TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 21, No. 5, October 2023, pp. 968~974
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v21i5.24678

Wavelet-based sensing technique in cognitive radio network

Mas Haslinda Mohamad[1], Nurusolihah Zamri[1], Nor Khairiah Ibrahim[2]
[1]Center for Telecommunication Research and Innovation (CeTRI), Fakulti Kejuruteraan Elektronik dan Kejuruteraan Komputer (FKEKK), Universiti Teknikal Malaysia Melaka (UTeM), Melaka, Malaysia
[2]Advanced Telecommunication Technology Research Lab, Universiti Kuala Lumpur British Malaysian Institute, Selangor, Malaysia

Article Info

Article history:

Received Oct 11, 2022
Revised May 09, 2023
Accepted Jun 05, 2023

Keywords:

Cognitive radio
Empirical data
Spectrum holes
Spectrum sensing
Wavelet detection

ABSTRACT

Cognitive radio is a smart radio that can change its transmitter parameter based on interaction with the environment in which it operates. The demand for frequency spectrum is growing due to a big data issue as many Internet of Things (IoT) devices are in the network. Based on previous research, most frequency spectrum was used, but some spectrums were not used, called spectrum hole. Energy detection is one of the spectrum sensing methods that has been frequently used since it is easy to use and does not require license users to have any prior signal understanding. But this technique is incapable of detecting at low signal-to-noise ratio (SNR) levels. Therefore, the wavelet-based sensing is proposed to overcome this issue and detect spectrum holes. The main objective of this work is to evaluate the performance of wavelet-based sensing and compare it with the energy detection technique. The findings show that the percentage of detection in wavelet-based sensing is 83% higher than energy detection performance. This result indicates that the wavelet-based sensing has higher precision in detection and the interference towards primary user can be decreased.

Corresponding Author:

Mas Haslinda Mohamad
Center for Telecommunication Research and Innovation (CeTRI)
Fakulti Kejuruteraan Elektronik dan Kejuruteraan Komputer (FKEKK)
Universiti Teknikal Malaysia Melaka (UTeM), Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
Email: mashaslinda@utem.edu.my

1. INTRODUCTION

Spectrum frequency is a vital resource used by wireless network to communicate with other devices in the network. At any given time, a certain amount of spectrum frequency is available to be allocated by a wireless network. The high growth of the Internet of Things (IoT) devices and big data issues in the network increased the demand for the frequency spectrum. IoT users encounter connectivity issues when mobile and incur a hefty cost for licensed spectrum. Moreover, as the number of IoT users increases, the available spectrum frequency shrinks, and the network communication quality becomes degraded.

In contrast, most licenced bands, including amateur radio, paging, and television broadcasting, are underutilised [1], [2]. The demand for spectrum frequency also varies depending on the number of users and the usage time. In order to overcome these challenges, cognitive radio (CR) was proposed by Mitola in 1999 [3], [4] to address the issue of unused spectrum. CR is a radio that can adjust or change the parameters of its transmitter in response to communication with the operating environment. Primary users (PU) and secondary users (SU) spectrums are part of CR architectures, with PU being license holders and SU being unlicensed users.

Spectrum sensing is a vital process in CR, the first phase of the CR process. Spectrum sensing is a process of sensing the frequency spectrums and then identifying the spectrum holes [5], [6]. Energy detection is a frequently used method since it is easy to use and does not require license users to have any prior signal understanding. However, one of the major difficulties in implementing spectrum sensing is the structure of wireless channels, which makes it possible for interference elements like multipath and shadowing effects to existing [7]. The energy detection technique lacked accuracy in detecting edge energy in a network [8], [9]. An excessive amount of energy scattered at the edge of the network would hinder the performance of the network.

Wavelet-based sensing technique is proposed to overcome the current limitation in energy detection. This method differs from the others because it can work in frequency and time domains [10]. Wavelet transform (WT) in the wavelet-based sensing technique can overcome the issue of instantaneous changes in the time domain in the Fourier series. In the traditional approach, the Fourier transform is used to denoise the signal by splitting them into high-and low-frequency components, and the noise is eliminated by deleting the high-frequency component. The high-frequency portion of the signal is distorted because the method simultaneously eliminates both the disturbances and the high-frequency relevant information. This technique is unique due to its time-frequency properties since it can localise a signal in frequency and time by using scaling and wavelet functions [11], [12].

There are three ways that the wavelet approach is applied to spectrum sensing. This method includes the continuous wavelet technique, discrete wavelet, and discrete wavelet packet [12]. The main difference between both types of wavelet transform is that continuous wavelet transform (CWT) uses every wavelet over an infinite number of scales and locations. On the other hand, the discrete wavelet transform (DWT) only employs a small number of wavelets defined at a particular range of scales and locations [13]. A few WT detection technique that has been used by wideband spectrum sensing are including multiscale modulus maxima (WTMM), WT multiscale product (WTMP), and WT multiscale sum (WTMS). WTMM is used in this work due to its property to characterize of a signal at the edge and reduce noise [11].

In this paper, a spectrum scanning of the frequency range between 2.4 GHz to 2.48 GHz has been executed using universal software radio peripheral (USRP) N210. The experimental data are analysreed, and waveform-based sensing is performed to detect spectrum holes. Waveform-based sensing is chosen as a spectrum sensing technique in this work as it can improve the detection at higher average SNR [14], [15] and performs good performance in the multiresolution analysis of a signal even at low SNR [16]. This paper's main contribution is the proposed wavelet-based sensing model based on the empirical data obtained from the scanning spectrum. The finding of this work is then compared with the energy detection technique. The paper is organised as: section 2 explains a detailed research method and overview of formulating the wavelet-based sensing model, and section 3 discusses a result and analysis of the model is presented. Finally, section 4 concludes the outcome presents in this paper.

2. RESEARCH METHODOLOGY

This work involves three main phases: phase 1 is to analyse the measured data, phase 2 is to formulate the wavelet detection algorithm, and phase 3 is to evaluate the algorithm's performance. In phase 1, the measured data from USRP N210 is analysed. The data from the USRP testbed in [17] sense the spectrum in the frequency range between 2.4 GHz and 2.48 GHz. The USRP uses LabVIEW software to process and synthesise communications signals for transmission or reception. The parameter used is shown in Table 1. block diagram in Figure 1 shows the measurement and data collection process using LabVIEW.

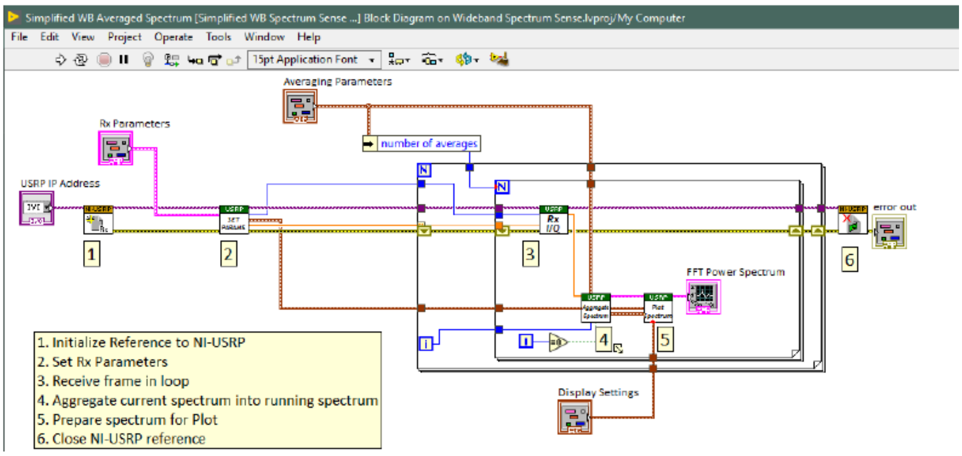


Figure 1. Block diagram of wideband spectrum sense in LabVIEW

Table 1. Parameter of USRP in LabVIEW software [17]

Parameter	Value
USRP IP address	192.168.10.2
Rate (s)	1 mega (M)
Acq duration (Hz)	1 mili (m)
Start carrier (Hz)	2.4 giga (G)
Stop carrier (Hz)	2.48 giga (G)
Gain (dB)	3

Then, phase 2 is executed based on the wavelet detection block diagram in Figure 2. The measured spectrum data from LabVIEW is the input, $y(t)$ of this block diagram. Wavelet detection is one of the spectrum sensing methods in the cognitive radio network that allows the identification of the spectrum frequency vacancies [18], [19]. From Figure 1, $y(t)$ is the sensed spectrum that will be converted to CWT, and $f(t)$ is the CWT function defined as [20].

$$W_f(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) g^* \left(\frac{t-b}{a}\right) dt \tag{1}$$

Where a is the scaling factor, b is the shift parameter same as τ in short time Fourier transform (STFT), and g is the window function. The power spectral density (PSD), $S_t(f)$ of CWT is used as the input to the wavelet edge. The PSD in spectrum band without noise can be defined as:

$$S_t(f) = \int_{F_{i-1}}^{F_i} S_i(f) df = F_i - F_{i-1} \tag{2}$$

Where F_i, $i = 1,2,3 \ldots. N$ represents frequency (Hz) in the sensed spectrum band. The continuous wavelet transform is defined as [21]:

$$W_f S_i(f) = S_i * \emptyset_a(f) \tag{3}$$

The value of $W_f S_i(f)$ measure a correlation between $S_i(f)$ and dilated wavelet function, $\emptyset_a(f)$ with the specific value of a. The dilation of wavelet function by scale a given as [22]:

$$\emptyset_a(f) = \frac{1}{a} * \emptyset(\frac{f}{a}) \tag{4}$$

The wavelet edge is considered while determining sensing decisions since a single spike in the signal represents the power density of a particular signal frequency, whereas multiple spikes represent the addition of noise. Wavelet transforms can also determine how smooth an edge is by looking at how they change over different scales. This gives detailed information about the intensity profiles of different types of edges in signals. The first-order or second-order derivatives of $W_f S_i(f)$ must be analysed as edges and irregularities in $S_i(f)$ are signified in the shapes of its derivatives:

$$W_f^1 S_i(f) = a \frac{d}{df} (S_i * \emptyset_a)(f) \tag{5}$$

$$W_f^2 S_i(f) = a^2 \frac{d^2}{df^2} (S_i * \emptyset_a)(f) \tag{6}$$

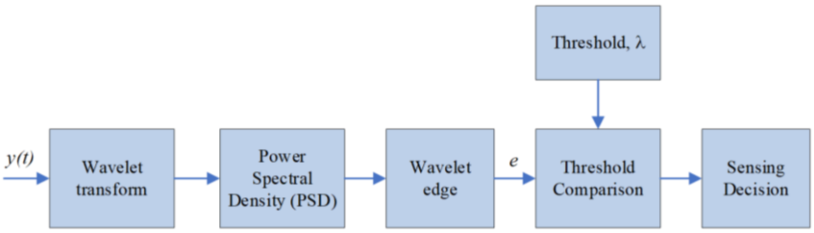


Figure 2. Wavelet detection block diagram [18], [23]

For fixed scales, the local maxima of wavelet modulus, $W_f^1 S_i(f)$ which refers to f, correspond to zero-crossings of $W_f^2 S_i(f)$ and inflexion points for $S_i(f)$ [24].

$$\widehat{F_n} = max\{|W_f^1 S_i(f)|\} \tag{7}$$

$$\widehat{F_n} = zeros\{|W_f^2 S_i(f)|\} \tag{8}$$

In order 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.

$$U_J S_i(f) = \pi_{j=1}^{J} W_{s=sj}^1 S_i(f) \tag{9}$$

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

$$\widehat{F_n} = max\{|U_J S_i(f)|\} \tag{10}$$

A key challenge in the wavelet threshold denoising method is determining the correct threshold. Threshold has a significant impact on the denoising effect. If the threshold value is too low, significant noise will remain, and if the threshold value is too high, some crucial aspect of the signal may be filtered out. There are numerous known ways of determining the threshold. Because of its simplicity and efficiency, the universal threshold is the most often used method among these. The universal threshold formula is written as [19]. Afterwards can analyse the two hypotheses, H_0 and H_1.

$$\lambda = \sigma\sqrt{2\,ln(N)} \tag{11}$$

Where σ is the average noise variance and N is the signal length. σ is computed using the median estimation approach. In order to compute the spectrum holes of spectrum frequency, the (12) is used [17]:

$$Spectrum\ Hole = \frac{length\ PU\ absent}{length\ of\ frequency} \times 100 \tag{12}$$

3. RESULTS AND DISCUSSION

Figure 3 shows the front panel of the wideband spectrum in LabVIEW software, where the spectrum of the received waveform is displayed as fast Fourier transform (FFT). The spectrum measurement has been done in the ISM band which is found in several devices such as peripherals, Wi-Fi, Bluetooth, microwave oven and home appliances which work in-between range 2.4 GHz to 2.48 GHz. These bands have been settled upon worldwide and unlike most other bands, they do not require a transmitting license to use.

Then, the dataset that has been imported in MATLAB is displayed in Figure 4. The spectrum displays in Figure 2 is in the Wi-Fi range from 2.43 GHz to 2.44 GHz with total number of samples obtained is 15010. These spectrums have been used throughout the wavelet detection technique.

Meanwhile, Figure 5(a) illustrates the PSD for all bands with an average power of 77.34 dB. The PSD is intended for utilisation 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 value of PSD is utilised to calculate the wavelet edge. The spike shown in Figure 5(b) represents the PSD without additional noise. The sensing decision is considered as PU present if the PSD exceeds the threshold value [25]. The detection results are shown in Table 2.

Figure 6 denotes the detection of the local maxima of $W_f^1 S_i(f)$ in dB. This detection identifies the boundaries of the frequency channel $\{F_i\}_{i=1}^{N-1}$. Table 2 shows that the wavelet detection achieved an 83.25% detection rate and 16.75% holes with a spectrum utilisation of 99.9%. Meanwhile, energy detection detected 43.56% of spectrum holes in the spectrum range.

Table 2. Spectrum sensing results in two techniques

Spectrum usage, N = 15010	Wavelet detection (%)	Energy detection (%)
Spectrum occupied by PU (%)	83.25	56.44
Spectrum holes (%)	16.75	43.56

Although wavelet detection is more complicated than energy detection, it gives better precision that provides higher accuracy, which is critical for CR functioning. CR functioning are include the detection of spectrum holes and avoid interference to PU. Wideband systems can also offer larger data rate communications than narrowband systems, which normally support lower data rate transmissions. The larger data rate will increase system capacity and then improve the network performance.

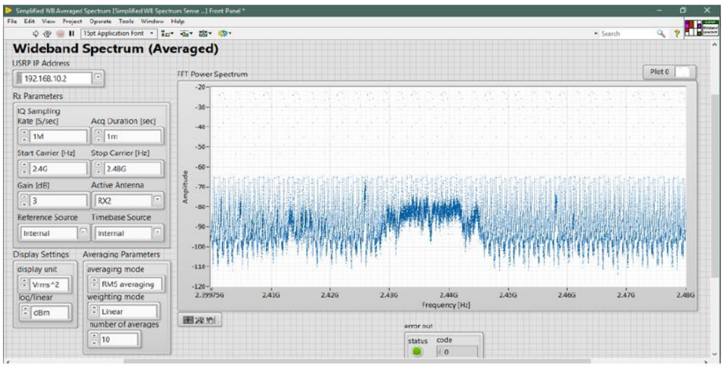


Figure 3. Front panel of wideband spectrum in LabVIEW software

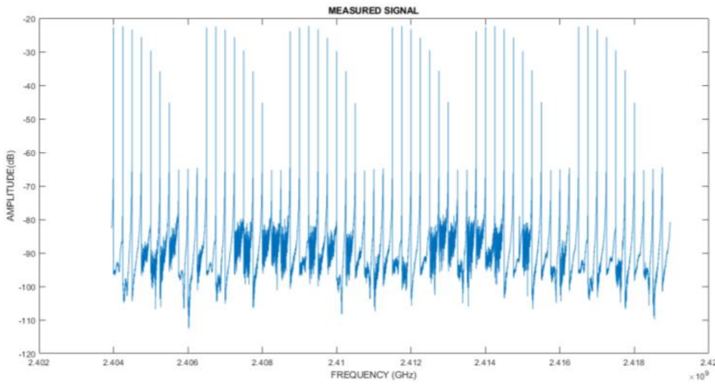
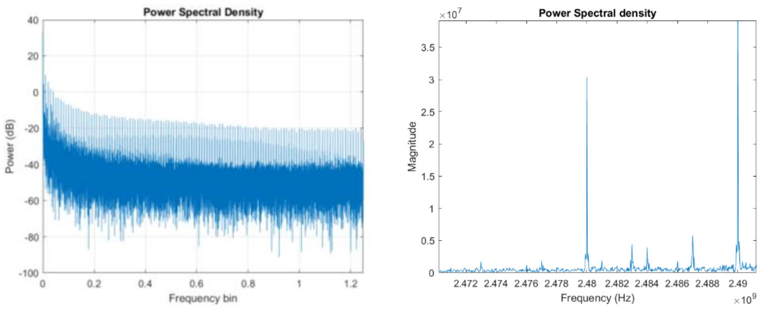


Figure 4. FFT signal plotted in MATLAB



(a) (b)

Figure 5. Power spectral density of signal: (a) PSD for all bands and (b) spike that represent PSD without additional noise

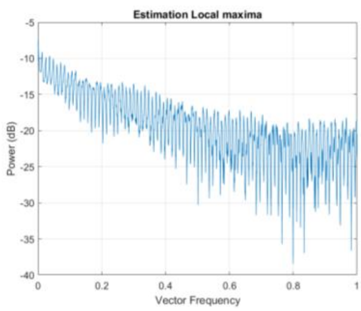


Figure 6. Estimation of local maximal

4. CONCLUSION

With the rising technology and IoT application, cognitive radio network is a critical aspect that needs to be focused on. Unused bandwidth or spectrum holes need to be eliminated to increase the efficiency of cognitive radio. In this project, wavelet-based sensing in cognitive radio is analysed to detect these spectrum holes. Simulation using the empirical data finding indicates that in the 2.43 GHz to 2.445 GHz range, 0.16% of spectrum holes have been detected. This is because the wavelet technique is intended for wideband spectrum sensing. Significant sample rates may be required to characterise the full wide bandwidth. It can also minimise spectrum scarcity by transmitting on the spectrum hole, preventing conflict with the primary license, and improving the quality of service (QoS). In conclusion, the status of the wavelet detection method is more suitable for CR implementation than energy detection.

ACKNOWLEDGEMENTS

The authors are grateful to the Centre for Research & Innovation Management (CRIM) and Universiti Teknikal Malaysia Melaka (UTeM) for the opportunity and support, including financial through relevant grants where applicable.

REFERENCES

[1] M. H. Mohamad and N. M. Sani, "Energy detection technique in cognitive radio System," *International Journal of Engineering and Technology*, vol. 13, no. 5, pp. 69-73, 2013. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.655.7983&rep=rep1&type=pdf

[2] B. Kumar, S. K. Dhurandher, and I. Woungang, "A survey of overlay and underlay paradigms in cognitive radio networks," *International Journal of Communication Systems*, vol. 31, no. 2, 2018, doi: 10.1002/dac.3443.

[3] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," in *IEEE Personal Communications*, vol. 6, no. 4, pp. 13-18, 1999, doi: 10.1109/98.788210.

[4] J. Mitola, "Cognitive radio for flexible mobile multimedia communications," *1999 IEEE International Workshop on Mobile Multimedia Communications*, 1999, pp. 3-10, doi: 10.1109/MOMUC.1999.819467.

[5] K. Kockaya and I. Develi, "Spectrum sensing in cognitive radio networks: threshold optimization and analysis," *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, no. 255, 2020, doi: 10.1186/s13638-020-01870-7.

[6] N. Goyal and S. Mathur, "Spectrum Sensing and Energy Efficiency Strategies in cognitive radio Networks-Perspective and Prospects," *International Journal of Applied Engineering Research*, vol. 13, no. 5, pp. 2395-2411, 2018. [Online]. Available: https://www.ripublication.com/ijaer18/ijaerv13n5_40.pdf

[7] M. E. Youssef, S. Nasim, S. Wasi, U. Khisal and A. Khan, "Efficient Cooperative Spectrum Detection in Cognitive Radio Systems Using Wavelet Fusion," *2018 International Conference on Computing, Electronic and Electrical Engineering (ICE Cube)*, 2018, pp. 1-6, doi: 10.1109/ICECUBE.2018.8610981.

[8] N. -S. Kim and J. M. Rabaey, "A Dual-Resolution Wavelet-Based Energy Detection Spectrum Sensing for UWB-Based Cognitive Radios," in *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 65, no. 7, pp. 2279-2292, 2018, doi: 10.1109/TCSI.2017.2781542.

[9] A. Kaur and K. Kumar, "A comprehensive survey on machine learning approaches for dynamic spectrum access in cognitive radio networks," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 34, no. 1, pp. 1–40, 2022, doi: 10.1080/0952813x.2020.1818291.

[10] L. Fugal, "Conceptual wavelets in digital signal processing: an in depth, practical approach for the non-mathematician," University of California: Space & Signals Technical Pub., 2009. [Online]. Available: https://books.google.co.id/books/about/Conceptual_Wavelets_in_Digital_Signal_Pr.html?id=IUFAAQAAIAAJ&redir_esc=y

[11] R. -M. Zhao and H. -M. Cui, "Improved threshold denoising method based on wavelet transform," *2015 7th International Conference on Modelling, Identification and Control (ICMIC)*, 2015, pp. 1-4, doi: 10.1109/ICMIC.2015.7409352.

[12] P. Y. Dibal, E. N. Onwuka, J. Agajo, and C.O. Alenoghena, "Application of wavelet transform in spectrum sensing for cognitive radio: A survey," *Physical Communication*, vol. 28, pp. 45-57, 2018, doi: 10.1016/j.phycom.2018.03.004.

[13] V. E. Jayanthi, P. M. Kumar, S. Sriram, M. Jagannath, D. Harshavarthanan, and K. Adalarasu, "Power Spectral Density for Detecting White Space in Wavelet Based Spectrum," *International Journal of Advanced Science and Technology*, vol 29, no 9s, pp. 7148–7153, [Online]. Available: https://www.researchgate.net/profile/Mohan-Kumar-24/publication/348550007_Power_Spectral_Density_for_Detecting_White_Space_in_Wavelet_Based_Spectrum/links/60033bb6458 51553a04c58c8/Power-Spectral-Density-for-Detecting-White-Space-in-Wavelet-Based-Spectrum.pdf

[14] S. V. R. K. Rao and G. Singh, "Wavelet Based Sepectrum Sensing Techniques in Cognitive Radio," *Procedia Engineering*, vol. 38, pp. 880-888, 2012, doi: 10.1016/j.proeng.2012.06.111.

[15] A. S. Kang, V. Sharma, and J. S. Singh, "Efficient Spectrum Sensing Using Discrete Wavelet Packet Transform Energy Detection in Cognitive Radio," *Advances in Wireless and Mobile Communications*, vol. 10, no 2, pp 193-212, 2017. [Online]. Available: https://www.ripublication.com/awmc17/awmcv10n2_02.pdf

[16] B. Rose and B. Arunadevi, "Multiscale Discrete Wavelet Transform based Efficient Energy Detection for Wideband Spectrum Sensing," *2022 2nd International Conference on Artificial Intelligence and Signal Processing (AISP)*, 2022, pp. 1-5, doi: 10.1109/AISP53593.2022.9760625.

[17] N. S. Hamdan, M. H. Mohamad, and A. Sali, "Sensing and analysis of spectrum holes in ISM band using USRP testbed," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 19, no 6, pp. 1761-1768, doi: 10.12928/telkomnika.v19i6.19888.

[18] F. Salahdine, "Spectrum sensing techniques for cognitive radio networks," *ArXiv*, 2017. [Online] Available: https://arxiv.org/abs/1710.02668

[19] C. He, J. Xing, J. Li, Q. Yang, and R. Wang, "A new wavelet threshold determination method considering interscale correlation in signal denoising," *Mathematical Problems in Engineering*, 2015. [Online]. Available: https://www.hindawi.com/journals/mpe/2015/280251/

[20] Z. He, *Wavelet analysis and transient signal processing applications for power systems*, John Wiley & Sons, 2016. [Online].

Available: https://www.wiley.com/en-ie/Wavelet+Analysis+and+Transient+Signal+Processing+Applications+for+Power+Systems-p-9781118977002.

[21] E. P. L. de Almeida, P. H. P. de Carvalho, P. A. B. Cordeiro, and R. D. Vieira, "Experimental study of a Wavelet-based spectrum sensing technique," *2008 42nd Asilomar Conference on Signals, Systems and Computers*, 2008, pp. 1552-1556, doi: 10.1109/ACSSC.2008.5074682.

[22] Z. Tian and G. B. Giannakis, "A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios," *2006 1st International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, 2006, pp. 1-5, doi: 10.1109/CROWNCOM.2006.363459.

[23] G. T. Bharathy, V. Rajendran, T. Tamilselvi and M. Meena, "A Study and Simulation of Spectrum Sensing Schemes for Cognitive Radio Networks," *2020 7th International Conference on Smart Structures and Systems (ICSSS)*, 2020, pp. 1-11, doi: 10.1109/ICSSS49621.2020.9202296.

[24] K. R. Arjun and T. P. Surekha, "Performance Analysis of Wavelet based Spectrum Sensing and Conventional Spectrum Sensing in Fading Environment for Cognitive Radios," *2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC)*, 2017, pp. 539-543, doi: 10.1109/CTCEEC.2017.8454971.

[25] K. D. Perumal, E. D. K. Ruby, M. Dhivya, G. A. A. Mary, V. Kavitha, and U. Kandasamy, "Experimental Analysis Using USRP for Novel Wavelet-Based Spectrum Sensing for 2.2 GHZ Band Communication Using LabVIEW," *Journal of Nanomaterials*, vol. 2022, doi: 10.1155/2022/4947224.

BIOGRAPHIES OF AUTHORS

Mas Haslinda Mohamad is currently a Senior Lecturer at Faculty of Electronic and Computer Engineering, Universiti Teknikal Malaysia Melaka (UTeM), Malaysia since May 2011. She obtained her PhD in Wireless Communication from Universiti Putra Malaysia in 2019. Her research interest includes cognitive radio, Internet of Thing (IoT), Long range communication (LoRa) and 5G. She can be contacted at email: mashaslinda@utem.edu.my.

Nurusolihah Zamri graduated her degree in Bachelor of Electronics Engineering Technology (Telecommunications) with Honours from Universiti Teknikal Malaysia Melaka (UTeM). She is presently pursuing a Master's degree at UTeM. She is interest studying in cognitive radio network, the Internet of Things, and 5G. She can be contacted at email: solihahz98@gmail.com.

Nor Khairiah Ibrahim received her BEng. in Electronic Engineering (Telecommunications) from University Teknologi Malaysia (UTM), Malaysia in 2003; MSc in Communications and Network Engineering from Universiti Putra Malaysia (UPM), Malaysia in 2009. She is a lecturer at Communications Technology, Universiti Kuala Lumpur British Malaysian Institute and currently pursuing her PhD in UPM under Wireless and Photonic Networks Research Centre of Excellence (WiPNet), Department of Computer and Communication Systems Engineering, Faculty of Engineering. Her current research interest includes cognitive radio networks, video coding and transmission, Internet of Thing (IoT) and 5G. She can be contacted at email: norkhairiah@unikl.edu.my.