n} = zeros\{W_s^2 S_r(f)\} \quad (12)$$

To examine edge detection and estimation, multiscale point-wise products of smoothed gradient estimators are formed. This method aims to reduce noise while enhancing multiscale peaks caused by edges.

$$U_J S_r(f) = \Pi_{j=1}^{J} W_{s=sj}^1 S_r(f) \quad (13)$$

To extract the boundaries of the investigated spectrum, $U_J S_r(f)$ is again subjected to the maximum extraction process.

$$\widehat{F_n} = max\{|U_J S_r(f)|\} \quad (14)$$

The most significant signal anomalies will pass through the final scale and be retrieved as maxima in the multiple-scale product scenario as opposed to single-scale segmentation.

2.1.5. Threshold

The wavelet transform is used in the threshold denoising approach to deconstruct the signal that has been contaminated by noise. As it relates to the wavelet coefficients, the thresholding function reflects different estimating techniques. The hard threshold, soft threshold, and improved threshold are the threshold functions that were used in signal denoising [9]. Those thresholds have the same concept, which is to eliminate small wavelet coefficients and reduce large wavelet coefficients. The hard thresholding function is represented as [23]:

$$\widehat{W'_{J,k}} = \begin{cases} W_{j,k}; & |W_{j,k}| \geq \lambda \\ 0; & |W_{j,k}| \geq \lambda \end{cases} \tag{15}$$

where λ is the threshold value, $W_{j,k}$ is wavelet coefficient and $\widehat{W'_{J,k}}$ is the new wavelet coefficient. The soft thresholding function is:

$$\widehat{W}'j,k = \begin{cases} sgn\,(W_{j,k})(|W_{j,k}| - \lambda); & |W_{j,k}| \geq \lambda \\ 0; & |W_{j,k}| < \lambda \end{cases} \tag{16}$$

The improved thresholding function is represented as [9]:

$$\widehat{W'}j,k = \begin{cases} W_{j,k} - \frac{2\lambda}{1+exp(\lambda - W_{j,k})} & W_{j,k} \geq \lambda \\ 0 & |W_{j,k}| < \lambda \\ W_{j,k} + \frac{2\lambda}{1+exp(\lambda + W_{j,k})} & W_{j,k} \leq -\lambda \end{cases} \tag{17}$$

In order to detect the spectrum hole, the threshold power needs to be identified first. From that, the average threshold power can be calculated and used to determine the threshold *y*, which is y_th. The y_th is the transpose of *y_abs* and must be greater than the average of threshold power. The base, bottom, and mini are determined based on the maximum, mean, and minimum value of *y_abs_transpose*, respectively. If the *y_abs_transpose(i)* is greater than the bottom, then it will be *W(i)=1*, indicating that the PU is present.

Otherwise, the PU is assumed to be absent (when the *W(i)=0*). The equation for the spectrum holes of the spectrum frequency is shown as:

$$Spectrum\ Hole = \frac{length\ PU\ absent}{length\ of\ frequency} \times 100 \tag{18}$$

2.1.6. ROC curves

The receiver operating characteristic (ROC) curve represents the detection performance and is used to evaluate different detection approaches. The shape and position of the curve's points can be analyzed to assess system performance and detection accuracy. The ROC curve plots the probability of detection (P_{DET})) against the probability of false alarm (P_{FA}), with both probabilities parameterized by the decision threshold (τ). It provides a mathematical representation of the fundamental detection problem, where the objective is to determine whether a measurement results from a signal or from noise and interference.

Based on this information, the corresponding probability of detection can be calculated as [26]:

$$P_{DET}(\tau) = \int_{r:D_1}^{\infty} P_r[D(\mu(k))|H_1 dD \tag{19}$$

with D_1 a partition (signals) of the measurement (decision) space, while H_1 is alternate signal hypothesis ("1"). The probability of false alarm is defined by:

$$P_{FA}(\tau) = \int_{r:D_1}^{\infty} P_r[D(\mu(k))|H_0 dD \tag{20}$$

where H_0 is refers to the non-signal/disturbance ("0").

2.2. Energy-based detection method

In the energy detection, the threshold determined by the noise is the only factor used to determine spectrum occupancy. The presence of the primary user is identified by comparing the threshold and perceived energy. Fundamentally, it attempts to distinguish between two states: first, if the primary user signal is not present it will indicate by H_O. The second state is when the primary user signal is present, it will indicate by H_1. The following hypotheses are tested by the energy detector [25]:

$$\begin{aligned} &H_O: Y(n) = W(n), && PU\ absent \\ &H_1: Y(n) = S(n) + W(n), && PU\ present \end{aligned} \tag{21}$$

where *Y(n)* is the signal received by the secondary user, *S(n)* is the signal transmitted by the primary user, and *W(n)* represents the additive white Gaussian noise (AWGN) with zero mean. In the energy detection process, the received signal is first pre-filtered by an ideal band-pass filter with bandwidth *W*. After filtering, the signal is converted to digital form using an A/D converter. The output of the converter is then squared and integrated over a specified period to obtain the test statistic. The equation for the test statistic is given in (22):

$$T = \sum_{n=0}^{N} |Y(n)|^2 \tag{22}$$

where $n = 0,1,2,3, \dots, N$ Represents the number of samples, which is known as the detection period. The central limit theorem states that the T test static distribution is a Gaussian distribution if *the* sample sizes are sufficient [27]. The binary hypothesis test is expressed as:

$$\begin{aligned} &H_O: T \sim Normal(N\sigma_n^2 + N2\sigma_s^4) \\ &H_1: T \sim Normal((\sigma_n^2 + \sigma_s^2), 2N(\sigma_n^2 + \sigma_s^2)^2) \end{aligned} \tag{23}$$

where σ_n^2 and σ_s^2 represent the noise variance and signal variance, respectively. To determine the presence of the primary signal, test statistic (*T*) is compared with the threshold (λ). Two parameters are used to evaluate the performance of energy detection methods: probability of detection, P_{DET} and probability of false alarm, P_{FA}. The corresponding equations are given as [28]:

$$P_{DET} = P\left(T > \frac{\lambda}{H_1}\right) = Q\left(\frac{\lambda - N(\sigma_n^2 + \sigma_s^2)}{\sqrt{2N(\sigma_n^2 + \sigma_s^2)}}\right) \tag{24}$$

$$P_{FA} = P\left(T > \frac{\lambda}{H_0}\right) = Q\left(\frac{\lambda - N\sigma_n^2}{\sqrt{2N\sigma_n^4}}\right) \tag{25}$$

3. RESULTS AND DISCUSSION

This section is divided into three parts: Part A, Part B, and Part C. Part A further discuss the results of spectrum hole detection using the wavelet transform. Part B analyzes the implementation of different threshold functions for signal denoising. The final part presents the performance comparison between wavelet detection and the energy detection method as an additional analysis.

3.1. Spectrum holes detection using wavelet detection

Figure 3 shows the result for the spectrum hole in the wavelet detection. There are two situations to indicate this graph. The first is the power will be 1 if there is the present of PU. If no PU is present, the value is 0. From this graph, the white spaces and blue spaces have been classified, where the spectrum holes are represented by the white spaces, and the presence of the PU is indicated by the blue spaces. According to this classification, the PU power signals are absent from the white spaces whereas they are heavily concentrated in the blue spaces.

3.2. Signal denoising using different thresholds

The traditional hard and soft thresholding functions are chosen in the experimental phase of the study because this study's main goal is to establish the threshold. In order to measure the denoising effect under different thresholds, the hard and soft thresholds are chosen as the thresholding function. For both traditional thresholds, the threshold value used is assumed to be 0.4 and 0.6. While for the improved threshold, the threshold value is set to above 1 [29]. Figure 4 illustrates the graph for the original signal based on the data that has been imported into the MATLAB. While for the improved threshold, the threshold value is set to above 1 [29].

When the hard and soft thresholds are selected, the denoising signal obtained by these thresholds is closer to the original signal compared when using the improved threshold. Even when different threshold values are used, there are no significant changes in the noisy signal. Figure 5 presents the result for signal denoising using the hard and soft threshold function.

When the improved threshold is executed as in Figure 6, it can be seen clearly that the denoising effect for noisy signals in this threshold performs better compared with the traditional thresholds. It means that noisy signal has been reduced, which has improved the denoise of the signal and preserved useful information. Besides, it solves the drawback of soft and hard threshold, where it can minimise the deviation between useful signal and denoised signal, and discontinuous throughout the whole wavelet domain [9]. This improved function clearly shows that it is more efficient to be used in the signal denoising in wavelet transform detection, as it has reduced more contaminated noise in the signal compared with another two threshold functions. From the results, it can be proved that the threshold function and denoising threshold value are the main parameters that impact the quality of noise removal as in [29].

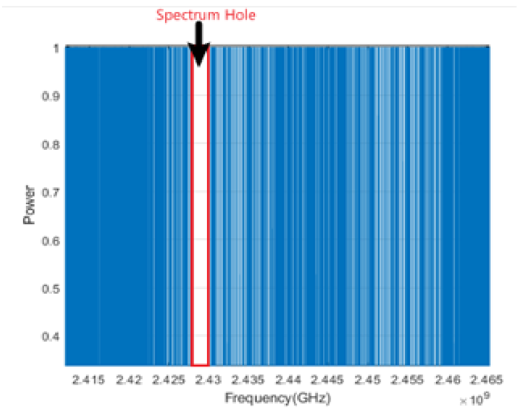

Figure 3. Spectrum holes detection

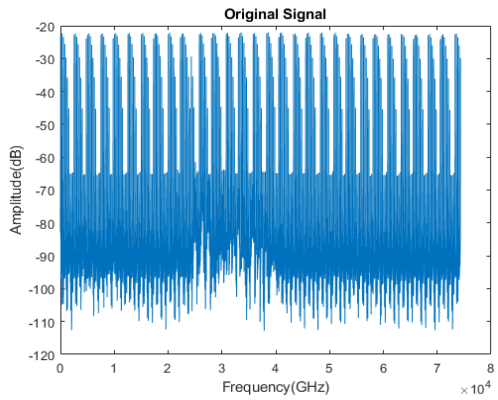

Figure 4. Original signal

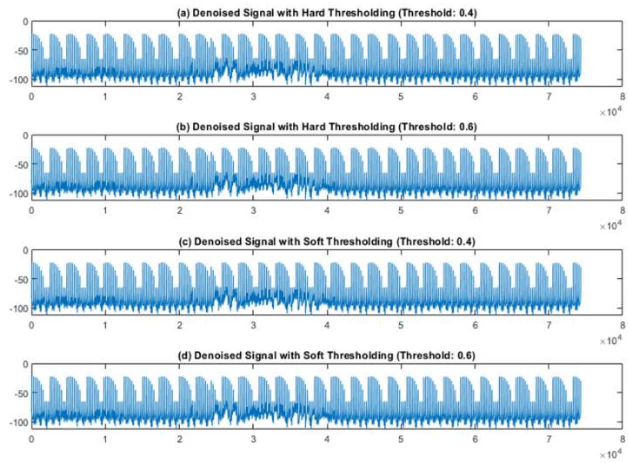

Figure 5. Signal denoise with soft threshold and hard threshold

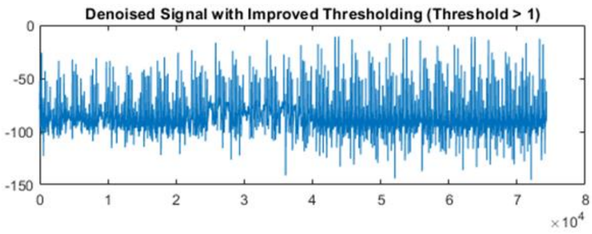

Figure 6. Signal denoise with improved threshold

3.3. Performance of wavelet detection with energy detection method

3.3.1. Wavelet detection technique

The wavelet detection and energy detection approaches have been used to determine the sensing performance of the proposed algorithm on different thresholds which indicates the value of SNRs that are being used in the signal denoising. The SNR values -20.2 dB, -21.5 dB and -22.8 dB respectively represented by the different threshold (improved threshold >1, threshold 0.6 and threshold 0.4).

Figure 7 shows the result for the performance of wavelet detection to compare the different proposed thresholds (threshold 0.4, threshold 0.6 and improved threshold). The P_{FA} is assumed to be 0.1. This is because when the probability of false alarm is smaller, the chances for spectrum utilization by SU will become higher [28]. As can be seen in Table 1, when $P_{FA} = 0.1$: improved threshold (-20.2 dB): $P_{DET} = 0.8227$; threshold 0.6 (-21.5 dB) = $P_{DET} = 0.6755$; threshold 0.4 (-22.8 dB) = $P_{DET} = 0.5618$. The performance of the wavelet detection depends on the SNR values from each threshold used [25]. According to this graph also can be analyzed that the probability of detection increases when the SNR threshold increases.

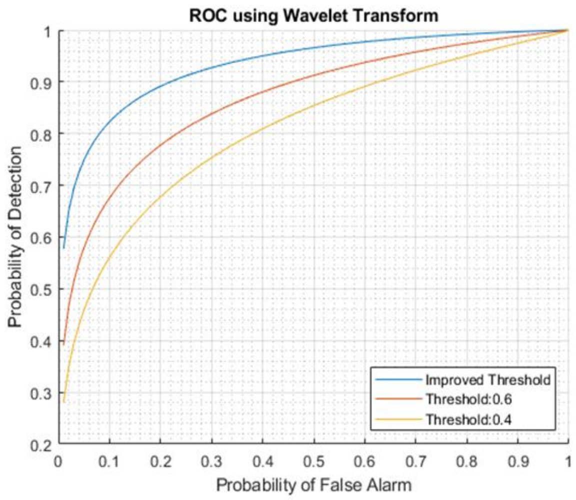

Figure 7. Performance of wavelet detection

Table 1. Performance of wavelet detection with different threshold

Threshold function	SNR value (dB)	Value of P_{DET} ($when\ P_{FA} = 0.1$)
Improved threshold (Threshold>1)	-20.2	0.8227
Soft threshold (Threshold:0.6)	-21.5	0.6775
Hard threshold (Threshold:0.4)	-22.8	0.5618

Based on [28], the probability of detection refers to the accuracy with which PU can be detected. As the probability of detection is higher, the more the PU is protected. Hence, it can be concluded that the improved threshold (-20.2 dB) has the best detection compared with the other thresholds, as it has the highest probability of detection values ($P_{DET} = 0.8227$) when the $P_{FA} = 0.1$.

3.3.2. Energy detection technique

This section discusses the analysis of the performance using the energy detection method. The performance detection using the energy detection method also depends on the SNR values at the different thresholds. using different SNRs from the threshold that being implemented. The same SNR values as mentioned in the wavelet detection technique are used for the different thresholds. Figure 8 shows the performance result by using the energy detection method.

Based on Table 2, the performance detection using the energy detection is highest at the improved threshold followed by the threshold 0.6. However, the value of P_{DET} by using the improved threshold in the wavelet detection technique shows the highest value compared with the energy detection method. This means that the performance detection by using the wavelet detection is better than the energy detection. The P_{DET} using threshold 0.4 shows the poor detection among of both methods as it recorded the smallest value of probability of detection.

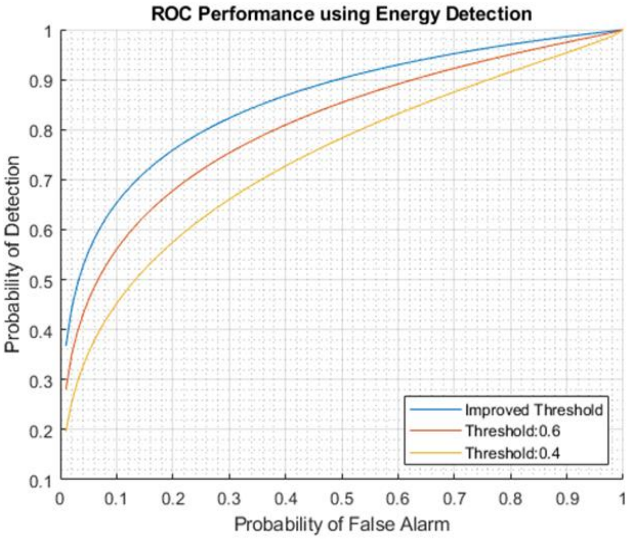

Figure 8. Performance of energy detection

Table 2. Performance of energy detection with different threshold

Threshold function	SNR value (dB)	Value of P_{DET} $(when\ P_{FA} = 0.1)$
Improved threshold (Threshold>1)	-20.2	0.6533
Soft threshold (Threshold:0.6)	-21.5	0.5605
Hard threshold (Threshold:0.4)	-22.8	0.4521

4. CONCLUSION

Generally, a cognitive radio network is a type of wireless communication where a transceiver can dynamically determine which channels are being used and not. The main concept of the cognitive radio network is to utilize the unused licensed spectrum, which is known as the spectrum holes. Spectrum sensing is the crucial element in the CR as it can avoid unwanted interference with authorized users and locate the available spectrum for better spectrum utilization.

The objective of this project has been achieved, where the location of the spectrum holes can be identified by using the wavelet detection method. This identification of the spectrum holes is important in CR as it increases the spectrum utilization by allowing the secondary user (SU) to strategically take advantage of spectrum voids. Next, improved threshold has shown the best results in denoising of noise in the signal compared with the soft threshold and hard threshold. From this result, it can be justified that the selection of threshold function is significant to reduce the contaminated noise in the signal, which can lead to better performance of spectrum sensing.

The wavelet-based detection achieved higher spectrum detection accuracy with the improved threshold ($P_{DET} = 0.8227$) compared to energy detection ($P_{DET} = 0.6533$). This demonstrates its effectiveness for cognitive radio networks and potential use in wireless communication, biomedical, geophysical, and military applications to enhance Quality of Service (QoS). However, this work is limited to MATLAB simulations and has not been tested on real hardware. Future research will implement the method on software-defined radio (SDR) platforms such as USRP and explore machine learning-based adaptive thresholding, as well as applications in 5G and 6G networks to further improve detection accuracy and spectrum efficiency.

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C : **C**onceptualization
M : **M**ethodology
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

This study did not involve human participants, personal data, or any individually identifiable information. Therefore, informed consent was not required. All experiments were conducted using hardware-based wireless communication measurement systems and complied with institutional research and ethical guidelines.

ETHICAL APPROVAL

Ethical approval was obtained for the conduct of this study. The research involved hardware-based wireless communication experiments using USRP platforms and did not include human participants, personal data, or animal testing.

DATA AVAILABILITY

The data supporting the findings of this study were obtained through experimental measurements using the USRP X300 platform and custom-developed signal acquisition scripts. The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

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