# Experimental Study of Spectrum Sensing Based on Energy Detection Using USRP

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*Abstract*—**Lack of unallocated spectrum and increasing demand for bandwidth in future wireless networks is forcing new devices and technologies to share frequency bands. Cognitive Radio (CR) is a key technology allowing users to benefit from the unused licensed spectrum to increase their bandwidth. One of the main challenges to achieve this concept is the spectrum sensing in order to detect unallocated bandwidths. Energy detector is known for its simplicity in hardware implementation with moderate performances compared to other methods in the literature. This paper presents an implementation of the energy detector based on the calculation of the energy in the time-domain and in the frequency-domain. Both methods were first simulated using Matlab and then implemented and tested in real environment using NI-USRP 2901. Implementation results show a good agreement with the simulation results.**

*Index Terms*—**spectrum sensing, cognitive radio, LabVIEW, USRP**

## I. Introduction

Wireless communication is a very important aspect of modern communications. With the advancement of technology, the demand for radio spectrum has increased tremendously. There are more users of bandwidth as compared to the capacity of the radio spectrum and the interference is becoming a nightmare for the communication industry. The overcrowding in the vital band of communications opens a gateway to find a better spectrum management technique. In order to achieve this goal, cognitive radio concept proposed by Mitola [1] presents an interesting solution allowing the user to increase temporary his bandwidth. In this context, users are classified into two categories:

- Primary users PU who uses a reserved licensed band of its activity.
- Secondary users SU who uses unused unlicensed or licensed bands of the spectrum.

SU has the lowest priority regarding spectrum usage. Indeed, the SU user must release immediately the licensed spectrum when the primary user appears. The implementation of this concept needs an effective and fast spectrum sensing algorithm to fulfill CR requirements. Several spectrum sensing algorithms were proposed in the literature. The Cyclostationary (CS) method are in particular based on the extraction of cyclic features of the received signal in the frequency domain. It has high implementation complexity despite having good performance. The matched filter method searches for the pre-known transmitted signal at the receiver, so it requires prior knowledge of the signal. The eigenvalue-based method computes the covariance matrix of the received multichannel signal so it requires multiple antennas at the receiver as [2] stated. Energy Detection ED method that computes the energy of the signal in the time domain is the simplest method. It does not need any prior knowledge of the transmitted signal. Moreover, it does not need high computational resources. However, it has the lowest performance in terms of probability of detection as mentioned by [3].

The aim of this paper is to implement low complexity real-time spectrum sensing for wide band (CR) application.

The rest of the paper is organized as follows. Section II presents the theoretical background of the energy detection algorithm in the time-domain and in the frequency-domain. The performance of the energy detection algorithm is evaluated via MATLAB simulations in Section III. Section IV describes the hardware implementation of spectrum sensing using USRP 2901. Finally, the conclusion is drawn in Section V.

### A. Theoretical Background

One of the main challenges of CR is the spectrum sensing task that helps to find the spectrum holes, allowing unlicensed user to use vacant licensed bands. Spectrum sensing essentially performs a binary hypothesis test on primary users' existence according to the following equations:

$$H_0: x(t) = w(t) \quad (1)$$

In (1) primary user is absent.

$$H_1: x(t) = h(t)^* s(t) + w(t) \quad (2)$$

In (2) primary user is present.

where $x(t)$ is the received signal, $w(t)$ is the noise term considered Additive White Gaussian Noise (AWGN), $s(t)$ is the received signal and $h(t)$ is the channel impulse response [4].

The performance of the spectrum sensing technique is evaluated by estimating three common probabilities:

- $P_d$ the probability of detection where either the signal is present and detected or the signal is not present and not detected.

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- $P_m$ the probability of misdetection where the signal is present and not detected.
- $P_f$ the probability of false alarm where the signal is not present and detected.

In the ideal case, an efficient spectrum sensing technique must have high probability of detection $P_d$ and lowest probability of false alarm $P_f$. In addition to the efficiency, the detection accuracy, the robustness and the implementation complexity have an important impact on the choice of spectrum sensing technique.

## II. Energy Detection Spectrum Sensing Technique

Energy Detection spectrum sensing method is the most known method to detect the existence of PU. It works on the basic principle of estimating the energy of the received signal. This method has the lowest computational and implementation complexities as the detector does not need to know about the incoming PU signal. Fig. 1 shows the block diagram of this method. The received signal passes first in a bandpass filter. Then, the signal is digitized using an analog to digital converter (ADC). After that, the energy is computed and compared with the given threshold.

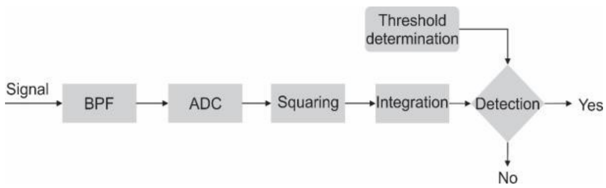


Figure 1. ED block diagram.

The energy of the signal can be calculated using the following equation:

$$Y_{ED} = \sum_{n=0}^{N-1} |r(n)|^2 \tag{3}$$

where $N$ is the number of samples. The decision on the usage of the band can be obtained by comparing $Y_{ED}$ against a fixed threshold λ. According to the received signal, the output of the detector is:

$$\begin{cases} Y^0{}_{ED} = \sum_{n=0}^{N-1} |w(n)|^2 \ under\ H_0 \\ Y^1{}_{ED} = \sum_{n=0}^{N-1} |x(n) + w(n)|^2 \ under\ H_1 \end{cases} \tag{4}$$

The noise is modeled as a zero-mean Gaussian random variable with variance $\sigma_w{}^2$:

$$w(n) = N(0, \sigma_w{}^2) \tag{5}$$

Using these equations, the probability of false alarm and the corresponding threshold are calculated and given by [5]:

$$P_f = Q\left(\frac{\lambda - N\sigma_n{}^2}{\sqrt{2N\sigma_n{}^2}}\right) \tag{6}$$

$$\lambda = \left(Q^{-1}(P_f) + \sqrt{N}\right)\sqrt{N} 2\sigma_w{}^2 \tag{7}$$

- If $\frac{Y_{ED}}{N} > \lambda$, it means the spectrum is occupied by primary users and we get one detection.
- If $\frac{Y_{ED}}{N} < \lambda$, it means the spectrum is idle and we get zero detection as [6].

Another way to implement the ED algorithm is to evaluate the energy from the frequency-domain as shown in Fig. 2. This method is inspired from the cyclostationary detection algorithm. The received signal is first digitized using analog to digital converter. Then, the spectrum of the signal is evaluated using FFT. After that the auto-correlation of the signal is applied. At the end, a peak detector decides whether there exists a user or not after comparing to the threshold as in [7].

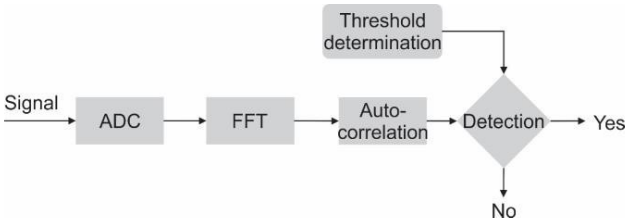


Figure 2. ED in frequency domain block diagram.

In order to illustrate the main idea of this method, let us consider that the received signal is composed of a pure cosine at frequency $W_0$ plus additive white noise. The FFT of this signal is illustrated in Fig. 3.

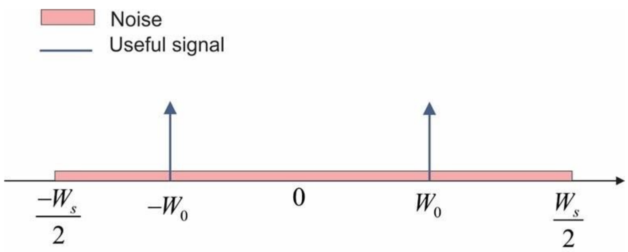


Figure 3. FFT of the signal.

The autocorrelation of the signal at the FFT blocks is calculated using the following equation:

$$C(d) = \sum_{m=0}^{NFFT-1} F(d+m)F^*(m) \tag{8}$$

If $\frac{C(d)}{N^2} > \lambda$, it means the spectrum is occupied by primary users and we get one detection.

If $\frac{C(d)}{N^2} < \lambda$, it means the spectrum is idle and we get zero detection as has been shown by [6].

The autocorrelation output is shown in Fig. 4. It is composed of three main Dirac functions with the highest peak at zero shift where the two Diracs of the useful signal coincide.

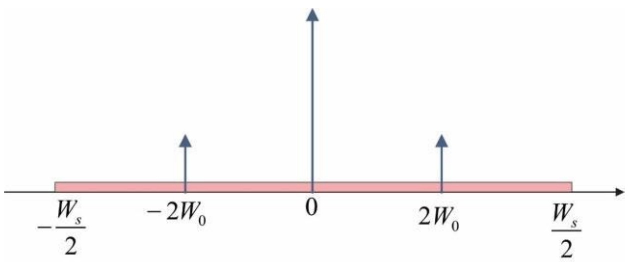


Figure 4. Auto-correlation process.

The other two Dirac functions in the autocorrelation output are located at - $2W_0$ and +$2W_0$ .

## III. MATLAB Simulation

The performance of the ED algorithm was evaluated by simulation using MATLAB.

Fig. 5 shows the performance of probability of detection in terms of SNR, where we change the value of SNR from -20dB to 0dB with a step of 0.2dB and a constant value of $P_f$=0.1 taking 1000 samples and using the threshold equation (6).

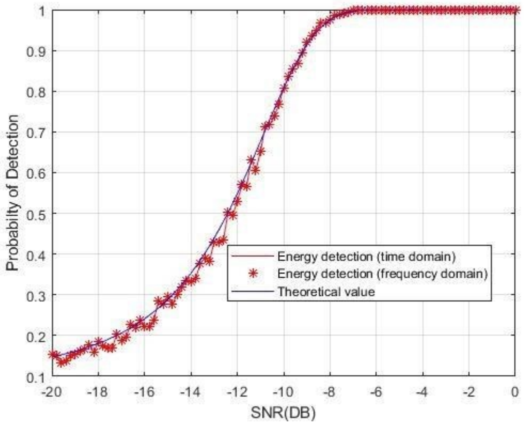


Figure 5. ROC of energy detection analytical.

It can be shown that both ways of energy detection calculation give the same result with a perfect agreement with theoretical result.

A small difference between the estimated probability of detection and the theoretical one can be noticed due the limited number of samples considered in the simulation.

## IV. Frequency Domain Energy Detection Review

In order to validate the concept of FDED method, a pure cosine signal S is considered, with frequency $f_0$ =20Hz and sampling frequency $f_s$ = 200Hz with amplitude A=5, with adding noise $w(n)$ to the signal as shown in Fig. 6.

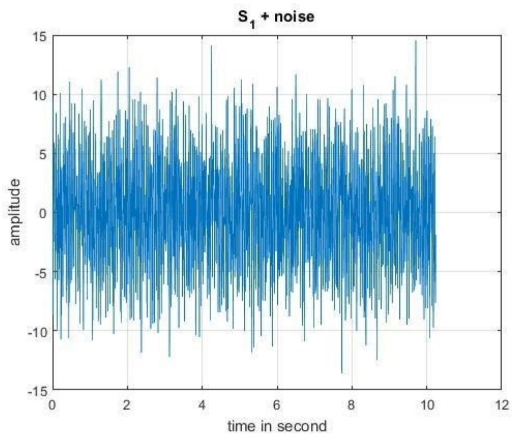


Figure 6. Signal with added AWGN noise.

$$s(n) = A * \cos\left(2 * \pi * \left(\frac{f_0}{f_s}\right) * n\right) + w(n) \quad (9)$$

The FFT of the signal is shown in Fig. 7.

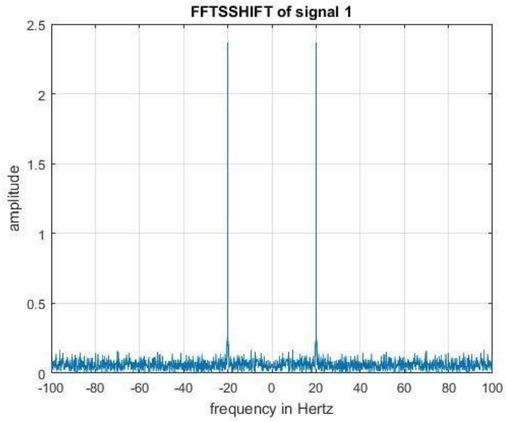


Figure 7. Signal after performing FFT.

The autocorrelation function after FFT of the signal is illustrated in Fig. 8.

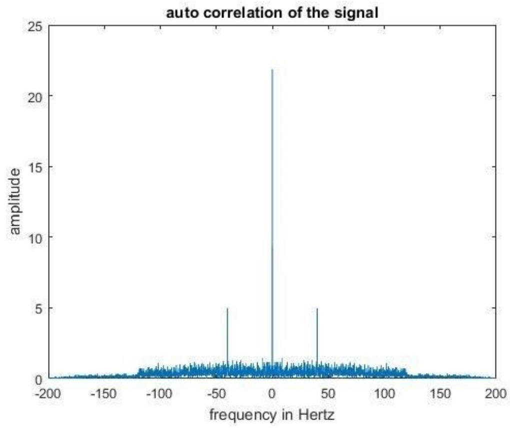


Figure 8. Signal after performing auto-correlation.

This result was expected according to the concept presented in Section II.

## V. Experimental Implementation

### A. Flow Charts

In order to validate the simulation results, a spectrum sensing experiment with wide band application was implemented using USRP 2901 that has 2 transmitters and 2 receivers with large bandwidth and fine frequency resolution as shown in [8]. Based on technical description of the USRP, the USRP must be configured before starting the signal acquisition; mainly the baseband bandwidth and the carrier frequency. As our aim is to scan large bandwidth, our scanning algorithm is composed of three main steps: configure, acquire and stop. Moreover, the producer-consumer loops model is used in our implementation in order to avoid any loss of acquired data. The producer loop sets the parameters of the USRP and sends the acquired data to the consumer loop for spectrum analysis and representation. Fig. 9 presents the flowchart of the code implemented in the producer and consumer loops respectively.

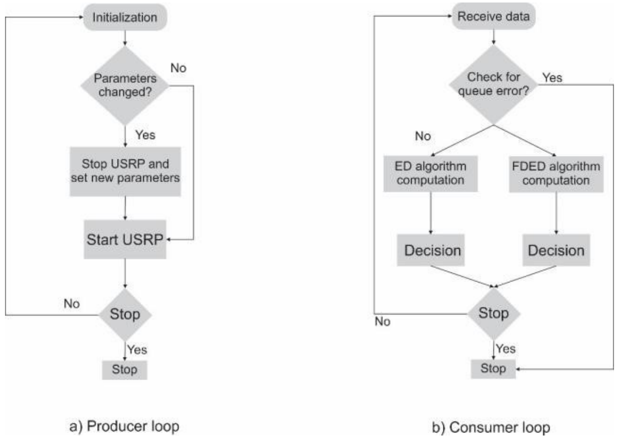


Figure 9. Producer and consumer loop block diagrams.

In the producer loop part, the algorithm checks first for any change in the parameters: the maximum frequency, the minimum frequency and the IQ rate. If the parameters are equal, the USRP continues to receive data. Otherwise, it stops and get the new parameters and then will be restarted.

In the consumer loop part, the received data will be processed by the two methods: time domain energy detection and frequency domain energy detection for each channel separately and a decision is made if a primary user exists or not.

## B. Transmitter Block Diagram

The evaluation of the performance of our proposed algorithm requires a priori knowledge of the presence of the signal in order to evaluate the probability of detection at the receiver side. For this reason, the use of existing signals like Wi-Fi signals is not possible as its standard does not have continuous transmission. For this purpose, a transmitter is implemented in the USRP to send a pure sine wave according to the parameters defined by the user as shown in Fig. 10.

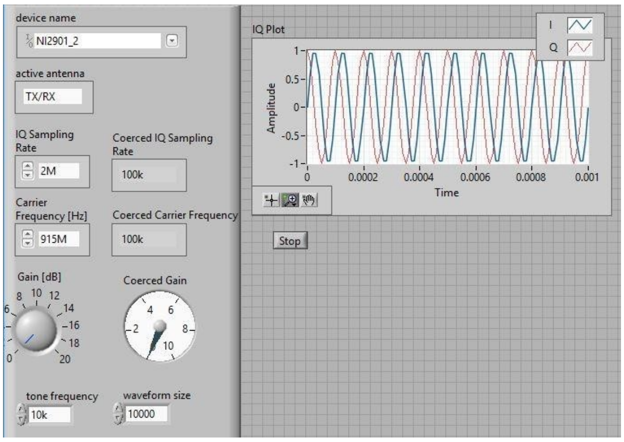


Figure 10. Transmitter front panel.

Fig. 11 presents the block diagram of the transmitter. First the USRP is configured using the parameters set by the user. Then, the two sine signals are generated and sent to the IQ channels.

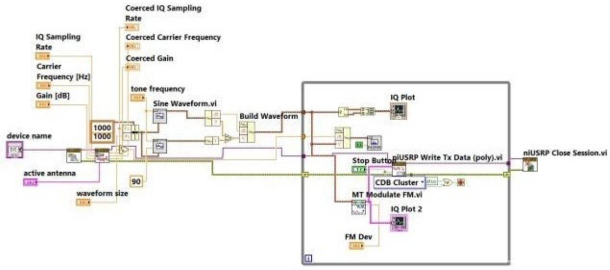


Figure 11. Transmitter block diagram.

## C. Receiver Block Diagram

Fig. 12 shows the front panel of the receiver. It is composed mainly of three blocks. The first block allows the user to set the device name, the number of samples per frame, the antenna name, and the channel list. The second block is reserved for the configuration of the maximum and minimum frequencies with the IQ rate and the gain. The last block shows the carrier frequencies array and the sweeping iteration with the band being processed. Moreover, two graphs are used to illustrate the autocorrelation result and the spectrum with the selected range frequency.

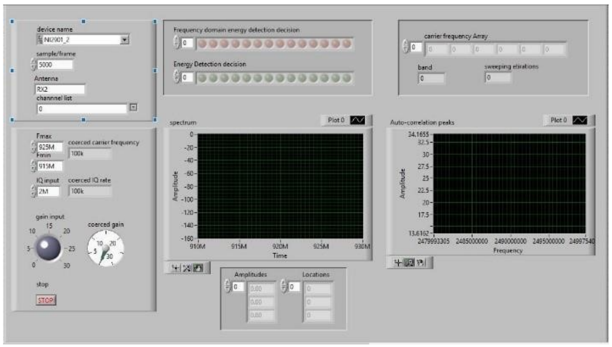

Figure 12. Receiver front panel.

The block diagram of the receiver is illustrated in Fig. 13. As previously mentioned, it is composed of two main loops: the producer loop and the consumer loop.

The main functions performed in the producer loop (see Fig. 13) are:

1) “niUSRP Open RX session.vi” that establishes the communication with the USRP.
2) “niUSRP Configure Number of samples.vi” allowing to reconfigure the USRP with the parameters defined by the user in the front panel.
3) “sweeping.vi” is a sub VI that generates the array of carrier frequencies and the number of sweeping iterations.
4) “niUSRP Abort.vi” to abort the acquisition process and “niUSRP Configure Signal.vi” to update the new set of parameters.
5) “niUSRP Initiate.vi” to start the acquisition and then “niUSRP Fetch RX Data.vi” to read the data and then to put it in the queue.
6) “Obtain Queue” to create the FIFO register where the data will be stored
7) An enqueue Element builds an array and set data in a queue to transfer it to the consumer loop.

8) "niUSRP Close Session.vi" to close the session and release the queue.

The main functions performed in the consumer loop (see Fig. 13) are:

1) "Dequeue Element" to read the data -stored in the queue and process it later
2) Implementation of the ED algorithm by getting the absolute value to be squared before integrating and comparing with the threshold to give decision.
3) Implementation of the energy detection in frequency domain by computing the FFT first and then the calculation of the autocorrelation is performed and the output is divided by $N^2$ where $N$ is the FFT size. Therefore, the detection is performed by comparing the autocorrelation outputs to the same threshold.

The spectrum at all subcarriers is reconstructed and displayed on a graph.

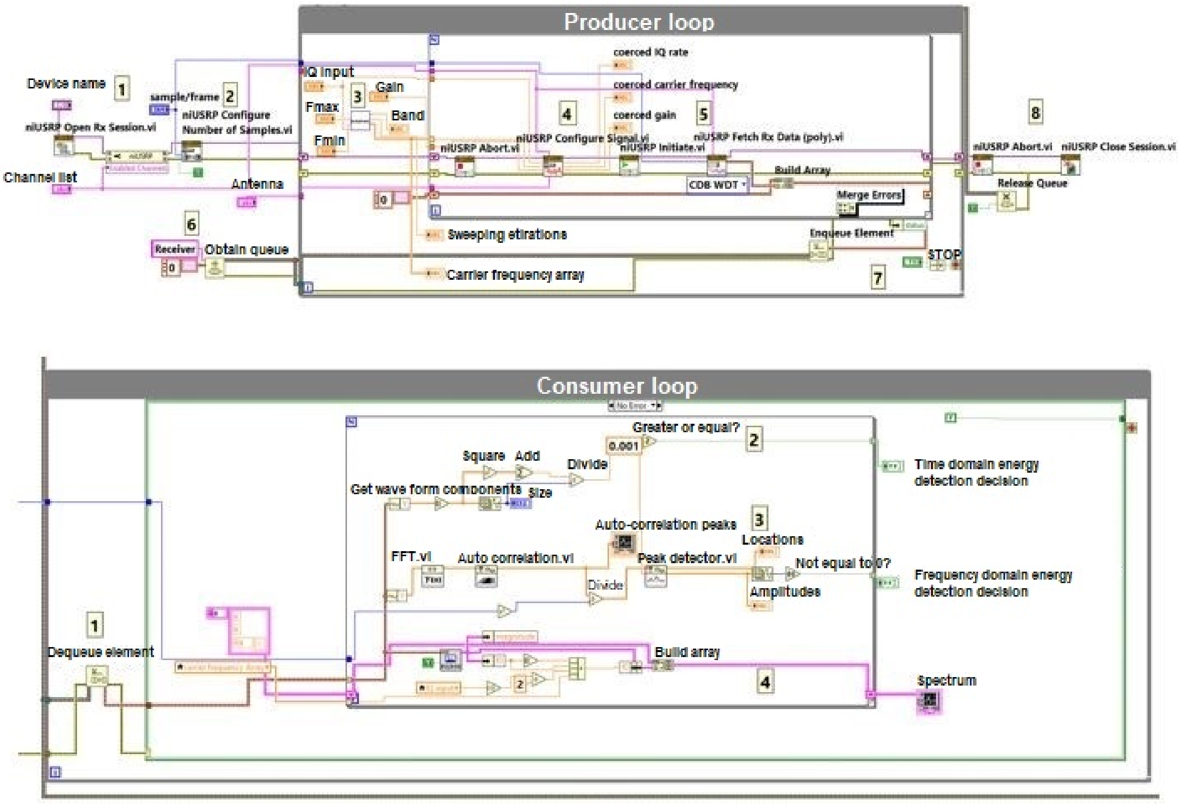


Figure 13. Receiver block diagram producer and consumer loop.

*D. Implementation Results*

The implementation scenario consists to first generate a pure sine wave at the carrier frequency of 918 MHz with very low gain. As the transmitter and the receiver are implemented in the same USRP, an RF isolator is used to separate the two antennas and to avoid any interference.

Fig. 14 shows the results of the two algorithms while scanning the entire useful bandwidth from 915 MHz to 925MHz with sub-channel of 2 MHz this means that the whole bandwidth will be divided into 5 sub-channels. It can be shown that both methods detect the transmitted signal at 918 MHz.

In order to obtain more flexibility to change the SNR and see its effect on the detection performance, the second scenario consists to implement the transmitter and the receiver on two different USRPs. In this case, the SNR can be controlled by the gain of each antenna and by the distance separating the two USRPs. Moreover, to increase the execution time of the evaluation process, only one channel is considered at the receiver side.

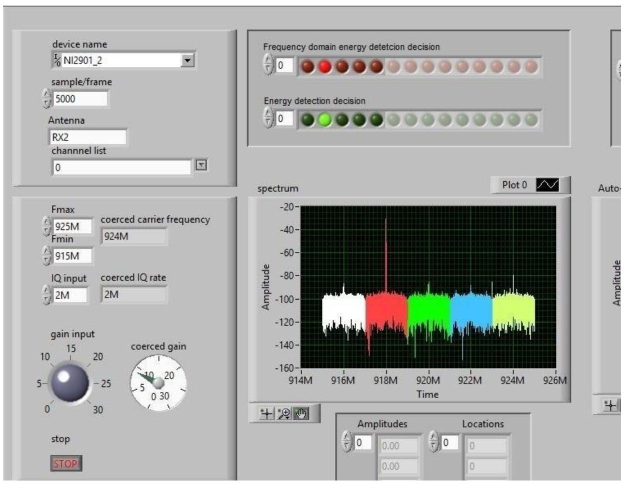


Figure 14. Parameters in the receiver front panel.

Two parameters can affect the probability of detection, the value of the threshold and the frequency resolution. Table I shows the estimated probability of detection where the transmitter and the receiver are separated by a distance of 1.5 meters with different frequency resolution values. It can be noticed that the lower the frequency resolution is, the higher the probability of detection. In fact, reducing the frequency resolution leads to reduce the amount of noise per channel and consequently increase the probability of detection as long as pure cosine signals are considered. However, reducing the frequency resolution will increase the execution time of the scanning process. So, the frequency resolution is a compromise between the probability of detection and the execution time.

TABLE I. RESULTS ACCORDING TO FREQUENCY RESOLUTION

| Signal exists | | Bandwidth | Number of iterations | Signal detected | Pd |
|---|---|---|---|---|---|
| Yes | No | | | | |
| X | | 2 MHz | 10,000 | 6903 | 0.690 |
| X | | 1 MHz | 10,000 | 8124 | 0.812 |
| X | | 500 KHz | 10,000 | 9464 | 0.946 |
| X | | 200 KHz | 10,000 | 9501 | 0.950 |

Table II shows the probability of detection for different threshold values using a frequency step of 1 MHz in different scenarios. The threshold ($Th$) value is determined experimentally by examining the noise level where there is no signal. In this experiment, two cases are considered where the experimental threshold is multiplied or divided by 2.

TABLE II. RESULTS ACCORDING TO THRESHOLD CHANGE

| Threshold | Signal exists | | Number of iterations | Signal detected | Pd |
|---|---|---|---|---|---|
| | Yes | No | | | |
| $Th$ | X | | 10,000 | 8124 | 0.812 |
| $\frac{Th}{2}$ | X | | 10,000 | 10,000 | 1 |
| $2 * Th$ | | X | 10,000 | 6211 | 0.621 |

In the table above it can be noticed that multiplying the threshold by two decreased the probability of detection since if the signal amplitude was faded a little, the system will consider it as noise, whereas if we divide the threshold by two the probability of detection will be 1, but when there is no transmitted signal a record of 1012 detection were measured that is probability of false alarm increased from zero to 10%.

## VI. CONCLUSION

This paper presents the implementation of ED algorithm in the time-domain and in the frequency domain both methods were compared and simulated using MATLAB. Simulation results were validated by hardware implementation using NI-USRP 2901. Different scenarios and different configuration parameters were considered. The system performance was studied in terms of the probability of detection and the probability of false alarm. In addition, it was shown that the frequency resolution represents a compromise between the probability of detection and the execution time.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

MS performed the theoretical study and the numerical simulations. Both AB and MS contributed to the hardware implementation. All authors provided critical feedback, discussed the results and contributed to the final version of the manuscript.

## ACKNOWLEDGMENT

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