Design of an Energy Detector in Simulink and its implementation on FPGA.

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ABSTRACT

Cognitive radio has been proposed as an alternative to employ radio-electric spectrum efficiently. In this regard, primary users (PUs) and secondary users (SUs) must be implemented sufficiently intelligent in order to detect user needs and to employ radio resources accordingly. CR paradigm must be implemented with two main capabilities: Cognitive, Learning and Reconfigurability. Energy detection (ED) is the most used measurement approach due to its low computational complexity. Furthermore, ED offers the ability to identify holes in the spectrum without requiring a prior knowledge of the transmission characteristics of PUs. However, setting a threshold for the ED requires some prior knowledge of the noise power, which can be supplied by appropriate estimation methods. Knowledge of accurate noise variance is crucial for most of the spectrum sensing algorithms such as power detection, matched filter detection, and cyclostationary detection. In this paper a practical scenario is considered where the noise variance is unknown and needs to be estimated before the spectrum detection process. The main goal of this work is pointed to implement an energy detector using the Software Defined Radio (SDR) technique in a reconfigurable hardware (FPGA). Estimation algorithms when the main parameters are unknown are developed by exploiting the histogram of the signal of PUs.

KEY WORDS: Cognitive Radio, Spectrum Sensing, Energy detection, SDR, FPGA.

1. INTRODUCTION

Recent reports show that a high percentage of the available spectrum is not being used efficiently. This mean that there are spectral bands widely used (some are used the 95% of the time) while others are virtually inactive (just the 2%) [1],[2]. In accordance with a report presented by the FCC (Federal Communications Commission) on spectrum utilization, licensed areas are ranged from 15% to 85% in the bands below 3 GHz, as shown in Fig. 1. This study indicates the need to improve the spectrum utilization [3],[4].

Traditional radio devices based on analog circuits can be modified only by direct and manual intervention. This results in a higher production cost and low flexibility to maintain several standard of waveform. In this subject, technology of SDR provides lower cost and more efficient solutions, allowing multi-mode, multi-band and multi-functional wireless devices, which can be improved using improved versions of wireless devices program. SDR defines a collection of hardware and software technologies where some or all operational radio functions are implemented in software or modifiable firmware. This may be implemented on Field Programmable Gate Arrays (FPGAs), Digital Signal Processors (DSPs) and General Purpose Processors (GPP) [5].

The cognitive radio, built on a software-defined radio, is defined as an intelligent wireless communication system. This system uses the methodology of learn from the environment to adapt itself to statistical variations in the input signal. This is in order to make an efficient utilization of the radio spectrum and obtain a highly reliable communication [6]. Cognitive systems should sense the spectrum continuously, thus the SU detects with high probability whether a PU is transmitting in order to find the unoccupied bands in the spectrum. The cognitive system make use of these gaps to transmit additional information without causing interference to the PU.

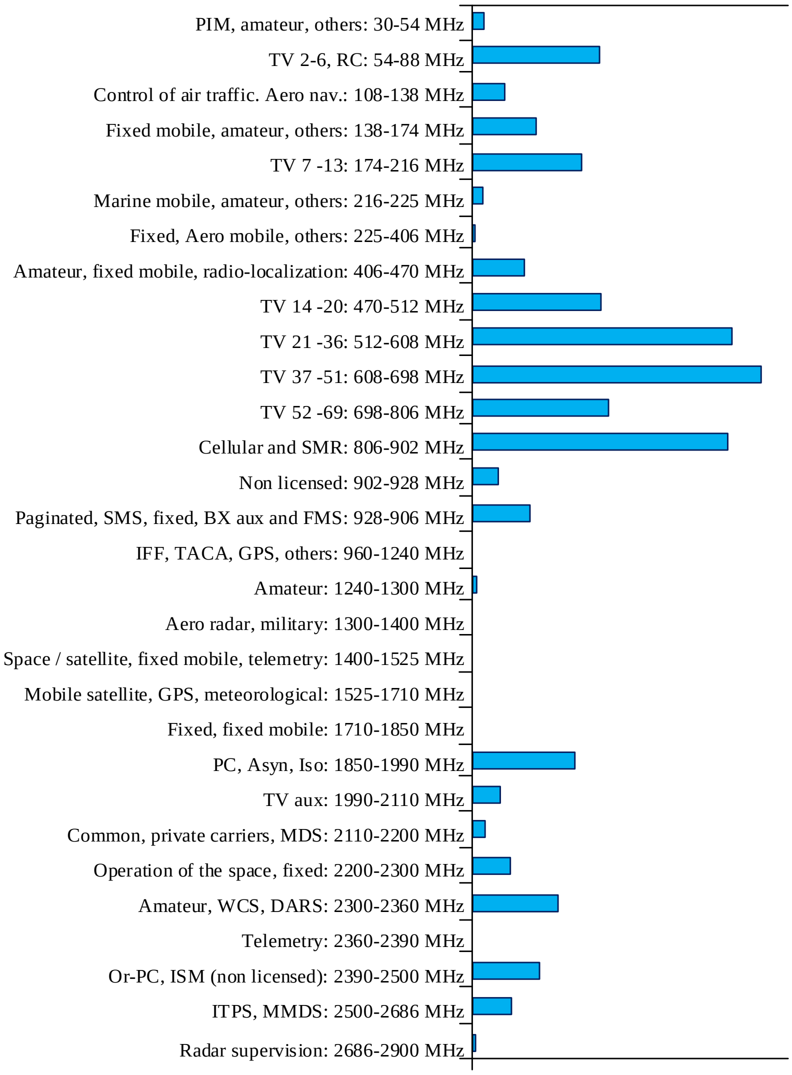


Figure 1: Instance of the spectrum use in the DTV band.

Cognitive radio main features are cognitive, learning and reconfigurability capabilities. These features bring to CR the ability to dynamically select the operating frequency and to adjust its transmission parameters. The cognitive ability is the capacity to recognize the information in the environment and interact with it in real time. The learning ability allows to learn from the results obtained. Reconfigurability is referred to capability of dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives and allows to employ a variety of technologies depending on the available spectrum.

Spectrum measurement and analysis represent the first stage of CR. By means of this information the transmission parameters are adaptively modified in agreement with the available spectrum. The spectrum measurement procedure can be implemented in time or frequency domains. The longer the sensing period is the better the system performance will be. However, throughput will be affected when the sensing time is increased, see Fig. 2. This is why it is important to balance performance measurement and QoS (Quality of services) [7].

The rest of the paper is organized as follows. Section 2 presents some of detection techniques, establishing a comparison between them. Section 3 describes energy detector operation. Section 4 explains the Neyman-Pearson Criteria. Section 5 addresses algorithms to estimate noise floor. Section 6, deals with hardware implementation issues of the proposed solution. Finally, Section 7 discusses some concluding remarks.

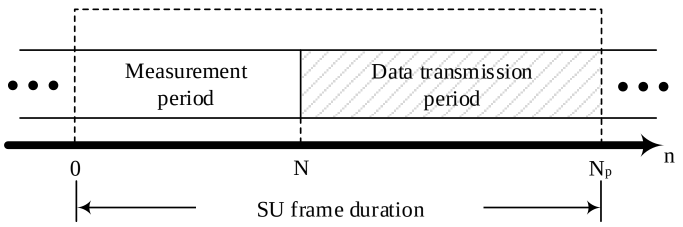


Figure 2: Measurement and transmission structure of US.

2. DETECTION TECHNIQUES.

Several detection methods have been developed depending on the available prior information, complexity and precision. Detection methods based on some prior knowledge about the desired signal have better outcomes than those who do not. The most used solutions are given by the matched or adapted filter and the feature detection. However, the energy detector is the most employed given its low complexity and the ease of implementation since the use of prior knowledge is avoided.

Adapted filter

Matched filter is the optimal way to detect any signal in scenarios of white additive Gaussian noise, provided that optimal signal-to-noise ratio (SNR) is achieved [8]. The system requires prior knowledge in regard to the characteristics of the signal to be measured: modulation type and order, format of the transmitted packet and pulse modeling. As well, synchronism with the carrier signal and knowledge of the symbol time parameter are required, and even, channel equalization must be performed. Despite of these restrictions, these systems are feasible to implement since several wireless services have pilot signals, preamble or sync words that can be used for coherent detection. The main advantage is given by the less time required to achieve equal probability of false alarm in comparison with any other method reported. Among its disadvantages stand out the need of prior knowledge regarding the parameters mentioned above and the limitation of these systems to require a dedicated receiver for each primary user who is being inspected.

Feature detection

Feature detection methods take advantage of the periodicities introduced by inherent processes of the transmission: modulation y codification whit cyclic prefix. The signal whose statistic parameters, like first order moments and autocorrelation, exhibit periodicities is known as cyclo-stationary. Using the autocorrelation function and the power spectral density we may detect peaks located at the cyclic frequency of stationary signals, for instance [9]. In applications where there is no cooperation between the PU (transmitter) and the SU (receiver), techniques that employ partial or full knowledge of the measured signal are not feasible to implement. That is why the use of the energy detector is recommended when the main signal parameters are unknown [10].

Energy detector

While the matched filter and detection features require prior information about the primary signal, none parameter of the transmitted signal is required by the energy detection technique. The detector determines where the energy of the measured signal is placed over a predetermined threshold level. ED is the spectrum measurement scheme more appropriate to detect white spaces on the spectrum. This solution applies for wireless and heterogeneous communication systems. These scheme offers the ability to identify holes in the spectrum without requiring prior knowledge of the transmission characteristics of PUs [11],[12].

Fig. 3 shows the block diagram of the conventional energy detector. In this particular case detection is performed in the time domain, which in turn demand the use of a bandpass filter. The output signal of the bandpass filter is squared to bring a measure of energy. Then an average procedure is performed in time. The output, named test statistic, is obtained and compared to a given threshold. However, given the poor performance of the energy detector compared to the measurement methods mentioned above, research to improve the performance of the energy detectors have yet to be made.

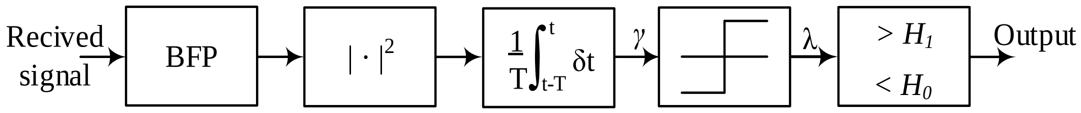


Figure 3: Functional diagram of ED.

3. ENERGY DETECTOR.

Energy detection is a spectrum measurement method that detects the presence or absence of the signal from the measurement of the received power. ED is based on two hypothesis related to signal detection of the primary user, the null hypothesis H_0 and the alternative hypothesis H_1.

$$H_0 : y[n] = w[n] \qquad n = 1,2,\ldots N \tag{1}$$

$$H_1 : y[n] = w[n] + s[n] \qquad n = 1,2,\ldots N \tag{2}$$

Where:

- y[n] is the signal at the receiver input.
- w[n] denotes the additive white Gaussian noise (AWGN) with zero mean and variance $N_0/2$.
- s[n] represents the signal transmitted by PU.
- N is the number of samples observed in a bandwidth *W* by *T* seconds, this is given by the product between time and width band as *N=WT*.

The decision metric of energy detection is, in principle, the energy content of the received signal. However, there is a considerable ambiguity in the definition of the test statistic by this measurement method. Early work on this direction [13-15] are based on the normalized energy of the received samples. The samples are normalized by the noise variance as:

$$v = \frac{1}{\sigma_n^2} \sum y[n]^2 \tag{3}$$

Where:

- σ_n^2 is the noise variance.
- y[n] represents the input signal.
- v denotes the test statistics.

The energy detector performance can be evaluated from two performance metrics: probability of false alarm (P_{fa}), and probability of detection (P_d). False alarm happens when the method gives the hypothesis H_1 at the output when the results should be H_0. In this scenario, the secondary user does not use the available spectrum and the opportunity to transmit is lost. Therefore, lower probabilities of false alarm give greater throughput of SUs [16].

The probability of detection is defined as the probability to have the right decision when happens. In case of failure detection, the user starts an unwanted secondary transmission, causing interference to licensed user of transmission.

$$P_{fa} = \Pr(detected\,signal \mid H_0) = \Pr(v > \lambda \mid H_0)$$

$$= \int_{\lambda}^{\infty} f(v \mid H_0)du \tag{4}$$

$$P_d = \Pr(detected\,signal \mid H_1) = \Pr(v > \lambda \mid H_1)$$

$$= \int_{\lambda}^{\infty} f(v \mid H_1)du \tag{5}$$

Where:

- f(v|Hi) represents the probability density function (*pdf*) of the test statics with the hypothesis i=0,1.
- λ is the detection threshold.

However, there is tradeoff between the efficient use of spectrum (the probability of false alarm) and performance (given by the probability of detection). Although the threshold between the probability of false alarm and the probability of detection can be adjusted by manipulating this value, it is not possible to simultaneously achieve a low false alarm probability and high detection probability, as illustrated in Fig. 4. In order to improve performance, the variance of each *pdf* must decremented. This can be achieved in two ways:

1. When the received SNR of the PU is improved.
2. When the dimension or degree of freedom of the received signal is incremented.

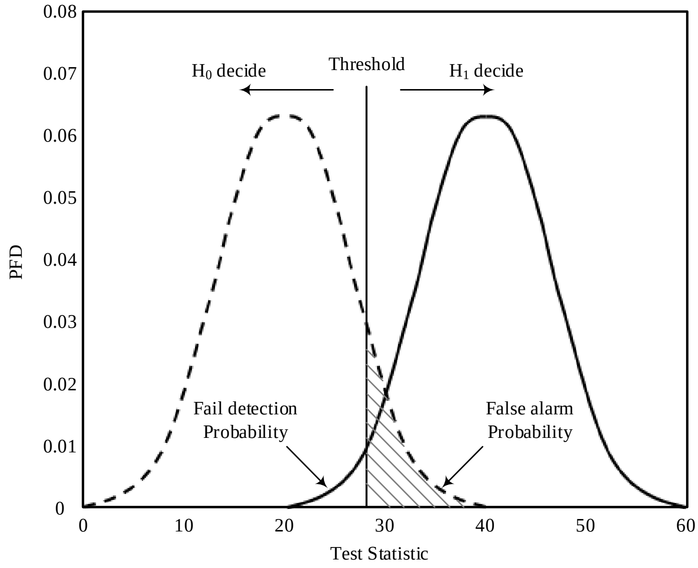


Figure 4: Relation between P_{fa} and P_d.

To improve the received SNR would be challenging in the context of a practical situation, due to factors that degrades the signal quality, such as noise, interference and multipath fading, whose effects are not predictable and unable to be compensated. Therefore, the focus should be made on increasing the freedom degree as taking into account complexity of implementation [17-19].

4. NEYMAN-PEARSON CRITERIA.

Neyman-Pearson criteria describes the principles to optimally distinguish a binary hypothesis [20]. The criteria states that when performing a hypothesis test between two simple hypotheses H_0 and H_1, the likelihood-ratio test L(x) rejects H_0 in favor of H_1 when:

$$L(x) = \frac{p(x \mid H_1)}{p(x \mid H_0)} > \lambda \qquad (6)$$

And the threshold value λ is given by:

$$\int_{(x \mid L(x) > \lambda)} p(x \mid H_0) dx = \alpha \qquad (7)$$

Where:

- α is the level of significance or simply probability of false alarm.
- The function L(x) is the likelihood ratio and indicates for each value of x, the probability of H_1 versus the probability of H_0.

When the number of samples increases the test statistic for both scenarios follows a normal distribution approximately. The resultant *pdf* is described by the Central Limit Theorem as:

$$v \approx \begin{cases} \mathrm{N}(N, 2N) & H_0 \\ \mathrm{N}(N(1+\gamma), 2N(1+\gamma)) & H_1 \end{cases} \qquad (8)$$

Where:

- γ is the SNR.
- N represents the normal distribution.

Therefore, the threshold for the Neyman Pearson Criteria yields:

$$\lambda = \sqrt{2N} Q^{-1}(P_{fa}) + N \qquad (9)$$

Where N is the number of samples and Q is the gaussian complementary distribution function, given by:

$$Q(x) = (1/\sqrt{2\pi}) \int_x^{\infty} \exp(-t^2/2) dt \qquad (10)$$

5. TECHNIQUES FOR ESTIMATING THE NOISE FLOOR.

In order to achieve the automatic operation of the energy detector, it is necessary to implement a robust estimator of noise variance. This is employed to estimate the value of the test statics in equation (3). In this regard, a variety of solutions are reported. Additionally a new method is described on the current Section.

Rank Order Filter (ROF)

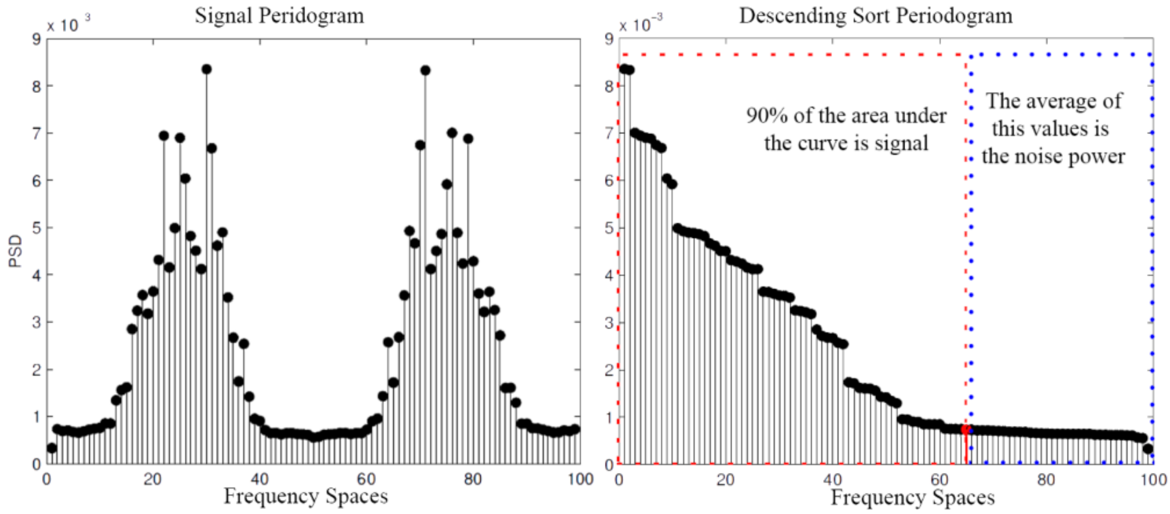
Rank Order (RO) filters are a subclass of Order Statistic (OS) filters, which have been shown to be useful for robust signal smoothing. In addition, the RO filters simultaneously preserve and smooth noise in a better way than linear filters. Although this type of filter has the disadvantage of flattening the signal, thus they are not recommended in situations where the channel is commonly busy. Besides, ROF requires large amounts of data processing.

Method of the 90% (Proposed method)

In this work, new approach to estimate noise variance of the signal is proposed as shown in Fig. 5. The 90% method consist on the following steps:

1. Frequency description of the signal: This is obtained by the Welch periodogram, as shown in Fig. 5a).

2. Ordering the frequency values from the periodogram: The periodogram obtained in step 1) is sorted from higher to lower values as shown in Fig. 5b).
3. Noise estimation: Based on the graph of Fig. 5b). The 90% of the frequency response is assumed to be the signal of interest (red square) while the other 10% is assumed to be noise (blue square). Finally, we find an average of the noise values to obtain the noise power by using the samples inside the blue square of Fig. 5b).



a) b)

Figure 5: Example of the 90% method.

From equations (4) and (5), and the *Pdf* of the test statistic on AWGN we may obtain:

$$P_d = Q\left(\frac{\lambda - N(1+\gamma)}{\sqrt{2N(1+\gamma)}}\right) \tag{11}$$

$$P_{fa} = Q\left(\frac{\lambda - N}{\sqrt{2N}}\right) \tag{12}$$

Where:

- λ is the threshold.
- N represents the normal distribution.
- γ is the SNR.
- Q denotes the Gaussian complementary distribution function, given in equation (10).

6. ENERGY DETECTOR IMPLEMENTATION AND RESULTS.

The proposed energy detector is based on the flow diagram shown in the Fig. 6. Based on this scheme, some parameters are modified from the conventional diagram in Fig. 3. The test statistic, at the output of the detector, is the result of normalizing the energy of the signal by the noise variance. The noise variance parameter most be estimated in accordance with method described the Fig. 5. Two hypothesis H_0 and H_1 are used, only noise and signal with noise are analyzed, respectively.

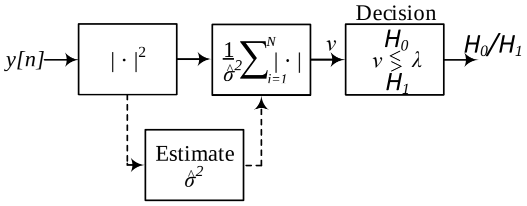


Figure 6: Proposed ED diagram.

The proposed ED was previously implemented in the Matlab Simulink, with the purpose of obtaining results in an oriented language of block design flow that is a first step for further implementation in FPGA when designed in Xilinx System Generator (XSG). Firstly was implemented the test signal, the only noise and signal whit noise stimulus, as shown in Fig. 7 the input signal is a BPSK modulation of a random signal that is centered in 1 kHz.

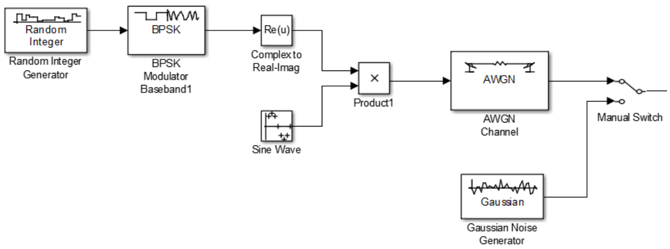


Figure 7. Stimulus signals implementation.

The second step was the implementation of the estimation method of the proposed noise variance, as shown in Fig. 8, making the signal periodogram and finding the 10% of the noise to be then averaged as shown in Fig. 9 Then the signal energy calculation is implemented, Fig. 10, and the test statistic is found, normalizing the energy between the estimated noise power to compare it with the threshold, resulting in 1 if there are signal and 0 if there are only noise, Fig. 11.

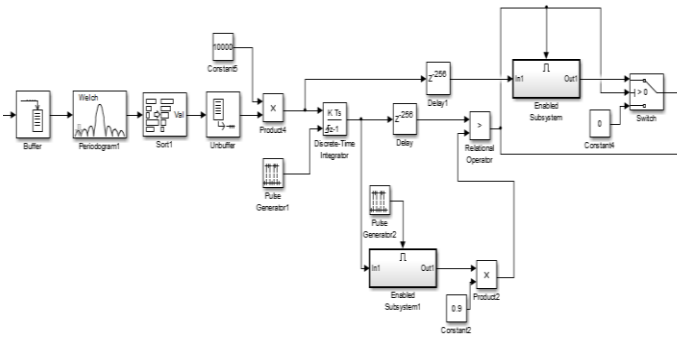


Figure 8. 90% Method implementation.

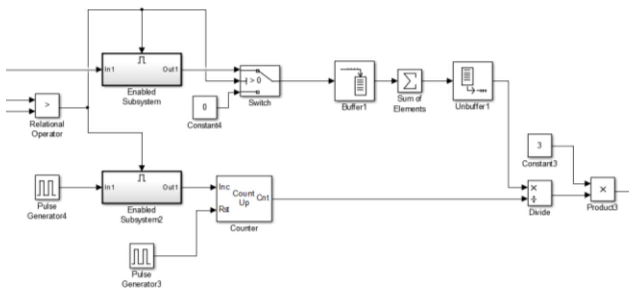


Figure 9. Mean of the noise samples.

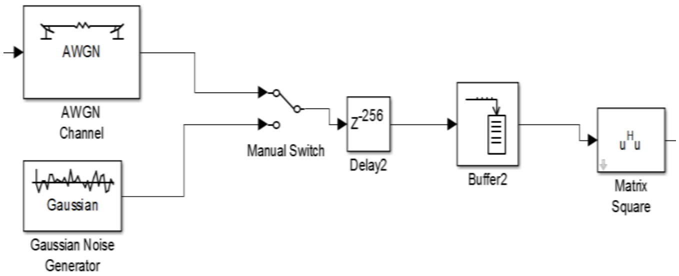


Figure 10. Calculation of signal energy.

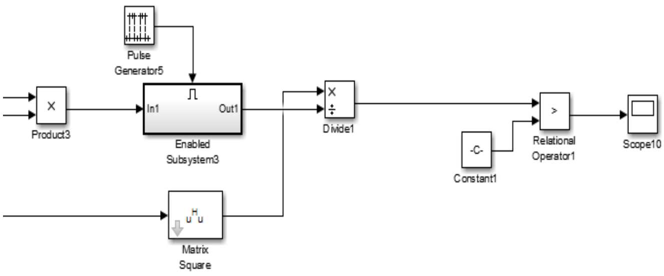


Figure 11. Comparison of the test statics whit the threshold.

In addition, this system has been developed for a Xilinx Spartan 6 FPGA using Xilinx System Generator (XSG) software. This tool integrates the kindnesses of FPGAs with a mathematical powerful assistant as MatLab. The signals must pass through the Gateway in and Gateway out blocks which are the input / output interface between the implementable part of System Generator and the rest of the Simulink model. In addition the system must have the System Generator block because this block allows to establish the FPGA version and clock frequency.

The first block is used to find the Fourier Transform using the Xilinx FFT 7.1 block. The input signals of this block are the real and imaginary part of the stimulus signal, in this case the real part is the same used for the implementation of only Simulink, observed in Fig. 7, while the imaginary input is 0. Another of the input signals of the FFT is the start signal, which indicates when the transform begins to work. Among the outputs of the block are the real and imaginary part, through which the desired magnitude is found. In addition, the edone outputs that activate a period before completion of transform and data valid which indicates when the data is ready to be read, see Fig. 12.

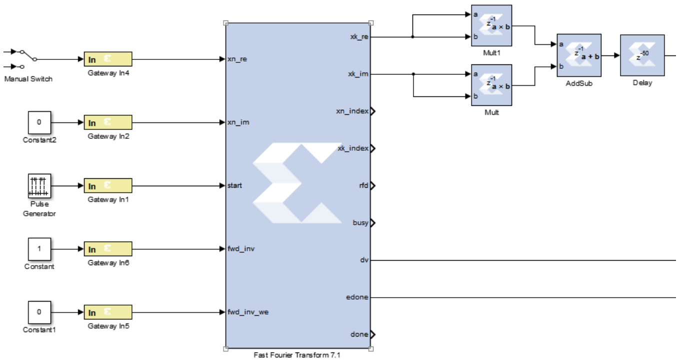


Figure 12. FFT7.1 implementation.

The following block implements the sorting operation, which was performed in VHDL because there was no specific block in XSG that allows to utilize more of 4096 bits in parallel mode. In order to adapt it to the System Generator blocks, the black box was used to export HDL code. This block in VHDL realize the conversion serial to parallel, the sorting and the conversion parallel to serial. The next blocks used in Fig. 13

return the noise power after implementing the 90% method, averaging the noise samples. ED block are presented in Fig. 14 and the general sub-blocks are shown in Fig. 15.

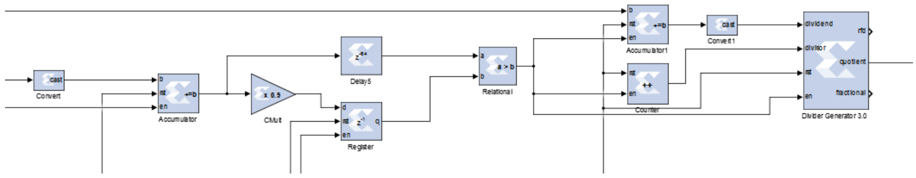


Figure 13. Average of the noise samples.

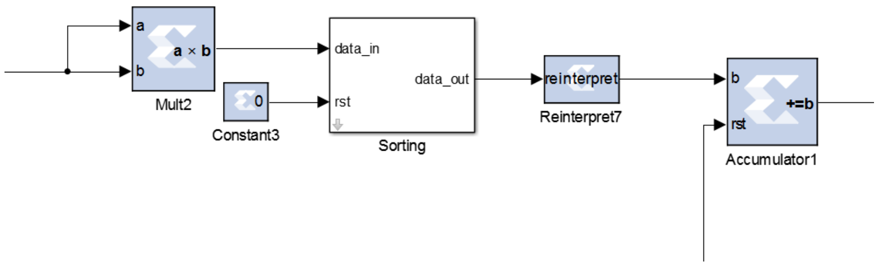


Figure 14. Calculation of the signal energy in fpga.

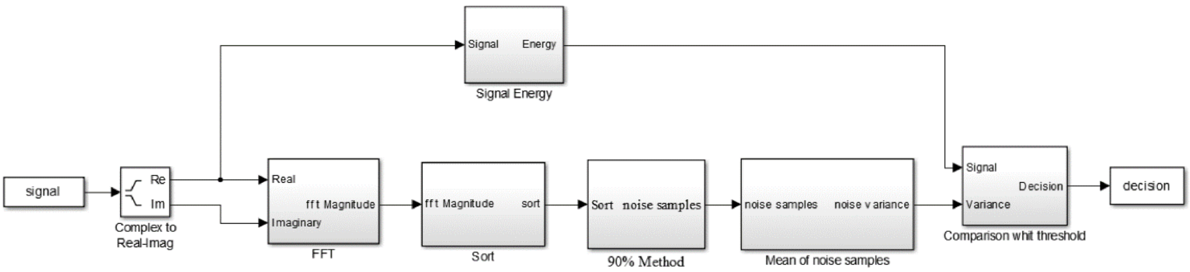


Figure 16: Proposed ED architecture in FPGA.

The tests of the proposed method of noise variance calculation offers good results to values between 0 and 10 dB de SNR, like shows Table 1.

Table 1. Estimate vs real values of noise variance with different signal to noise radio (Pfa_ideal=0.0001, N=1024).

SNR(dB)	Estimate Value	Real Value	Relative Error
20	0,058	0,005	***1060***
15	0,06	0,0158	***279,7468***
10	0,065	0,05	***30***
5	0,13	0,158	***17,72152***
0	0,425	0,5	***15***
-5	1,27	1,58	***19,62025***

Among the tests carried out in the detector implemented in Simulink, it was possible to conclude that as the Pfa_ideal of the signal increases, the Pd increases, see Table 2. And as the number of samples increases, the Pd like is shown in Table 3.

Table 2. Pfa_ideal vs Pd with different fixed probability of false alarm (Pfa_ideal=0.001 to 0.1, SNR=0dB, N=256).

Pfa_ideal	Pfa	Pd
0.001	0.001	0.7437
0.005	0.002	0.8428
0.01	0.0025	0.8884
0.05	0.0095	0.9655
0.1	0.021	0.979

Table 3. N vs Pd with different samples numbers (N=256, 1024, 4096, Pfa_ideal=0.1, SNR=-5dB)

N	Pfa	Pd
256	0.005	0.2327
1024	0.211	0.4194
4096	0.211	0.7347

7. CONCLUSSIONS.

A detailed analysis of spectrum sensing methods was carried out, reaching the conclusion that the energy detector is the best method to apply when prior knowledge of signals is not available. New schemes were investigated to improve detection and estimating noise variance. The ED is designed to be implemented on hardware reconfigurable, for instance FPGA technology. The implementation in FPGA provides the advantage to optimize area or speed, which represents a major advantage when real time applications are developed using low cost devices. The scheme is simulated in MatLab environment using Xilinx System Generator (XSG) and Simulink blocks. It allows the programmer to evade HDL code or high-level programming, which is rather complex for testing and developing purposes.

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