Performance of Energy Detection Spectrum Sensing for Cognitive Radio Using GNU Radio

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***Abstract*—The increasing number of wireless communication applications has led to spectrum scarcity problems. On the other hand, the current system in allocating the spectrum frequency is inefficient. To mitigate this issue, a cognitive radio (CR) system is proposed. CR is a smart radio that is able to sense the environment, locate the spectrum holes, and adapt its transmission parameter to exploit the existing spectrum holes. This underlines the importance of the spectrum sensing module to enable the operation of the CR system. The objective of the spectrum sensing module is to achieve the best utility from the available spectrum frequency. CR system is implemented in the unlicensed secondary users allowed to rent the spectrum currently not used by primary users (PU). In this paper, energy-detection-based spectrum sensing is implemented on the GNU Radio platform. We first implement the power spectral density (PSD) estimation method based on the periodogram by exploiting the Embedded Python block facility on the GNU Radio. Next, we implement the spectrum sensing decision module in the GNU Radio, which compares the PSD estimate of the PU signals corrupted by noise with a threshold. The PU signal is simulated as a bandpass random process occupying a particular frequency band. The spectrum sensing decision module is developed to allow the computation of the probability of detection (PD) and the probability of false alarm (PFA), which is performed by exploiting the Embedded Python block. One indicator to evaluate the performance of the spectrum sensing module is the receiver operating characteristic curve based on the computed PD and PFA on the GNU Radio. We evaluate the performance of the spectrum sensing for different SNRs and thresholds. The result shows that the energy-detection-based spectrum sensing is able to locate the existence of the PU when the signal-to-noise ratio (SNR) is sufficiently high.**

***Keywords*—Cognitive Radio, Energy Detection, GNU Radio, Spectrum Sensing.**

I. INTRODUCTION

The rapid growth of wireless communication technology has been followed by the emergence of newer wireless applications. While two decades ago, wireless communication facilities were used to mainly support voice communication, they are currently employed to provide any possible form of multimedia communication. It has placed a much greater demand for a higher transmission rate as well as a better quality of service [1]. Since, in wireless communication systems, electromagnetic waves are transmitted using unguided media, the frequency spectra become extremely essential resources as one must ensure that the same frequency band is not allocated to different sources of signal without a clear regulation so that interference between signals can be avoided. It is obvious that the wider the frequency band, the larger the amount of data that can be transmitted within a certain duration of time. Unfortunately, the availability of frequency spectra is naturally limited [1]. This fact combined with the introduction of a large number of new wireless applications in the recent decade has led to a spectrum scarcity problem. The spectrum scarcity problem can be mitigated by optimizing the utility of the existing frequency spectrum. However, when the optimization is not carefully conducted, interference between signals from different users might occur leading to errors in the transmitted data and poor communication quality.

The conventional spectrum management policy and strategies are regulated by the government [2]. In general, frequency spectrum is allocated by the government only to licensed users. Unfortunately, the licensed frequency spectrum might not always be used efficiently. The Federal Communication Commission (FCC) reports indicated that the frequency spectrum utility ranges from 15% to 85% [3]. It implies that the current allocation of the frequency spectrum has led to inefficient and sporadic spectrum utilization [1], [4]. On the other hand, most of the frequency spectrum has been allocated, leading to difficulties in providing spectrum resources for new wireless services [5]. To overcome this spectrum scarcity problem, it is necessary to invent a new technique that is able to manage the allocation of spectrum resources efficiently [1], [6]. In other words, innovative approaches that can solve the spectrum scarcity problem are demanded.

In recent years, cognitive radio (CR) has been proposed as one possible solution for the spectrum scarcity problem. According to [7], a CR system is an intelligent radio communication system having the capability to alter its transmitter parameters based on its interactions with the surrounding environment. Extensive research has been conducted on CR and it covers a wide range of topics such as spectrum management [8], spectrum decision [9], CR-based internet of thing system [10], and spectrum sensing. In CR networks, the existing radio spectrum users are classified into primary users (PUs) or licensed users (LUs) and secondary users (SUs). A PU is a user that is granted a license by the government to occupy a particular frequency band as well as to transmit its signals in that band. Meanwhile, SU is a user that does not possess a license for any frequency band but is allowed to use the frequency spectrum possessed by the PUs when they are inactive [11]. In other words, the interference between the PUs and SUs transmitted signals should be minimal [2]. To help the SUs decide the existence of the PUs at particular

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[Received: 4 January 2022, Revised: 12 April 2022]

frequency bands, a spectrum sensing mechanism is required [12], [13].

Spectrum sensing techniques allow the unlicensed SUs to identify spectrum holes, which can be unlicensed spectra as well as licensed spectra that are currently not occupied by the PU possessing the license [9]. The existence of spectrum sensing techniques prevents the SU from transmitting signals in the frequency bands where the PUs are currently active. Some popular spectrum sensing methods include matched filter detection [14], cyclostationary feature detection [15], and energy detection [16]. Energy detection is the most popular approach because of its simplicity [17], [18]. The energy detection approach generally does not require any information about PU parameters though it still requires information related to the noise. Hence, energy detection is classified as a semi-blind method [19]. Consequently, the energy detection approach has a low complexity level. In the energy detection approach, the decision on the existence of a PU in a particular frequency band is obtained by comparing the energy of the received signal in that band with a threshold.

Since the development of CR systems can be very complex, the existence of a platform that can simulate important aspects of the CR system before CR systems are designed and developed can be very beneficial. In this paper, the energy-detection-based spectrum sensing approach for CR applications was simulated using the GNU Radio open-source program. GNU Radio allows a signal processing block to be simulated on a software-defined radio [20]. GNU Radio can simulate a radio system before the hardware implementation. If it is required, GNU Radio can also be used together with inexpensive external hardware to implement a radio system. GNU Radio has a large number of signal processing block library that can be used to perform specific functions [4]. GNU Radio also provided facility to design a functional block, which was a spectrum sensing block in this research's case, by employing the existing signal processing block library.

Several researches have evaluated the energy-detection-based spectrum sensing approach simulated using a GNU Radio [16], [18], [20], [21]. In this paper, a spectrum sensing decision block that compares the energy of a signal and the threshold was built. In addition, blocks whose function is to calculate the probability of detection (PD) and the probability of false alarm (PFA) were also built. The resulting receiver operating characteristic (ROC) curve produced by collecting the calculated PD and PFA was presented using MATLAB.

II. COGNITIVE RADIO AND SPECTRUM SENSING

It is well-known that the data transmission rate is proportional to the transmission bandwidth. However, the demand for a higher transmission rate in wireless communication systems might conflict with the aforementioned spectrum scarcity problem, which is caused by inadequate spectrum allocation techniques [12]. The conventional spectrum allocation approach, which allows LUs or PUs to occupy a particular frequency band, has resulted in limited but underutilized spectral resources [13]. This old-fashioned spectrum allocation approach is not able to cope with an ever-increasing demand for new high-speed wireless communication applications.

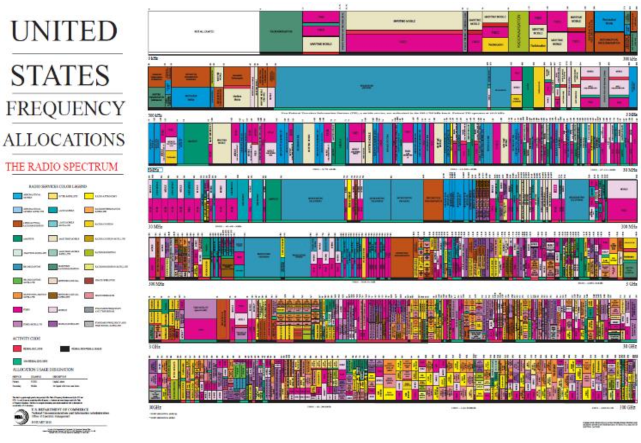


Fig. 1 United States frequency allocations [22].

To underline the aforementioned spectrum allocation issue, the recent report about frequency allocation by the National Telecommunication and Information Administration (NTIA) is presented in Fig. 1. It can be observed that most of the licensed frequency has been allocated for several services [22] leading to difficulties in allocating frequency spectrum for new wireless applications, which continue to emerge due to the innovation in wireless communication technology [12]. On the other hand, PUs do not always use their licensed frequency. It is exactly where the aforementioned CR approach can play a role as a more innovative spectrum allocation approach is required to solve the current inefficient use of spectrum leading to an increased number of available spectra that can be allocated for new wireless applications.

The concept of CR was initially proposed by Joseph Mitola III at the end of the 20th century [23]. In [2], CR is defined as a wireless communication system that possesses intelligence and awareness about the surrounding neighborhood, builds knowledge about its environment, and adapts itself to changes in the received signal by modifying its communication parameters in order to ensure very high reliability in communication process on one hand and improve efficiency in spectrum utilization on the other hand. Apart from the aforementioned properties possessed by CR, it is also mentioned in [2] that CR should also offer reconfigurability.

In [3], CR is defined as an intelligent radio system that can interact with its environment and can alter its transmitter parameters based on its environment. Based on this definition, two main characteristics of CR can be summarized, i.e., cognitive capability and reconfigurability [3]. Cognitive capability is the capacity of CR to collect information from its environment leading to a complete knowledge of the current state of spectrum usage [3]. Reconfigurability refers to the possibility of dynamically programming CR based on changes in the surrounding environment, which also implies that the CR system is able to transmit and receive information at different frequencies [3].

In CR networks, an LU or PU possesses a license on a particular frequency spectrum, hence, they have a higher priority to use the corresponding frequency band. Only when this frequency band is not occupied by the PU (due to its inactivity), an SU can commence transmitting its signal in that band. It implies that the SU should able to gauge whether the PU is active or not at a particular time. In other words, the SU should have a CR capability. There are several functionalities that should exist in a CR network, which include spectrum sensing, spectrum management, spectrum mobility, and spectrum sharing [3]. It has been obvious from the previous section that spectrum sensing plays a vital role in a CR network [1] as it provides SU with the capability to determine the presence of PU in a licensed frequency.

As indicated in the previous section, the main purpose of spectrum sensing in the CR network is to conclude the presence of PU at a particular frequency band. It helps the SU to decide whether it can transmit its signal at that band or not without interfering with the PU signals [24]. Applying spectrum sensing on a CR system is preferred because it requires a simpler infrastructure and can be easily accommodated in a wide range of applications [6]. In the CR system, spectrum sensing aims for identifying the characteristics of spectrum utilization not only in the perspective of the frequency domain but also in the perspective of the spatial and temporal domain [6]. If necessary, the spectrum sensing module can also be configured in order to determine the type of signals that is currently occupying a particular frequency band and their parameters e.g., bandwidth, carrier frequency, modulation technique, and type of waveform [1].

Fig. 2 gives an illustration of the CR system sensing the frequency spectrum to locate spectrum holes in the frequency domain. Spectrum holes correspond to frequency bands that are currently not being used by PUs or that are not allocated to any PUs. The existence of spectrum holes identified by the spectrum sensing process is identical to the absence of any PUs or other active users in the corresponding frequency band. In order to decide on the absence of PU (or, equivalently, the spectrum holes) in a particular frequency band, the spectrum sensing module needs to estimate the power of the signal measured in that band, the measured noise level, and the measured interference levels. Spectrum holes can be classified into two categories. The first one is the spatial hole which refers to a frequency band that is not allocated to any PUs. This implies that an SU is immediately allowed to occupy the spatial spectrum holes as long as they are not occupied by other SUs. Another type is the temporal spectrum hole which refers to a frequency band that is allocated to a PU but the PU is currently inactive in that band. When it exists, the temporal spectrum hole can be occupied by an SU [25]. However, the SU is required to continuously sense this temporal hole during its signal transmission in this spectrum hole to identify if the PU possessing this band is suddenly active. When this is the case, the SU must relinquish this spectrum hole and stop its signal transmission. Based on the number of SUs and the existence of cooperation in spectrum sensing among them, spectrum sensing can also be classified into noncooperative sensing and cooperative sensing. Examples of cooperative spectrum sensing can be found in [26]‒[28].

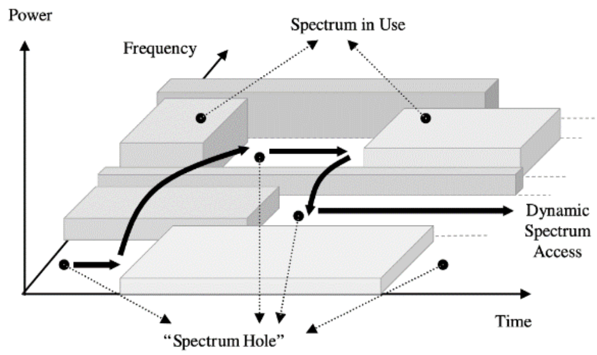


Fig. 2 Spectrum hole [3].

III. GNU RADIO

An open-source software tool called GNU Radio can be used to establish a software-defined radio. It consists of several blocks of signal processing library that can be combined to perform particular functions with a certain objective [16]. During the experiment, the implementation and design of a radio system using GNU Radio can minimize the cost especially due to its ability to operate with inexpensive radio frequency hardware by using software-defined radio. In addition, GNU Radio can also simulate radio systems without any hardware implementation [29]. Moreover, a new signal processing block having a specific function can easily be formed in GNU Radio. GNU Radio has been employed in many research in the field of wireless communication and radio systems conducted by industry, government, and academics.

In the GNU Radio application, there are several data types that can be used, as illustrated in Fig. 3. Different colors in Fig. 3 represent different data types. It should be noted that several blocks can only process input with a particular data type. As a result, in this research, additional blocks for data type conversion were employed in order to ensure that the type of the input was compatible with a particular signal processing block. The example is an Add block producing output with the data stream type. When this output is going to be processed as an input of the fast Fourier transform (FFT) block, it needs to be converted into a vector data type since the FFT block can only process input in this form.

IV. SYSTEM MODEL

The energy detection method is widely adopted as a spectrum sensing method for CR applications thanks to its low complexity, which is mainly caused by the fact that this method does not require any previous information on PU. While energy detection can generally be used in both cooperative and noncooperative frameworks, [3] categorizes energy detection into noncooperative detection as this method can be used by a single CR system to decide the existence of PU without cooperating with other CR systems. Energy detection is considered an optimal detector when the receiver could detect PU without information on PU [3]. Energy detection can be considered semi-blind sensing because the energy-detection-based spectrum sensing only requires the information of the power of the random noise.

Energy-detection-based spectrum sensing decides the presence of PU in a certain frequency band by comparing the energy of the received signal with the threshold. Energy-detection-based spectrum sensing generally decides between two binary hypotheses as shown in the following equation.

$$y(t) = \begin{cases} w(t), & H_0 \\ s(t) + w(t), & H_1 \end{cases} \quad (1)$$

where $y(t)$ is the measured received signal, $w(t)$ is the contribution of the additive white Gaussian noise (AWGN), and $s(t)$ is the contribution from the signal transmitted by the PU. Both hypotheses represent the binary state of the received signal on a particular frequency band. H_0 is the null hypothesis, which indicates that the PU is absent in a certain frequency band; meanwhile, H_1 is the alternative hypothesis, which indicates that PU is present in that band. If $y(t)$ is sampled, its digital representation $y[n]$ can be written as follows.

$$y[n] = \begin{cases} w[n], & H_0 \\ s[n] + w[n], & H_1 \end{cases} \quad (2)$$

with $n = 1, 2, 3, \ldots, N$, where N is the number of digital samples collected during the observation period and n indicates the sample index. In the energy detection method, the energy of the received signal during a sensing period is calculated to obtain the test statistic of energy. The decision on the existence of PU is then obtained by comparing the test statistic of the energy of the signal with threshold τ. The test statistic for energy detection is given by (3).

$$\Lambda = \sum_{n=1}^{N} |y[n]|^2 \quad (3)$$

where Λ is the test statistic of the received signal and $|y[n]|^2$ is the squared magnitude of the sample $y[n]$. As the spectrum sensing process was conducted using a digital signal processor, the quantization process was applied during the sampling process, which might lead to quantization errors. In the energy detection method, the energy of the received signal $y[n]$ is normalized in order to reduce the noise variance and minimize the quantization errors. The normalized test statistic Λ was then given by (4).

$$\Lambda = \frac{1}{N} \sum_{n=1}^{N} |y[n]|^2. \quad (4)$$

Instead of performing (4), it is also possible to first compute the periodogram as an estimate of the power spectral density (PSD) of the received signal, which can be written as in (4a) [30].

$$P_y(j\omega) = \frac{1}{N} \left| \sum_{n=1}^{N} y[n] e^{-j\omega n} \right|^2 \quad (4a)$$

where $P_y(j\omega)$ represents the periodogram, which is computed by involving the application of discrete-time Fourier transform (DTFT) on the received digital samples $y[n]$. In practice, the periodogram was implemented by replacing the DTFT operation in (4a) with discrete Fourier transform (DFT) using the FFT algorithm. Fig. 4 illustrates the implementation of the energy detection method applied on the periodogram which is implemented using FFT. Here, the squared magnitude of the FFT at M adjacent frequency bins is averaged. The detection of

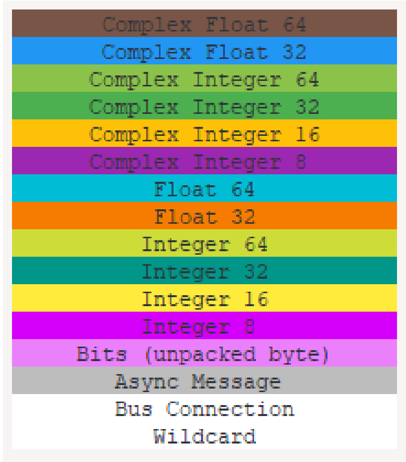


Fig. 3 Types of data on GNU Radio.

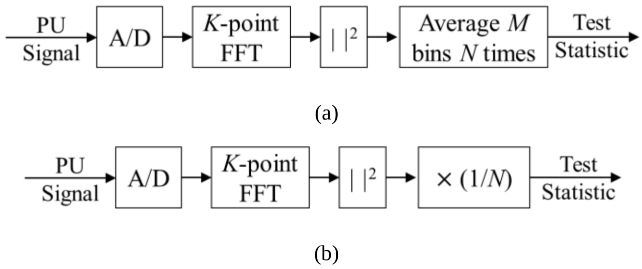


Fig. 4 Periodogram-based energy detection implemented as the spectrum sensing approach in, (a) previous research [12] and (b) this research.

PU based on periodogram-based energy detection is quite popular thanks to its low complexity and computational cost. In summary, in periodogram-based energy detection, the energy is measured at different frequency points.

In this research, energy detection was also applied to the computed periodogram. However, the spectrum sensing method based on the periodogram-based energy detection that was implemented in this research did not follow the procedure illustrated in Fig. 4(a), but the procedure illustrated in Fig. 4(b). In summary, the result of the squared magnitude of the FFT at adjacent frequency points was not averaged. Instead, the squared magnitude at an individual frequency point was directly used as the test statistics to evaluate the existence of the PU at that frequency point. Λ_f is considered as the test statistic in Fig. 4(b), corresponding to the normalized squared magnitude of the periodogram measured at the frequency f. A particular threshold τ was then applied to the test statistic Λ_f. If the test statistics Λ_f is higher than the threshold τ, it is concluded that a PU is present at frequency point f (the alternative hypothesis H_1 is true). On the other hand, if the test statistic Λ_f is lower than the threshold τ, it is assumed that no PU exists at frequency point f and the null hypothesis H_0 is correct. This is summarized as follows.

$$\begin{matrix} \Lambda_f < \tau, & H_0 \\ \Lambda_f > \tau, & H_1 \end{matrix}. \quad (5)$$

The performance of the energy-detection-based spectrum sensing method for CR is presented in terms of its ROC curve, which was computed by varying the value of the threshold. In general, the application of the binary hypothesis testing in (5) might result in one of the following events.

- True positive, which is defined as the declaration that the PU is present when H_1 is correct. It defines the value of the probability of detection (PD), which is $P(H_1|H_1)$.
- True negative, which is defined as the declaration that the PU is absent when H_0 is true. It also defines the value of the PD, which is $P(H_0|H_0)$.
- False positive, which is defined as the declaration that the PU is present when H_0 is correct. It defines the value of the probability of false alarm (PFA), which is $P(H_1|H_0)$.
- False negative, which is defined as the declaration that the PU is absent when H_1 is true. It defines the value of the probability of missed detection (PM), which is $P(H_0|H_1)$.

A high value of PD is an indication of a good quality of sensing process, implying that the SUs has a very decent chance of correctly detecting the presence and absence of PUs. On the other hand, a high value of PFA and PM indicates poor quality of the spectrum sensing process. The false alarm event (which incorrectly decides that the PU is present while it is absent) prevents the SU from exploiting the existing spectrum hole leading to inefficient spectrum utilization. The miss detection event (which incorrectly decides that the PU is absent while it is present) leads to an interference between the PU and SU signals because the decision misleads the SU so that the SU is not aware of the presence of PU at the considered frequency band and transmits its signals in that band. It is obvious that the spectrum sensing process should result in a good detection performance which is indicated by a low value of PFA and PM and a high value of PD. This performance can be examined by evaluating the resulting ROC curve.

In this research, GNU Radio was employed to simulate the energy-detection-based spectrum sensing approach illustrated in Fig. 4(a). The PU signal in simulation study was generated by filtering an AWGN, where the passband of the filter was configured to simulate the case where the PU occupied the frequency band corresponding to that passband. In this way, it was possible to simulate different PU signals occupying any frequency bands with different values of power. To evaluate the performance of the simulated spectrum sensing approach, two different frequency bands were examined to calculate PD and PFA. The energy detection method was applied to the frequency band occupied by PU to evaluate PD. On the other hand, PFA was evaluated by applying the energy detection on the frequency band where only noise was present.

V. EXPERIMENTAL SCENARIO

This section discusses the simulation of the energy-detection-based spectrum sensing approach in Fig. 4(a) using GNU Radio. The scenario employed in the simulation process is also discussed. The simulation of energy-detection-based spectrum sensing in the GNU Radio consists of four main sections, which are illustrated in the block diagram in Fig. 5. Every block or section performs a specific function, and they are explained in the following subsections.

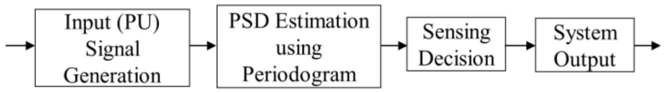


Fig. 5 Four main sections in the energy-detection-based spectrum sensing approach simulated in the GNU Radio.

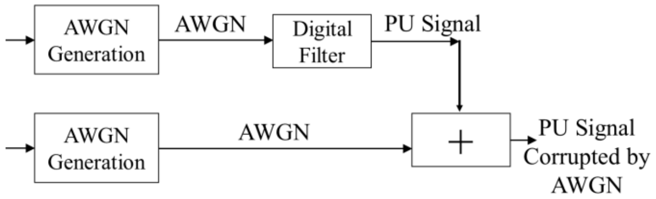


Fig. 6 The generation of PU signal corrupted by AWGN, which becomes the input of the simulated energy-detection-based spectrum sensing block.

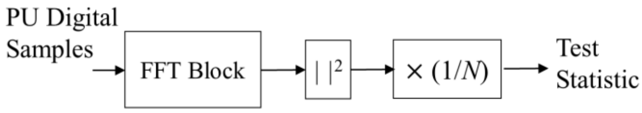


Fig. 7 Illustration of the PSD estimation that was simulated in GNU Radio.

A. PU Signal Generation

The first step in the simulation of energy-detection-based spectrum sensing in GNU Radio was the generation of the PU signals in the form of digital samples, which is illustrated in Fig. 6. The PU signals played a role as one of the inputs for the energy-detection-based spectrum sensing block simulated in the GNU Radio. As illustrated in Fig. 6, two digital signals were generated for this simulation. Two Noise Source blocks that already existed in the GNU Radio platform were used to generate these signals. The first digital signal was the AWGN and the second was the PU signal. The AWGN could be generated by setting the parameter of the noise distribution in the Noise Source block to Gaussian. The PU signal was obtained by first generating another AWGN that was then passed into a digital filter with the passband of the filter was set to a particular frequency band. This particular frequency band was nothing but the band that was occupied by the PU in the simulation scenario. The term "white" in AWGN implies that the AWGN possesses uniform power across all the frequencies. The filtered AWGN thus would have power only at the frequencies corresponding to the passband of the filter. Once both the first AWGN signal and the PU signal were generated, the first AWGN signal was then added to the PU signal to simulate a PU signal that was corrupted by the AWGN. This PU signal corrupted by the AWGN played a role as an input for the energy-detection-based spectrum sensing block simulated in the GNU Radio.

B. PSD Estimation

Variable $y[n]$ in (4a) was assumed to represent the received PU signal corrupted by AWGN shown in Fig. 6. Subsequently, the estimation of PSD of $y[n]$ was conducted by first applying the FFT (using the FFT block in GNU Radio) on $y[n]$. The next step was to compute the squared magnitude of the result of the FFT process, representing the squared magnitude of the spectrum of $y[n]$ at different frequencies. The test statistic at

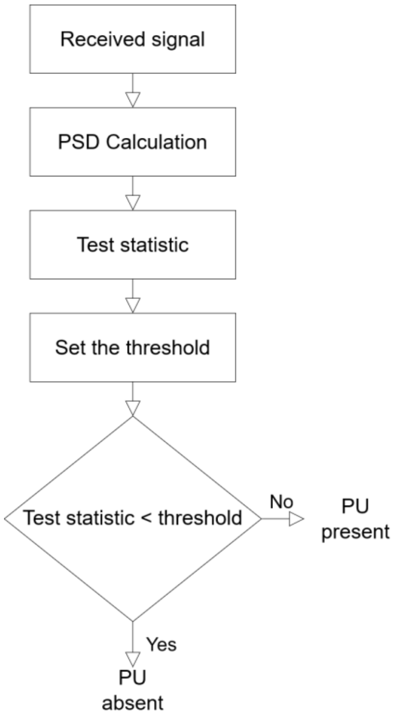


Fig. 8 Block diagram illustrating the sensing decision process.

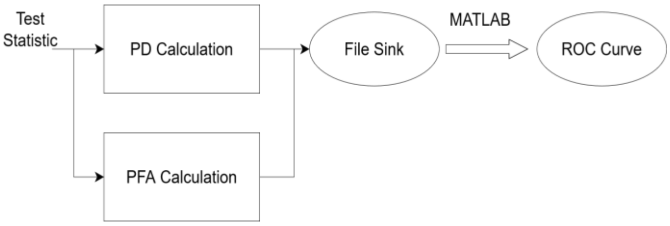


Fig. 9 PD and PFA calculation followed by the ROC presentation.

different frequency points was then obtained by normalizing the squared magnitude of the spectrum by the number of digital samples *N*. This normalization was performed by using the Fast Multiply Constant block in the GNU Radio. Note that the PSD estimation that was simulated in the GNU Radio is nothing but the periodogram method. Fig. 7 presents the PSD estimation process simulated in the GNU Radio.

C. Sensing Decision

Sensing decision is the evaluation product of the test statistic, which is derived from the results of PSD estimate produced in the previous subsection (subsection B). By solving the binary hypothesis problem formulated in (5), the sensing decision was performed on individual frequency points to decide whether a PU existed at a particular frequency point or not. The block diagram illustrating the sensing decision process is shown in Fig. 8. As shown in Fig. 8, the null hypothesis H_0 was selected whenever the test statistic was lower than the threshold, otherwise H_1 was preferred. This process was applied to all the test statistics at different frequency points as indicated in (5).

The output of the sensing decision is presented in QT GUI Vector Sink in the form of a plot of indication of (primary) user existence metric. When the value of the test statistic was greater than the threshold for a particular frequency point, the value of

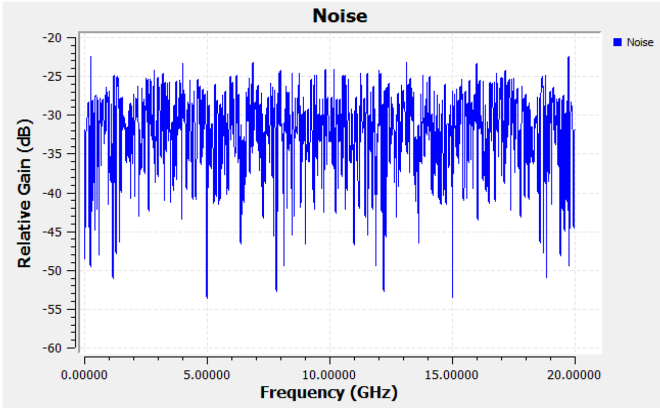


Fig. 10 Noise is displayed with QT GUI Frequency Sink.

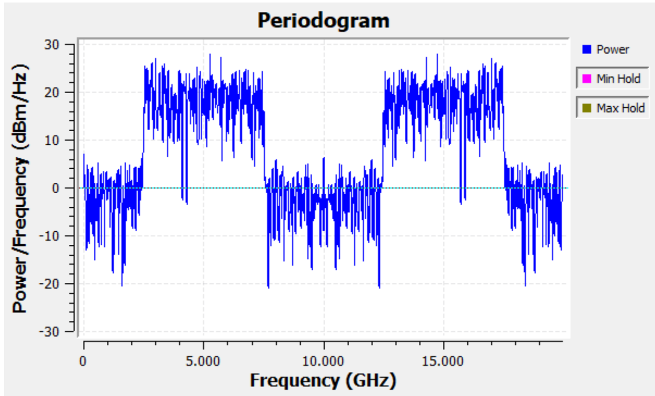


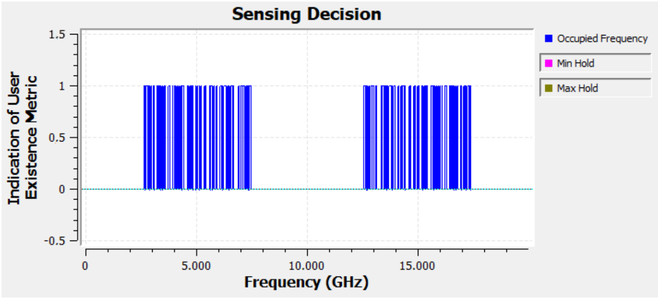
Fig. 11 The output of the PSD estimation of corrupted PU Signals displayed using the QT GUI Vector Sink.

the indication of the user existence metric is set to 1. Otherwise, it is set to 0. The evaluation of the test statistics for different frequency points was performed multiple times for different realizations of PU signals and noise. By varying the threshold values, the PD and PFA could be calculated for each threshold value and the ROC curve could be computed.

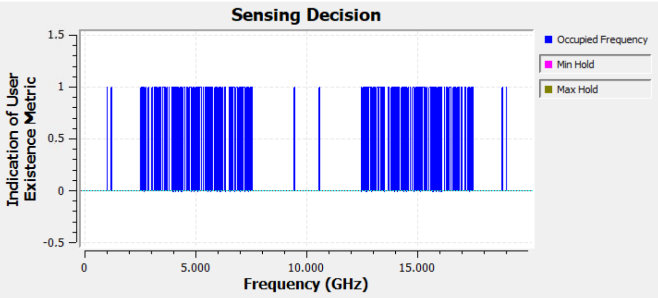
D. Spectrum Sensing Result

The PD and PFA calculations are based on the events when the threshold value is exceeded by the value of the statistical tests. The detection events that contribute to the PD calculation were evaluated on the frequency bands assigned to the PUs (which were the passband of the digital filter applied to the AWGN noise to generate the PU signals). On the other hand, the false alarm events contributing to PFA computation were evaluated on frequency bands other than the ones assigned to the PUs. The total number of detection events and that of false alarm events at different frequency points were then divided by the number of experiments and the number of frequency points of interest leading to the PD and PFA, respectively.

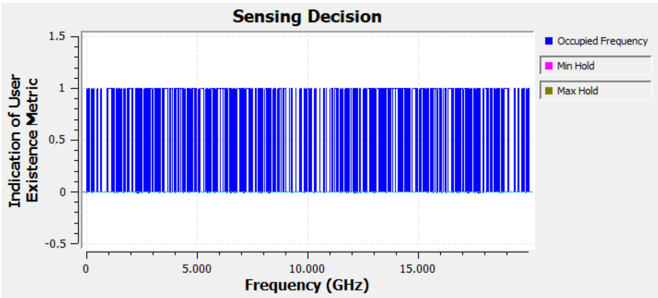
The results of sensing decisions and PD and PFA calculations were displayed with the Sink block in the GNU Radio. Fig. 9 illustrates the procedure for producing an ROC plot based on the results of PD and PFA calculations. The results of the sensing decisions can be observed with the QT GUI Vector Sink. The results of the PD and PFA calculations were then saved using the File Sink block in the form of a



(a)



(b)



(c)

Fig. 12 The PU power at its frequency band set to 100 mW while the noise variance is set to (a) 1 mW, (b) 25 mW, and (c) 100 mW.

binary file. In order to read this binary file and produce the ROC curve, MATLAB software was used by employing the fopen() syntax. The ROC curve (which was the plot of PD versus PFA for different thresholds) was then displayed using the MATLAB platform. This procedure is illustrated in Fig. 9.

VI. RESULTS

This section evaluates the simulation of the energy-detection-based spectrum sensing in the GNU Radio platform and discusses its detection performance for a particular scenario. The analysis of the detection performance for that scenario was conducted by considering the resulting ROC plot.

As mentioned in Section V, two realizations of AWGN using the Noise Source block in the GNU Radio platform were generated first. The first realization was used to simulate the existence of the additive noise in the CR receiver. Fig. 10 illustrates the representation of AWGN in the frequency domain displayed on GNU Radio using the QT GUI Frequency Sink. The AWGN was generated with the noise variance of 1 mW according to the Gaussian distribution. As previously described, the AWGN contaminated the PU signals, which

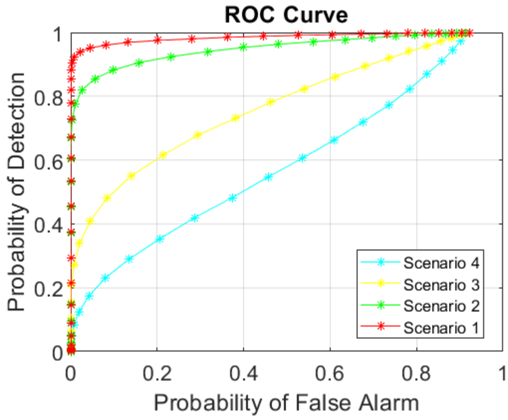


Fig. 13 ROC curve of the energy detection process.

TABLE I
DETECTION PERFORMANCE SCENARIOS

Scenario	Relative PU's Signal Power to Noise Power at the Frequency Band Occupied by a PU
1	10
2	5
3	2
4	1

were produced by filtering another AWGN having a variance of 100 mW at frequency 2.5 GHz to 7.5 GHz. The addition of PU signals and AWGN is performed using Add block.

Once the signal generation was completed, the PSD of the PU signal corrupted by noise was estimated using the periodogram approach and the result displayed using QT GUI Vector Sink is shown in Fig. 11. The PSD estimation gives an illustration of how the energy of the corrupted PU signals is spread across different frequency points. It is shown in Fig. 11, in which the PSD estimation correctly identifies the existence of PU at a frequency between 2.5 and 7.5 GHz (which is the simulated frequency band of the PU signals). Note that the sampling frequency was set to 20 GHz, thus the value of the PSD estimate at the frequency between 10 and 20 GHz was the mirror of the PSD estimate at the frequency between 0 and 10 GHz.

Fig. 12 indicates the sensing decision that declares the existence of users at different frequency points. The sensing decision process declared the existence of a user at a particular frequency point if the energy sensed at that frequency point was higher than the threshold. In this case, the indication of the user existence metric (see Fig. 12) was set to 1. The threshold value used to obtain the results in Fig. 12 was 10 dBm. The output of the sensing decision process was indicated by the user existence metric, which was set to 1 if the sensing process concluded the existence of PU at a particular frequency point and 0 otherwise. Fig. 12 shows that a better sensing decision is made when the SNR value is larger. For example, when the power of the PU at its active band was 100 mW and the noise variance was 1 mW, it is indicated in Fig. 12(a) that the spectrum sensing process only declares the existence of a PU signal at the actual frequency band of the PU. If the noise variance is increased to 25 mW (the standard deviation is set to 5 $mW^{0.5}$), it is shown in Fig. 12(b) that the spectrum sensing tool in SU starts to produce an incorrect decision by declaring the existence of a user at some frequency points that actually contain only noise. It implies that false alarm events have occurred. The sensing decision process produced a poor result when the noise variance was increased to 100 mW (the standard deviation was set to 10 $mW^{0.5}$). In this case, the PU power in its frequency band was the same as the noise variance. This situation is illustrated in Fig. 12(c), where the sensing decision process declares the existence of PU almost at all frequency points leading to a very high false alarm rate.

The calculation of PD and PFA was performed by the PD and PFA calculation block in the GNU radio, which was constructed from the Embedded Python block. The FFT size in the experiment was set to 1,024. The calculation results were saved using a File Sink block and then further processed to allow the production of the ROC curve. The ROC curve based on the PD and PFA calculation was plotted in MATLAB. Fig. 13 illustrates the ROC curve for the energy detection process simulated in the GNU Radio. This ROC curve provides the values of PD that correspond to different values of PFA, which are produced by varying the threshold. Four experimental scenarios provided in Table I were conducted. It can be observed that the energy-detection-based spectrum sensing generally has a better performance for a higher SNR. As mentioned in Section IV, a higher PD and a lower PFA correspond to a better sensing decision. For instance, in Scenario 1 where the noise variance was set to 1 mW and the PU power at its frequency band was set to 100 mW, the performance of the energy detection was very good. In this scenario, the value of PD was higher and the value of PFA was lower than those in the other scenarios. On the other hand, the performance of the developed energy detection in Scenario 4 is poorer than that in other scenarios due to a very low SNR. From the aforementioned results, it can be concluded that the spectrum sensing decision based on energy detection has a high sensitivity to noise as the energy-detection-based spectrum sensing only compares the received energy at a particular frequency point to a threshold irrespective of other characteristics that might distinguish the transmitted signal from the noise. Moreover, knowledge about the noise variance is required to determine an appropriate threshold value.

VII. CONCLUSION

In this paper, the simulation of energy-detection-based spectrum sensing on the GNU Radio platform was performed. The PSD of the corrupted PU signal was calculated using the periodogram, which is one of the PSD estimation techniques. The periodogram block was implemented in GNU Radio by exploiting the Embedded Python block provided in the GNU Radio platform. Based on the result of the periodogram, the spectrum sensing process declares the existence of the PU by comparing the test statistic of energy and threshold. The PD and the PFA on GNU Radio were computed by exploiting the Embedded Python block to evaluate the quality of the sensing decision process. The performance of the energy detection method was examined by evaluating the resulting ROC curve of PD and PFA plotted based on the different thresholds. The simulation was performed for different values of SNR. The results suggest that the energy detection has a better performance for a higher SNR, indicating the high sensitivity of this method to noise. It should be noted, however, that the energy detection requires information only about noise variance, and it does not require prior information about PU signals. Therefore, the complexity of the energy detection method is low.

CONFLICT OF INTEREST

The authors declare that the article entitled “Performance of Energy Detection Spectrum Sensing for Cognitive Radio Using GNU Radio” has no conflict of interest.

AUTHOR CONTRIBUTION

Conceptualization, methodology, software, validation, formal analysis, and resources, Hudaya Muna Putra, Sigit Basuki Wibowo, and Dyonisius Dony Ariananda; writing—original draft preparation, Hudaya Muna Putra; review, editing, and supervision, Sigit Basuki Wibowo, Dyonisius Dony Ariananda, and Wahyu Dewanto.

REFERENCES

[1] T. Yücek and H. Arslan, “A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications,” *IEEE Commun. Surv. Tut.*, Vol. 11, No. 1, pp. 116–130, 2009.

[2] S. Haykin, “Cognitive Radio: Brain-Empowered Wireless Communications,” *IEEE J. Sel. Areas Commun.*, Vol. 23, No. 2, pp. 201–220, Feb. 2005.

[3] I.F. Akyildiz, W.Y. Lee, M.C. Vuran, and S. Mohanty, “NeXt Generation/Dynamic Spectrum Access/Cognitive Radio Wireless Networks: A Survey,” *Comput. Netw.*, Vol. 50, No. 13, pp. 2127–2159, Sep. 2006.

[4] R.A. Rashid, *et al.*, “Enabling Dynamic Spectrum Access for Cognitive Radio Using Software Defined Radio Platform,” *2011 IEEE Symp. Wirel. Technol., Appl. (ISWTA)*, 2011, pp. 180–185.

[5] A. Ghasemi and E.S. Sousa, “Spectrum Sensing in Cognitive Radio Networks: Requirements, Challenges and Design Trade-Offs,” *IEEE Commun. Mag.*, Vol. 46, No. 4, pp. 32–39, Apr. 2008.

[6] M. Nayak, *et al.*, “A Real Time Implementation of Spectrum Sensing System Using Software Defined Radio,” *2017 Int. Conf. Intell. Comput. Instrum. Control Technol. (ICICICT)*, 2018, pp. 603–607.

[7] *Facilitating Opportunities for Flexible, Efficient, and Reliable Spectrum Use Employing Cognitive Radio Technologies*, FCC-03-322, Federal Communications Commission, Washington, D.C., USA, Dec. 2003.

[8] I.F. Akyildiz, W.Y. Lee, M.C. Vuran, and S. Mohanty, “A Survey on Spectrum Management in Cognitive Radio Networks,” *IEEE Commun. Mag.*, Vol. 46, No. 4, pp. 40–48, Apr. 2008.

[9] M.T. Masonta, M. Mzyece, and N. Ntlatlapa, “Spectrum Decision in Cognitive Radio Networks: A Survey,” *IEEE Commun. Surv. Tut.*, Vol. 15, No. 3, pp. 1088–1107, 2013.

[10] F.A. Awin, Y.M. Alginahi, E.A-. Raheem, and K. Tepe, “Technical Issues on Cognitive Radio-Based Internet of Things Systems: A Survey,” *IEEE Access*, Vol. 7, pp. 97887–97908, 2019.

[11] D.D. Ariananda, “On Wavelet Based Spectrum Estimation for Dynamic Spectrum Access”, Master thesis, Delft University of Technology, Delft, Netherlands, 2009.

[12] I. Budiarjo, M.K. Lakshmanan, and H. Nikookar, “Cognitive Radio Dynamic Access Techniques,” *Wirel. Pers. Commun.*, Vol. 45, No. 3, pp. 293–324, May 2008.

[13] E. Axell, G. Leus, E.G. Larsson, and H.V. Poor, “Spectrum Sensing for Cognitive Radio: State-of-the-Art and Recent Advances,” *IEEE Signal Process. Mag.*, Vol. 29, No. 3, pp. 101–116, May 2012.

[14] F. Salahdine, H.E. Ghazi, N. Kaabouch, and W.F. Fihri, "Matched Filter Detection with Dynamic Threshold for Cognitive Radio Networks," *2015 Int. Conf. Wirel. Netw., Mobile Commun. (WINCOM)*, 2015, pp. 1–6.

[15] J. Chen, A. Gibson, and J. Zafar, "Cyclostationary Spectrum Detection in Cognitive Radios," *IET Semin. Cogn. Radio, Softw. Defined Radios: Technol., Techn.*, 2008, pp. 1–5.

[16] M.A. Sarijari, *et al.*, "Energy Detection Sensing Based on GNU Radio and USRP: An Analysis Study," *2009 IEEE 9th Malaysia Int. Conf. Commun. (MICC)*, 2009, pp. 338–342.

[17] M.R. Manesh, M.S. Apu, N. Kaabouch, and W.-C. Hu, "Performance Evaluation of Spectrum Sensing Techniques for Cognitive Radio Systems," *2016 IEEE 7th Annu. Ubiquitous Comput. Electron., Mobile Commun. Conf. (UEMCON)*, 2016, pp. 1–7.

[18] J. Talukdar, B. Mehta, K. Aggrawal, and M. Kamani, "Implementation of SNR Estimation Based Energy Detection on USRP and GNU Radio for Cognitive Radio Networks," *2017 Int. Conf. Wirel. Commun. Signal Process., Netw. (WiSPNET)*, 2017, pp. 304–308.

[19] M.A. Fouda, A.S.T. Eldien, and H.A.K. Mansour, "FPGA Based Energy Detection Spectrum Sensing for Cognitive Radios under Noise Uncertainty," *2017 12th Int. Conf. Comput. Eng., Syst. (ICCES)*, 2017, pp. 584–591.

[20] G. Swetha and B.N. Bhandari, "Energy Detection Spectrum Sensing on DPSK Modulation Transceiver Using GNU Radio," *2017 2nd Int. Conf. Converg. Technol. (I2CT)*, 2017, pp. 974–978.

[21] K.S. Gill and A.M. Wyglinski, "Heterogeneous Cooperative Spectrum Sensing Test-Bed Using Software-Defined Radios," 2017 *IEEE 86th Veh. Technol. Conf. (VTC-Fall)*, 2017, pp. 1–5.

[22] United States Department of Commerce, "United States Frequency Allocations Chart," 2016.

[23] J. Mitola and G.Q. Maguire, "Cognitive Radio: Making Software Radios More Personal," *IEEE Pers. Commun.*, Vol. 6, No. 4, pp. 13–18, Aug. 1999.

[24] D. Cabric, A. Tkachenko, and R.W. Brodersen, "Spectrum Sensing Measurements of Pilot, Energy, and Collaborative Detection," *MILCOM 2006 - 2006 IEEE Mil. Commun. Conf.*, 2006, pp. 1–7.

[25] A. Bujunuru and T. Srinivasulu, "A Survey on Spectrum Sensing Techniques and Energy Harvesting," *2018 Int. Conf. Recent Innov. Elect. Electron., Commun. Eng. (ICRIEECE)*, 2018, pp. 751–755.

[26] F. Zeng, C. Li, and Z. Tian, "Distributed Compressive Spectrum Sensing in Cooperative Multihop Cognitive Networks," *IEEE J. Sel. Topics Signal Process.*, Vol. 5, No. 1, pp. 37–48, Feb. 2011.

[27] S. Maleki, A. Pandharipande, and G. Leus, "Energy-Efficient Distributed Spectrum Sensing for Cognitive Sensor Networks," *IEEE Sensors J.*, Vol. 11, No. 3, pp. 565–573, Mar. 2011.

[28] D.D. Ariananda, D. Romero, and G. Leus, "Cooperative Compressive Power Spectrum Estimation in Wireless Fading Channels," 2017 *Int. Conf. Elect. Eng., Inform. (ICELTICs)*, 2017, pp. 18-23.

[29] B.B. Harianto, A.P. Prabowo, and N. Prabudiyatno, *Komunikasi Analog dan Digital dangan Software Defined Radio dan GNU Radio*. Surabaya, Indonesia: Deepublish, 2020.

[30] P. Stoica and R. Moses, *Spectral Analysis of Signals*. Upper Saddle River, USA: Prentice Hall, 2005.