Low Complexity Spectrum Sensing Approach applying Random Sampling in Cognitive Radio Networks

N. Boumaaz, H. Semlali, A. Maali, A. Soulmani, J.-F. Diouris, A. Ghammaz

Abstract—**Cognitive Radio appears as a natural solution to the problems of spectrum scarcity resulting from the great popularity of wireless communications and the evolution of radio technologies. This technology allows an unlicensed user to use the licensed frequency bands in an opportunistic manner. In order to determine whether a given band is occupied or vacant, a spectrum sensing feature is required. Energy detector is the most popular technique used for spectrum sensing for its low computational requirements. In this contribution, we investigate the application of the Discrete Fourier Transform and random sampling combined with the energy detector technique in a cognitive radio system in order to reduce its complexity. We have evaluated the performance of the proposed approach in terms of the Receiver Operating Characteristics (ROC curves), the false alarm probability, complexity and losses in Signal to Noise Ratio. The obtained results are compared with an approach based on the LU (Gaussian Elimination) algorithm.**

Index Terms—**Cognitive radio, Energy detector, DFT, Random Sampling, Spectrum sensing.**

I. Introduction

Wireless communication systems and mobile services are becoming increasingly popular. In this context, it is interesting to have devices which are able to support high performance multi-standard operation in terms of throughput and transmission quality, and to satisfy customers who are looking for multi-standard equipment. From this idea, the software defined radio (SDR) was born. This technology allows equipment to communicate with several radio communication standards by reconfiguring hardware components or by modifying the embedded software. To do this, software defined radio proposes to use a simple and universal analog block at the head of the receiver and to digitize the signal as close as possible to the antenna. The rest of the processing must be done digitally in order to facilitate reconfiguration [1-3]. This makes it possible to make users, service providers and manufacturers more independent of standards.

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However, this growth in wireless communication systems has also been accompanied by an increase in demand for the spectral resources available to wireless technology, which has become increasingly scarce and can no longer meet the demand. Future generations will therefore have to take advantage of the existence of unoccupied frequency bands, thanks to their ability to listen and adapt to their environment. This has enabled the evolution from software defined radio to intelligent radio. Smart radio or cognitive radio (CR) is defined as the integration of reasoning into software defined radio [4, 5].

Cognitive radio has been proposed to ensure optimal use of the spectrum that is currently suffering from scarcity with the rapid growth of new technologies. In this regard, cognitive radio as a technology divides the users of radio receivers into two categories. The primary user (PU) has priority to use the spectrum band, while the secondary user (SU) is an opportunistic user who can transmit on that band as soon as it is available. In order to determine whether a given band is occupied or vacant, spectrum sensing (SS) functionality is required, as well as an appropriate algorithm to detect whether a primary user is transmitting or not.

Various techniques proposed for spectrum sensing operation, among others, Energy Detection (ED) [6-9], Cyclostationary features Detection (CSD) [6, 10], Matched Filter detection (MF) [6, 8, 10], Maximum Eigenvalue Detection (MED) [8,10-12]. Each one has its own characteristics, complexity and accuracy of detection. Energy detection is the most popular and suitable spectrum sensing method since prior knowledge of the licensed user signal is not required.

In this work, we propose the application of the Discrete Fourier Transform (DFT) [6, 13] and random sampling (RS) [14-17] combined with the energy detector technique in a cognitive radio system. The application of the DFT is less complex and very flexible (in comparison with the quadratic minimization methods) in the sense that restricts the calculation of the frequency components to the channel of interest. However, the application of a random sampling sequence in cognitive radio systems presents more flexibility in sampling frequencies choice, due to the absence of forbidden bands encountered in regular sampling [6, 14, and 18].

The performances are evaluated in terms of the Receiver Operating Characteristics (ROC) curves, the false alarm probability, complexity and losses in Signal to Noise Ratio (SNR) as a function of the number of samples. In this application, we have used both sampling modes (random sampling and uniform sampling). The obtained results are compared with an approach based on the LU (Gaussian Elimination) algorithm [6, 19] in order to highlight the usefulness of our proposed approach.

The reminder of this paper is organized as follows. An overview of spectral components calculation and channel filtering based on the DFT in a random sampling case is presented in the following section. Section 3 presents a theoretical analysis of the energy detector technique. Section 4 evaluates the performance of the proposed approach in terms of the ROC curves, the false alarm probability, complexity and losses in SNR, and the contribution is concluded in section 5.

II. Spectral Components Calculation based on the DFT Method in a Random Sampling Mode

In the present work, we suppose that the analysed signal is randomly sampled using a Jittered Random Sampling Sequence (JRS) in view of its popular use [6, 15, 19], and we propose to use a low complexity method for spectral components calculation and channel filtering based on modified Discrete Fourier Transform for the case of irregular sampling. The application of the DFT is less complex and very flexible (in comparison with the quadratic minimization method) in the sense that restricts the frequency components calculation to the channel of interest.

Let us consider a multi-band signal $x(t)$ characterized by an effective band $I = U\, I_i$. The I_i represent the various sub-bands of the signal and U is the union operator. The samples are identified by $((t_i), x_i = x\,(t_i))$ with i ranging from 1 to N, where N is the number of samples obtained during the time observation T_0. The t_i are the sample times.

The sampled signal can be reconstructed based on the following interpolation expression:

$$\hat{x}(t) = \sum_{k=1}^{M} c_k \exp(\,2\,j\pi f_k t) \tag{1}$$

where:

c_k represent the spectral components of the multi-band signal $x(t)$ and are estimated by the DFT expression:

$$c_k = \sum_{i=1}^{N} x(t_i)\exp(-2\,j\pi f_k t_i)(t_i - t_{i-1}) \tag{2}$$

f_k are M frequencies chosen in the signal bandwidth [6,17].

A useful channel can be reconstructed by its corresponding coefficients c_k (Fig. 1) through the expression (1). Indeed, let's consider the spectrum of the real 3-band signal presented in Fig. 1 and that the problem consists in selecting the second channel. Il will be possible to reconstruct the second channel through (1) using the associated coefficients $\{c_p\ ...\ c_q\}$ and their associated frequencies $\{f_p\ ...\ f_q\}$. The reconstructed channel is in the system band. In the case of baseband reconstruction, we can rebuild the desired channel by using the same coefficients $\{c_p\ ...\ c_q\}$ associated with their frequencies translated into baseband by the central frequency f_0: $\{f_p\text{-}f_0 \dots f_q\text{-}f_0\}$.

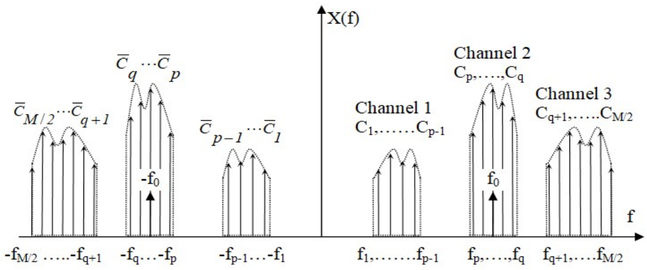

Fig. 1. Example of a real 3-band signal spectrum

III. Energy Detector for Spectrum Sensing

The basic idea of the energy detector consists in computing the energy of the received signal in the desired band. The calculated energy is compared to a pre-computed threshold value λ_E [10] in order to decide the accessibility of the desired band. This corresponds to the differentiation between the following hypotheses:

$$x(n) = \begin{cases} \omega(n) & : H_0 \\ s(n) + \omega(n) & : H_1 \end{cases} \tag{3}$$

where $x(n)$ is the received signal, $s(n)$ is the the signal to be detected (PU), $\omega(n)$ is an Additive White Gaussian Noise (AWGN) sample, and n is the sample index. H_0 and H_1 denote respectively, the absence and presence of the PU.

The energy detector statistical test T_{ED} is formulated by :

$$T_{ED} = \frac{1}{P}\sum_{k=1}^{P} \left|C_k\right|^2 \tag{4}$$

where P is the frequency components number in the desired band.

Two probabilities are used for evaluating the performance of a detection algorithm [6-8]: the probability of detection (P_d) and the false alarm probability (P_{fa}). These probabilities can be determined by:

$$\begin{cases} P_{fa} : \text{Prob}\ \{T_{ED} > \lambda_E / H_0\} \\ P_d\ \ : \text{Prob}\ \{T_{ED} > \lambda_E / H_1\} \end{cases} \tag{5}$$

The theoretical expressions for the ED probabilities are given respectively, by [6, 7]:

$$P_{fa} = \frac{\Gamma(\text{N},\ \lambda_{\text{E}}/2)}{\Gamma(\text{N})} \tag{6}$$

$$P_d = Q_N(\sqrt{2\,SNR}\ , \sqrt{\lambda_E}\,) \tag{7}$$

where λ_E is the threshold used, $\Gamma(\text{a})$ denotes the gamma function, $\Gamma(\text{a,x})$ is the incomplete gamma function, Q_N (a,b) is the generalized Marcum Q-function and SNR is defined as the ratio of the signal variance σ_s^2 to the noise variance σ_ω^2.

$$SNR = \frac{\sigma_s^2}{\sigma_\omega^2} \quad (8)$$

By plotting the receiver operating characteristic (ROC) curve, which presents the evolution of P_d as a function of P_{fa} for different values of the threshold, the detector's performance can be evaluated.

IV. Application and Simulation Results

The goal of this section is to evaluate the performance of our proposed approach for both random sampling and uniform sampling and compares it to the same approach based on the LU direct algorithm. Figure 2 illustrate the simulation diagram block.

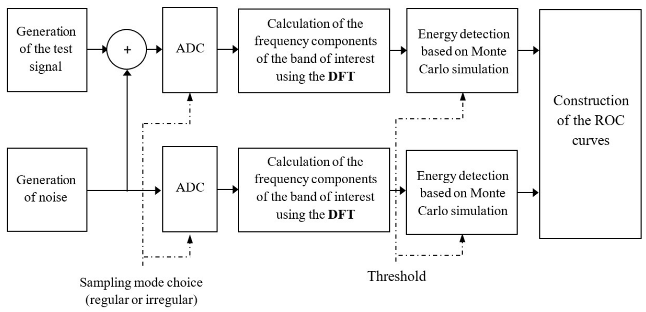

Fig. 2. Block diagram of simulation

After digitizing the received signal, we compute the frequency components of the desired channel using the DFT. Then, based on the energy detector, the occupancy of the radio frequency spectrum is analyzed. Monte Carlo method is used in our application to estimate both the P_d and P_{fa} in order to plot the ROC curve.

The test signal is a multi-band signal constituted of *5* carriers separated by *8MHz*, modulated in QPSK then filtered by a raised cosine filter with a roll-off coefficient equal to *0.5*. Each carrier has a symbol rate $R_{sym}=4.10^6 sym/s$.

The non-uniformly sampled signal is obtained by using a JRS sampling sequence of length N, with average sampling rate $f_s=100MHz$.

A. Evaluation of our approach in terms of ROC Curves

In this section, we evaluate the proposed scheme in terms of its ROC curves. Figure 3 illustrates the ROC curves over an AWGN channel. For this issue, two central frequency values are considered: the first one is located inside the allowed bands (AB) while the second value is situated inside the forbidden bands (FB), and using the two sampling modes mentioned above. We note that the allowed band is defined as a band where there is no spectrum aliasing. For these simulations, the number of samples is $N=1000$ and the SNR is *-20dB*.

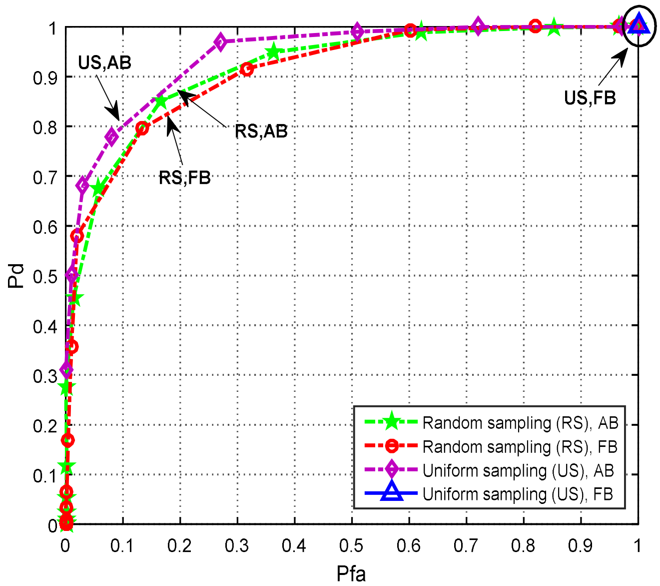

Fig. 3. ROC curves of the proposed approach using both sampling modes at two different values of central frequency, one at the *AB* band and the other at the *FB* band

From figure 3, by using the random sampling, we can notice that whatever the value of the center frequency the ROC curves appear almost similar.

However, by using uniform sampling, we have obtained two ROC curves cases:

1) When the center frequency belongs to the AB, the ROC curves resemble to those of the RS case.
2) For central frequency value belongs to the FB, a spectrum aliasing is produced in the desired channel and hence a high level of energy is present in this channel even if it is free. This explains the obtained ROC curve which is reduced to a point (Pd=Pfa=1), which means that the energy detector does not work properly.

Through this evaluation, we can note that the random sampling overcomes the limitation of forbidden bands imposed by the uniform sampling process.

B. Effect of the SNR on the ROC Curves

In this section, we analyze the effect of the SNR on the ROC curves (figure 4) using the proposed approach for spectrum sensing. According to this figure, it can be noted that by increasing the SNR, the probability of detection P_d increases. This issue can be explained by the fact that by increasing the SNR, the signal level is well above the noise level, which leads to an increase in the probability of detection (P_d tends to 1).

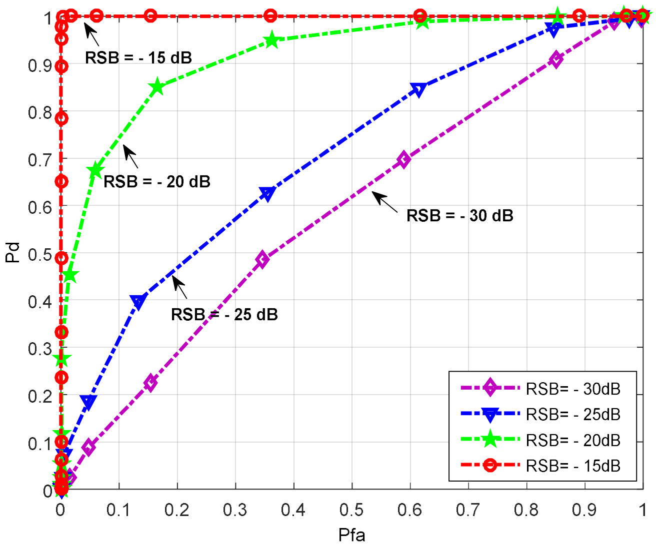

Fig. 4. ROC curves for various values of SNR using a random sampling mode

C. Complexity Analysis

To analyze the complexity of the proposed approach for spectrum sensing and the approach based on the LU algorithm for the calculation of the c_k frequency components of the desired band, we compute the number of elementary operations in flops (floating point operations) of each of the used algorithms: LU algorithm [6, 18] and the DFT. The following table presents the complexity in number of operations.

TABLE I
NUMBER OF OPERATIONS FOR THE LU ALGORITHM AND THE DFT METHOD

Algorithm	Number of Operations in flops
LU algorithm	$\frac{2}{3}M^3 + 2M^2N + \frac{3}{2}M^2 + 2MN + \frac{35}{6}M - 7$
DFT	$5MN - M$

M and N represent the number of frequency components and the number of samples, respectively. To facilitate the complexity analysis, we suppose that N is equal to M (in reality, $N \geq M$).

Comparing the number of elementary operations of the DFT and the LU algorithm, we note that the DFT ($O(M^2)$) is less complex than the LU algorithm($O(M^3)$).

Figure 5 illustrates the complexity in number of operations of the DFT and LU versus the number of samples (N) for a fixed M.

From this illustration, we can notice that the complexity in number of LU operations is always higher compared to the DFT whatever the number of samples. So from complexity point of view, DFT is always less demanding compared to the LU whatever the number of samples N.

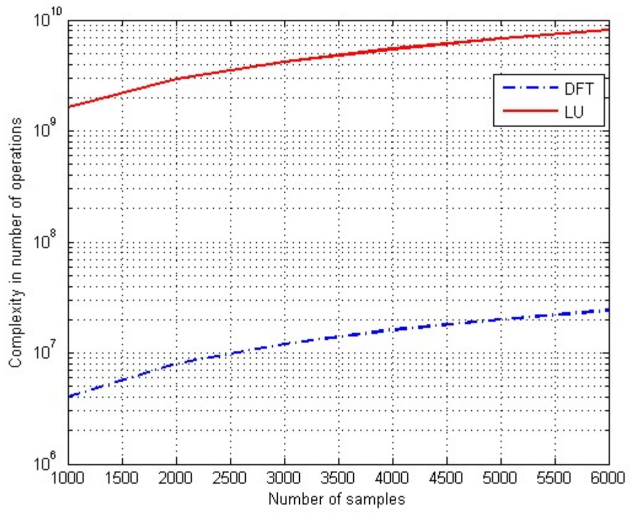

Fig. 5. Complexity in number of operations of the DFT and the LU algorithm versus the number of samples

D. Performance Comparison of the Proposed Approach with the same Approach based on the LU Algorithm in terms of P_{fa}

In this subsection, we compare the performance of the proposed approach with the approach based on the LU algorithm in terms of P_{fa} for different values of SNR by considering two central frequency values: one value inside the allowed bands and another in forbidden bands. Both types of sampling are considered in order to show the interest of our approach.

The performance of this structure is compared with the same structure based on the LU algorithm for calculating the frequency components of the desired band. The P_d is fixed at 0.9 and it is of interest to have low false alarm probability. Figure 6 shows the obtained performance in terms of P_{fa} for various values of SNR.

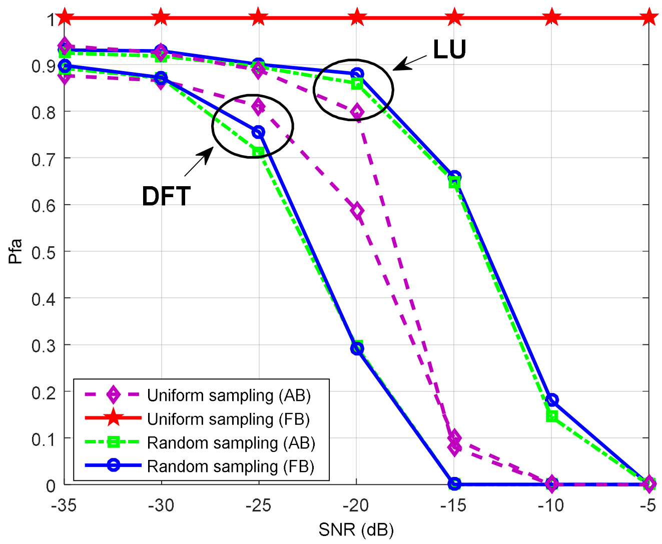

Fig. 6. Comparison of the Pfa of the proposed approach using the DFT and the LU algorithm for both sampling modes

From this figure, we can notice that using a uniform sampling mode, the two approaches present almost the same performance.

However, using a RS mode, the DFT-based approach shows performance degradation compared to the LU-based approach. We notice a loss of about 8dB which is due to the sensitivity of the DFT to noise. In order to minimize these losses, the number of samples N should be increased.

E. Losses in SNR in function of the number of samples

In this section, we calculate the losses of *SNR* between our proposed approach and the approach based on the LU algorithm for different values of *N*.

Figure 7 illustrates the average curve of losses in *SNR* between these two approaches and the complexity versus the number of samples. According to this figure, we can note that increasing the number of samples reduces the losses in *SNR* between the two approaches. In that case, the proposed approach is still less complex than the approach based on the LU algorithm.

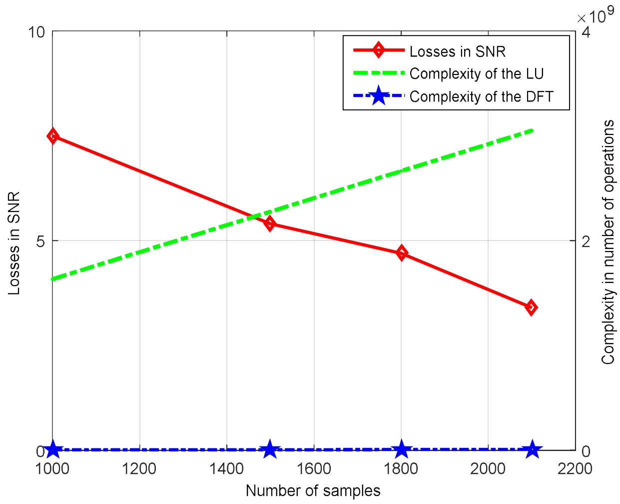

Fig. 7. Average losses in SNR and complexity of the LU and the DFT versus the number of samples

V. Conclusion

In this article, we investigated the application of the Discrete Fourier Transform and random sampling combined with the energy detector technique in a cognitive radio system in order to reduce its complexity. We have evaluated the performance of the proposed approach in terms of ROC curves, the false alarm probability, complexity and losses in SNR. The obtained results are compared with an approach based on the LU matrix decomposition algorithm.

The application of a RS sequence in cognitive radio systems provides a great flexibility in sampling rates choice and less constraint on sampling frequency (sampling frequency just above the Nyquist frequency). These advantages are desirable and appreciable at the multi-standard systems particularly in the operation of sampling frequency conversion. Furthermore, the reduced complexity of the DFT compared to other methods facilitates the implementation in particular for SR and CR systems.

The association of the random sampling, the energy detector and the DFT will allow the realization of optimized cognitive radio systems.

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