Hardware Implementation of Spectrum Sensing Applying Random Sampling in Cognitive Radio Networks

Asmaa Maali, Romulus Terebes, Sara Laafar, Hayat Semlali, Najib Boumaaz, Abdallah Soulmani

***Abstract*— Cognitive Radio has presented to solve the spectrum rarity problem and to improve its utilization. It is created to accord an opportunistic access for unlicensed users to utilize the available licensed frequency band. Spectrum sensing is a critical issue and an active research area in cognitive radio. It allows the identification of the state of a specific frequency band. The proposed work aims to study the feasibility of implementing random sampling in cognitive radio networks. Considering this issue, this article presents a hardware implementation of two spectrum sensing techniques using an ADSP-BF533 Digital Signal Processor, by applying random sampling. The performances of these methods have been evaluated in term of sensing (detection) and execution time. At last, the experimental results are compared with the results obtained from MATLAB simulator.**

***Index Terms*— Cognitive Radio, hardware implementation, spectrum sensing, random sampling**

I. Introduction

The growth of wireless technologies and devices leads to spectrum penury. In response to this shortage, in order to cognitive radio (CR) technology has been developed [1]. The CR is presented as a technology allowing exploiting the under-utilized radio spectrum by introducing the opportunistic use of the primary user's frequency band [2,3].

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From the Federal Communication Commission (FCC), "Cognitive radio is a type of a system or radio which can sense electro-magnetic waves from the surrounding environment. It dynamically, autonomously modifies its radio operative constraints to smoothly run the system procedure. For example, adjusting maximum throughput, moderating interferences, interoperability facilitating for the accessing of market" [4]. Moreover, CR is an advanced software defined radio that permits the users to select the suitable available bands (Spectrum Management), arrange access to this band with other users, get out of the band when a licensed user is detected and decide which fragments of the spectrum are available that can be exploited and then detect the licensed users presence when a user operates in a licensed band (spectrum sensing).

This technology proposes new categories of users; the licensed or primary users (PU) are the users who have the highest priority for using a frequency band and the unlicensed users or secondary users (SU) who can exploit the frequency band without affecting or interrupting the operation of the PU [5]. For this purpose, Spectrum Sensing function (SS) is the more ambitious issue in CR that permits detecting the spectrum occupancy. It enables the SU to find unused positions of spectrum or spectrum holes by adjusting to the radio environment, without any interference to the primary users. This policy should be adopted before that the secondary user accesses to the spectrum to detect whether the channel is not active.

In the literature, various methods of SS are given such as: matched filter detection (MF) [6, 7], energy detection (ED) [8, 9] and cyclostationary feature detection (CSD) [6, 10] where all have their own advantages and disadvantages. The MF detector offers efficient detection but needs a total knowledge of signal characteristics of the main user (PU). The CSD exploits the periodicity in the acquired signal to detect the presence of PU. Its main benefit is its robustness to noise uncertainties. However, its high computational complexity and long sensing time to achieve processing gain are considered as principal disadvantages. The ED is the most widely used technique among the spectral detection methods because it has few mathematical expressions and its material design is not complicated. This technique does not need any prior knowledge of the main user's signal. However, it does not give a correct sensing at low Signal to Noise Ratio (SNR). To face up noise uncertainty difficulty encountered by the

ED, the Maximum eigenvalue detection (MED) can be used [11-17].

The utilization of SS techniques is expensive in terms of analog to digital converters (ADC) since they require a high sampling frequency and high signal processing components [5]. In this case, numerous advantages have been presented by the use of the random sampling (RS) which are not present in the uniform sampling case [5].

In the literature, many works on the SS methods presented where based on uniform sampling. In this contribution, we implement both MED and ED spectrum sensing methods applying random sampling on a Digital Signal Processor (DSP) platform. The association of the RS with spectrum sensing methods can optimize CR systems by taking advantage of the benefits of random sampling cited above.

The organization of this article are as follows: In Section 2, the maximum eigenvalue based detection is presented. Section 3 introduced the energy detection method. Random sampling theory is discussed in Section 4. Section 5 assesses the performance of the hardware implementation in term of the execution time and the receiver operating characteristic curves (ROC curve). Conclusions are drawn in the section 6.

II. MAXIMUM EIGENVALUE BASED SENSING

This paper focuses on the SS that is the important operation in cognitive radio networks. This function enables detecting the transmissions of the PU in a specific frequency band at a specific time and then decide whether the secondary user could reuse the frequency band or not.

Let x_n be the received signal:

$$x_n = s_n + \omega_n \tag{1}$$

where:

s_n represents the PU signal

ω_n: represents the noise channel; in our study, Additive White Gaussian Noise (AWGN) is considered and n is the sample index.

The decision on the band occupancy can be made up by comparing the statistical test T with a fixed threshold λ. This is like the difference of these two hypotheses [18]:

$$\begin{aligned} H_0&: x_n = \omega_n \text{ (Vacant)} \\ H_1&: x_n = s_n + \omega_n \text{ (Occupied)} \end{aligned} \tag{2}$$

H_0 is the statement when the PU is absent; while H_1 states the presence of the PU in the concerned channel.

The false alarm probability (P_{FA}) and the detection probability (P_D) which are defined by (3) can evaluate the efficiency of any SS technique [4, 8]:

$$\begin{aligned} P_{FA}&: \text{Prob}\,\{T > \lambda / H_0\} \\ P_D&: \text{Prob}\,\{T > \lambda / H_1\} \end{aligned} \tag{3}$$

P_{FA} denotes the probability of SU proclaiming that a PU is present when the spectrum is actually inactive while P_D denotes the probability of SU proclaiming that a PU is present when the spectrum is truly active by the primary user.

The SS process implemented is based on the maximum eigenvalue and energy detectors, as they do not require any prior knowledge of the PU signal.

The idea of exploiting the properties of eigenvalues for spectral detection is first proposed by Haddad et al. [18]; the authors calculate the eigenvalues of the covariance matrix and use a test statistic as a function of the eigenvalues. Then the authors in [14,19] used the eigenvalues to develop a spectral detection technique. Maximum eigenvalue detector (MED) is based on the evaluation of the eigenvalues of a matrix formed by the acquired samples. It can be considered as the most reliable among the methods cited in the literature. This method has many advantages according to the authors in [14-19]. The concept of MED technique is presented in the following block diagram:

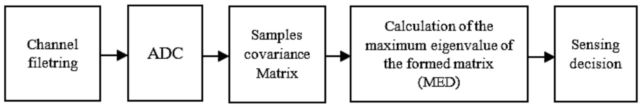

Fig. 1. Maximum Eigenvalue Detector diagram block

The approximated statistical covariance matrix $\widehat{R}_x$ is defined by [14] as:

$$\widehat{R}_x(N_s) = \begin{bmatrix} \xi(0) & \xi(1) & \dots & \xi(L-1) \\ \xi(1) & \xi(0) & \dots & \xi(L-2) \\ \xi(\vdots) & \xi(\vdots) & \xi(\vdots) & \xi(\vdots) \\ \xi(L-1) & \xi(L-2) & \dots & \xi(0) \end{bmatrix} \tag{4}$$

where ξ(l) is the sample auto-correlations of the acquired signal and L is the number of consecutive samples. ξ(l) is given by:

$$\xi(l) = \frac{1}{N_{MED}} \sum_{m=0}^{N_{MED}-1} x(m)x(m-l)\,, l = 0,1,\dots,L-1 \tag{5}$$

where N_{MED} represents the available samples number.

From Random Matrix Theory (RMT), the P_{FA} for the MED method is given as:

$$P_{FA} \approx 1\text{-}F_1\left(\frac{\lambda_{MED}N_{MED}-\mu}{\vartheta}\right) \tag{6}$$

where :

$$\mu = \left(\sqrt{(N_{MED}-1)} + \sqrt{L}\right)^2 \tag{7}$$

$$\vartheta = \left(\sqrt{(N_{MED}-1)} + \sqrt{L}\right)\left(\frac{1}{\sqrt{(N_{MED}-1)}} + \frac{1}{\sqrt{L}}\right)^{1/3} \tag{8}$$

And F_1 defines the TRACY-WIDOM distribution of order 1 [14].

The sensing threshold used for the decision process is computed from a given P_{FA}, N_{MED} and L, using the expression (9).

$$\gamma = \frac{(\sqrt{N_s}+\sqrt{L})^2}{N_s}\left(1 + \frac{(\sqrt{N_s}+\sqrt{L})^{-2/3}}{(N_s L)^{1/6}}\, F_1^{-1}(1+P_{FA})\right) \tag{9}$$

The following points can define the sensing algorithm based on MED: **first** determine ξ(l) in (5) and construct the matrix defined in (4), **secondly** search the highest eigen-value for the covariance matrix ξmax by implementing the decomposition technique of eigen-value and **third** make decision: ξmax

$>\lambda_{MED}*\sigma_{\omega}^{2}$, PU exists, else, it does not. (where σ_{ω}^{2} refers to the noise variance)

III. Energy Detection Based Sensing

Energy Detector was proposed for the first time in [9]. As the MED method, the ED does not need prior information of the PU signal. Its principle is based on the computation of the energy of the samples in the frequency band of interest and compare this energy with a threshold defined by (11). If the energy of the system is greater than its threshold value, the primary user signal is reflected firstly, otherwise the primary user is vague. The Fig. 2 can be explained as: the band pass filter block is used to remove the out of band signals by selecting the interested frequency band. After signal digitizing using an ADC, the received signal energy is estimated by a simple block of square and average. Energy detection compares the test statistics T_{ED} with $\boldsymbol{\lambda}_{ED}$, to sense the presence of the PU's signal [5].

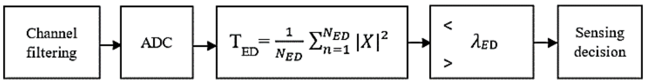

Fig. 2. Energy Detector diagram block

The statistical test used for energy detector is given by [11]:

$$T_{ED}=\frac{1}{N_{ED}}\sum_{n=1}^{N_{ED}}|Xn|^2 \qquad (10)$$

where N_{ED} is the number of samples.
For a given P_{FA}, the threshold can be obtained as presented in [14]:

$$\lambda_{ED}=\sqrt{\frac{2}{N_{ED}}}Q^{-1}(P_{FA})+1 \qquad (11)$$

Where:

$$Q(t)=\frac{1}{\sqrt{2\pi}}\int_{t}^{+\infty}e^{-\frac{u^2}{2}}.du \qquad (12)$$

IV. Signal Reconstruction Using Random Sampling

The principle of RS is to convert a continuous analog signal X(t) to a discrete time representation Xs(t) (Fig. 3) where the sampling instants are distributed in the non-uniform way.

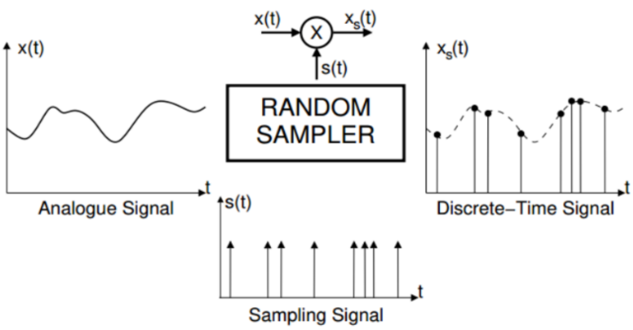

Fig. 3. Random sampling principle

The RS utilization provides a large flexibility in sampling frequencies choice and makes it possible to reduce the spectrum aliasing [21, 22].

There are two modes of random sampling namely Additive Random Sampling (ARS) and Jitter Random Sampling (JRS), which are the most used in the literature. The present contribution proposes the application of JRS mode for its simplicity of implementation.

JRS is a random process where the sampling instants are described by the following expression:

$$t_n = nT + \tau_n \qquad T>0,\ n=1, 2, ... \qquad (13)$$

The mean period of sampling is T.
τ_n defined a set of independent random variables identically distributed with a probability density $p(\tau)$, a variance $\sigma 2$ and mean=0 which can be generated using uniform or normal distribution.

Signal's reconstruction from a finite number of its samples can be reduced to solve the following linear system:

$$Xs = A * C \qquad (14)$$

where:

- Xs is a vector of dimension equal to the number of samples N, $Xs = [x(t_1), x(t_2)\dots x(t_N)]$.
- A is a matrix of dimension N x M formed by the elements of the base $A_m(t_n)$.
- C is a vector of dimension M with the complex elements c_k to calculate.

Now for the greater samples values by comparing with the mean of Nyquist frequency (express by the actual bandwidth). The orthogonal origin of difficult exponential function is the best choice for restoration course [23]. Hence, every element of the matrix "A" is rewritten as:

$$A_{ik}=e^{2\pi j f_k t_i} \qquad (15)$$

The recovered signal is defined by the following formula:

$$\hat{x}(t)=\sum_{k=1}^{M}c_k e^{2\pi j f_k t_i} \qquad (16)$$

The frequency components f_k are chosen in the signal bandwidth. The c_k coefficients are found by minimization of the squared error:

$$E_q^2=||Ac-x_s|| \qquad (17)$$

The minimum of the (17) is obtained from the following formula:

$$A^H Ac = A^H x_s \qquad (18)$$

The SVD (Singular Value Decomposition) algorithm [23] is a suitable way to solve (18).

After calculating the coefficients ck, the signal can be recovered by (17) and compared to the original signal using the expression (19):

$$E_m^2 = \frac{\sum_k |x(t_k) - \hat{x}(t_k)|^2}{\sum_k |x(t_k)\,|^2} \qquad (19)$$

The SNR of reconstruction can be defined by: $-10\ \log_{10}(E_m^2)$.

V. Hardware Implementation and Results Discussion

In this section, we present a hardware implementation of the studied SS algorithms applying random sampling on a hardware platform ADSP-BF533 from the manufacturer Analog Devices.

A DSP (Digital Signal Processor) is a special type of microprocessor. It is characterized by the fact that it integrates a set of special functions. These functions are intended to make it particularly powerful in the field of digital signal processing. Most DSPs are particularly intended for real-time applications, in which processing time is essential. Thus, they are characterized by an architecture optimized for processing a large amount of data in parallel with each clock-cycle, which gives DSP-based applications a high degree of flexibility.

Like any conventional microprocessor, a DSP is implemented by associating memories (RAM, ROM) and peripheries. It generally takes the form of a microcontroller integrating, depending on the manufacturer's brand and range, memories, timers, fast synchronous serial ports and various I/O ports.

In general, there are two languages available for DSP programming, namely C and assembly programming languages. The assembly programming is the most powerful because it allows generating an optimal code in execution time (being very close to the hardware) nevertheless it is very complex because it is linked to the processor. C programming is easier but less optimal.

The DSP BF533 platform is presented in Fig. 4. It is characterized by variable clock frequency, up to 750 MHz and a RAM memory capacity of 4GB and connected to the PC via an USB connection. The implementation scheme is illustrated by Fig. 5.

Fig. 4. DSP BF533

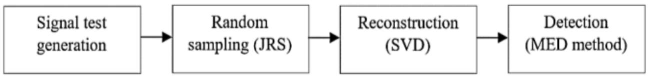

Fig. 5. Implementation scheme

The implementation scheme can be explained as follows: firstly, we generated a random sequence (Fig. 6) modulated in QPSK and filtered with a Gaussian low pass filter (BT = 0.3) (Fig. 7). So then, the input signal is sampled with the JRS random sampling mode (Fig. 8). Subsequently, the signal is reconstructed by applying the SVD (Singular Value decomposition) algorithm (Fig. 9). Finally, we applied the spectrum sensing method desired (MED/ ED).

The code was written in C programming language using VisualDSP++ [24,25] as Integrated Development Environment. In our study, the execution time defined as the required time for the algorithm to detect the presence of the signal is chosen as the performance criterion.

Table I depicts the execution time for each function of our implementation scheme and for the entire implemented code. The results show that the random sampling does not need much time of executing. We can also notice that the most consuming function is the reconstruction (SVD algorithm). For this reason, we plan to improve this work by changing the method of the reconstruction used (Singular Value Decomposition) to reduce the execution time related to this method; while keeping a good detection of the signal which is the challenge for each spectrum sensing method proposed.

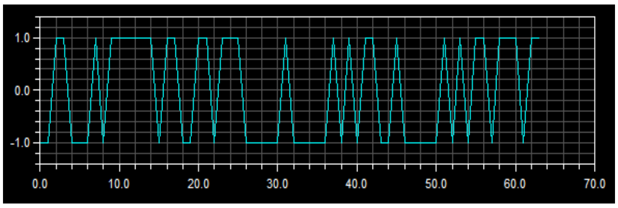

Fig. 6. Random sequence

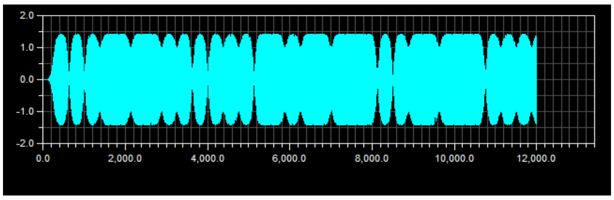

Fig. 7. Modulated signal

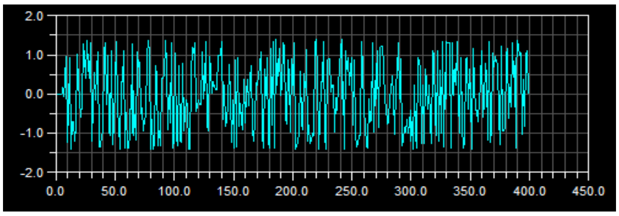

Fig. 8. Sampled signal

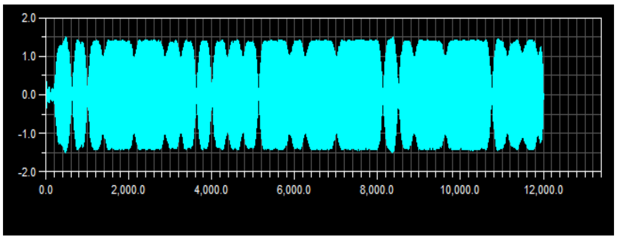

Fig. 9. Reconstructed signal

After executing the code programmed under the VisualDSP ++ Integrated Development Environment, we verified the process of sensing by plotting the ROC curve of both studied methods. For this reason, the values obtained on VisualDSP++environment are taken and inserted in MATLAB. The Fig. 10 illustrates the detection probability P_D of the studied method as a function of the false alarm probability P_{FA}.

TABLE I

EXECUTION TIME OF THE IMPLEMENTATION FOR EACH METHOD

Maximum Eigenvalue Detector Estimation		
Function	Number of the clock cycles	Execution time (s)
Modulation	128215081	1,70e-01
RandomSampling	652547	8,70e-04
Reconstruction	1,6466e+11 (164660430414)	2,20e+02
Spectrum sensing (MED)	49453033	6,59e-01
Whole code	1,6484e+11 (164840452325)	2,40e+02
Energy Detector Estimation		
Function	Number of the clock cycles	Execution time (s)
Modulation	128215081	1.70e-01
RandomSampling	652547	8,70e-04
Reconstruction	-	-
Spectrum sensing (ED)	2515334	3.35e-03
Whole code	133083615	1.77e-01

The Fig. 10 represents the Receiver Operating Characteristics (ROC) curves of Energy Detector and Maximum Eigenvalue for observing the detection performance. In this figure, the experimental curves are superimposed with the simulation ones. We notice that for each of the studied methods, the ROC curves are almost similar.

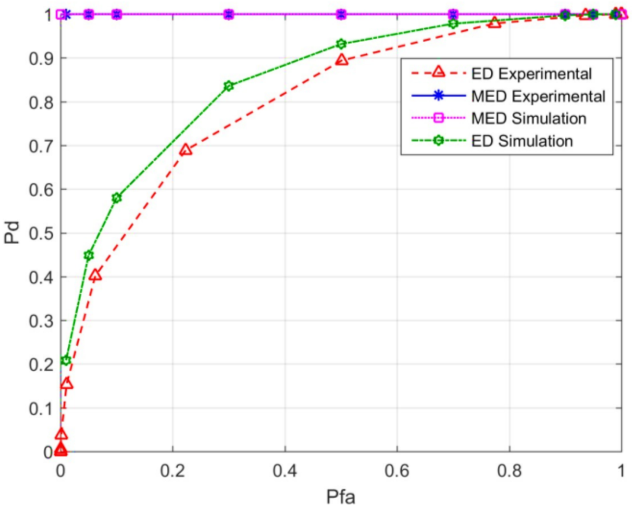

Fig. 10. ROC curve (P_D Vs P_{FA}) for both spectrum-sensing methods

VI. CONCLUSION

Actually, the Cognitive Radio is considered as an exceptional innovation being used in modern wireless communications. In this work, we were interested by the fundamental function in CR technology which is the spectrum sensing. We proposed an approach, combined the spectrum sensing function and random sampling. It was implemented on the ADSP-BF533 hardware platform. According to obtained results, we notice that the function of random sampling does not require a high execution time. Therefore, we can deduce that the implementation of the random sampling combined with the spectrum sensing methods may present an interesting solution in CR networks since it gives a good quality of detection.

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