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Effect of random sampling on spectrum sensing for cognitive radio networks

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ABSTRACT

Cognitive radio is a mechanism allowing dynamic access to spectrum channels. Since its beginnings, researchers have been working on using this inventive technology to control and manage the spectrum resources. Consequently, this research field has been progressing rapidly and important advances have been made. Spectrum sensing is a key function of cognitive radios that helps prevent the harmful interference with licensed users, as well as identifies the available spectrum to improve its utilization. Several spectrum sensing techniques are found in scientific literature. In this paper, we investigate the effect of the random sampling in spectrum sensing. We propose a spectrum sensing approach based on the energy detection and on the maximum eigenvalue detection (MED) combined with random sampling. The performance of the proposed approach is evaluated in terms of the receiver operating characteristics curves and in terms of the detection probability for different values of signal to noise ratio. The obtained results are compared to the uniform sampling case to show the added value of random sampling.

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1. INTRODUCTION

There is a vast demand for novel wireless technologies in the frequency domain spurred by the exponential advancements in the wireless telecommunication industry. Recent studies, however, demonstrate that the predetermined spectrum assignment strategies currently in use do not utilize the spectrum efficiently. Cognitive radio (CR) has been presented as a viable answer to the aforementioned issue since the spectrum is a precious resource and need to be utilized effectively [1].

CR is a technology that combines software defined radio (SDR) and artificial intelligence (AI). As mentioned in [2], the cognitive radio technology will allow the users to:

- select the suitable available band (spectrum management),
- coordinate access to this band with other users (spectrum sharing) [3],
- vacate the band when a licensed user is detected (spectrum mobility) [4],
- and determine which portions of the spectrum are available and detect the presence of licensed users when a user operates in a licensed band (spectrum sensing), which is a main function of CR.

Spectrum sensing (SS) is used to inform of the status of the spectrum (vacant/occupied). This allows for the spectrum to be accessed by a secondary user (SU) without interfering with the primary user (PU) [5].

In the laste decade, various spectrum sensing methods that can be divided into two categories have been suggested: narrowband and wideband. Narrowband sensing methods analyze one frequency channel at a time while wideband sensing methods analyze several frequencies at a time. The narrowband sensing techniques include energy detection [6], [7], cyclostationary features detection [6], [8], matched filter detection [8], [9], covariance based-detection [10], [11], and machine learning-based sensing [12]-[14]. Each one has its own pros and cons [6]. Wideband sensing techniques include power efficient version, sequential sensing, and basic pursuit [2].

Given that the aim of spectrum sensing in cognitive radios is to determine the availability of the spectrum and detect the presence of the primary user when a user operates in a licensed band, the narrowband sensing approaches can be ineffective. This is because they require longer times and higher energy due to the use of high-resolution analog-to-digital converters (ADC), which are both costly and impractical for timely communications [6], [7]. To overcome this disadvantage, several solutions including the compressive sensing method have been proposed [15], [16].

In this paper, we are focused on the association of random sampling with spectrum sensing techniques. We scope our study to the SS algorithms presented below, with the objective to show the advantages of applying non-uniform sampling [15], [17] in the context of spectral detection. In [18], the authors show the utility of random sampling in the context of cognitive radio based on the energy detector (ED). In this work, we contribute to the research by exploring the application of random sampling to both the energy detector and to the maximum eigenvalue detector (MED). The spectrum sensing methods choice is motivated by the fact that these methods do not need any previous information from the primary signal transmission. The proposed approach's performance will be assessed and then compared to the uniform sampling case reported in [19]. This paper is structured as follows: section 2 presents an overview of the random sampling theory. As for section 3, it explains the energy detection and the maximum eigenvalue detection methods. Simulation results and discussion are given in section 4 before conclusion.

2. RANDOM SAMPLING THEORY

In software radio systems, the analog to digital converter (ADC) receives broadband radio frequency signals with a large dynamic range. The number of bits necessary to code the received signal is largely non-trivial, and the sampling frequency is very high, leading to a high-energy consumption, whereas not all the standards are needed to be used every time. Therefore, the bandwidth that needs to be analyzed may vary over time. This is something that the uniform sampling ADC is not able to accommodate easily, as it always operates at the same frequency, with the same energy consumption. Therefore, in order to increase energy efficiency, it would be interesting to be able to adapt either the sampling frequency or the number of bits of the ADC to reduce its energy consumption [15], [19].

One of the solutions proposed that can help optimize the CR system is random sampling, where an average sample rate slightly greater than the Nyquist frequency may be sufficient to reconstruct the information received [15]. Using random sampling provides a greater flexibility in sampling rate choices and makes it possible to reduce the spectrum aliasing (or to eliminate it in the case of a stationary sampling sequence) [17], [20], thus helping reduce the constraints on the various elements of the transmission chain. In the literature, there are two commonly used random sampling modes, namely additive random sampling (ARS) and jitter random sampling (JRS). In this work, we use the JRS mode for its ease of implementation [15].

Random sampling consists of converting a continuous analog signal x(t) into a discrete time representation xs(t) as shown in Figure 1 where the sampling instants are non-uniformly distributed. The JRS mode is a random process where the sampling times are described by the following expression:

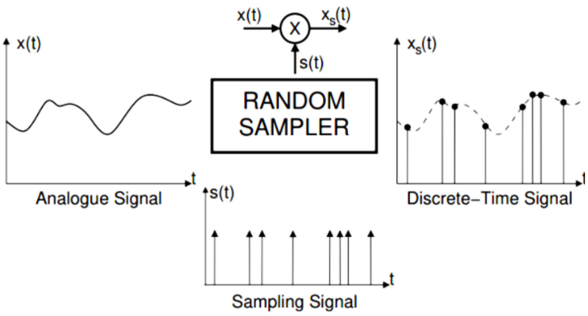

Figure 1. Random sampling principle

$$t_n = nT + \tau_n \qquad , n = 1, 2, \ldots \tag{1}$$

T represents the mean sampling rate.
τ_n denotes a set of independent random variables identically distributed with a probability density p(τ), a variance σ^2 , and a mean=0, which can be generated using uniform or normal distribution.

3. THEORY OF ENERGY AND MAXIMUM EIGENVALUE DETECTION

Suppose that the received signal has the following simple form:

$$x_n = s_n + \omega_n \tag{2}$$

In (2), n means the sample index. The primary user signal (the signal to be detected) is represented by s_n, while ω_n refers to the additive white Gaussian noise (AWGN). When there is no transmission by the primary user, (2) can be written as $x_n = \omega_n$. The problem of detection is equivalent to the following states [5]:

$$\begin{aligned} &H_0:\ x_n = \omega_n && \text{Signal is absent} \\ &H_1:\ x_n = s_n + \omega_n && \text{Signal is present} \end{aligned} \tag{3}$$

where H_0 is the null hypothesis that the primary user is absent and H_1 indicates the presence of a primary user in the channel of interest.

The SS aims to choose between H_0 and H_1 based on the observation x_n. The model presented in (3) is used to evaluate the studied technique. Therefore, two criteria are examined: the probability of false alarm (P_{fa}) and the probability of detection (P_d). P_{fa} is the probability that the test gives a wrong declaration about the occupancy of the considered band, whereas P_d denotes the probability to correctly detect the PU on the considered band. These probabilities can be defined as follows [10]:

$$\begin{aligned} &P_{fa}: Prob\,\{T_d > \lambda/H_0\} \\ &P_d: Prob\,\{T_d > \lambda/H_1\} \end{aligned} \tag{4}$$

where T_d is the statistical test of detection which is compared to the threshold λ to make decision.

3.1. Energy detection

The basic spectrum sensing technique presented in the literature is Energy detection (ED) which was proposed for the first time in [8]. It does not need any prior information on the signal-to-be-detected to determine whether the channel is occupied or not. The Figure 2 presents the block diagram summurized the principle of ED.

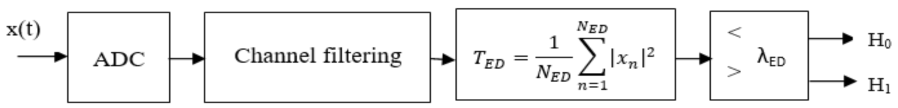

Figure 2. Block diagram of an energy detection

The out of band signals is removed using the input band pass filter by choosing the central frequency fc and the bandwidth of interest. After the signal is digitized by an analog to digital converter (ADC), a simple square and average block is used to estimate the received signal energy. Energy Detection compares the decision statistic T_{ED} with a threshold 'λ_{ED}' to decide whether a signal is present 'H_1' or not 'H_0' [5]. The following equation represents the statistical test of ED [21]:

$$T_{ED} = \frac{1}{N_{ED}} \sum_{n=1}^{N_{ED}} |Xn|^2 \tag{5}$$

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

$$\lambda_{ED} = \sqrt{\frac{2}{N_{ED}}}\, Q^{-1}\left(P_{fa}\right) + 1 \tag{6}$$

where $Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^{+\infty} e^{-\frac{u^2}{2}}\, du$. The theoretical detection and false alarm probabilities can be expressed as [22]:

$$P_{fa} = \frac{\Gamma\left(N, \frac{\lambda_{ED}}{2}\right)}{\Gamma(N)} \tag{7}$$

$$P_d = Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda_{ED}}\right) \tag{8}$$

λ_{ED} represents the threshold, Γ (a, x) is the incomplete gamma function, Γ(a) is the gamma function and Q_m (a, b) is the generalized Marcum Q function.

3.2. Maximum eigenvalue detection

The idea of exploiting the properties of eigenvalues for spectral detection is first proposed by M. Haddad *et al* [23]; the authors calculate eigenvalues of the covariance matrix and use eigenvalue-dependent test statistics. The authors of [10]-[12], [24] used the eigenvalues to develop a spectral detection technique which is mainly based on evaluating the matrix eigenvalues constituted by the acquired samples. This technique can be considered as the most reliable among the methods presented previously and this is due to the fact that it presents many advantages such as: no prior information needed on the primary signal; it allows good detection at low signal to noise ratio (SNR) and it overcomes the noise problem encountered in the case of energy detector [10]-[12]. In the MED technique, in order to formulate the detection algorithm based on the sample covariance matrix of the received signal, the random matrix theory (RMT) is used.

Let L be the number of consecutive samples, $\hat{x}(n)$ an estimation of the received signal, $\hat{s}(n)$ an estimation of primary signal to be detected and $\hat{w}(n)$ an estimation of the noise. We define the following vectors form:

$$\hat{x}(n) = \begin{bmatrix} x(n) \\ x(n+1) \\ \vdots \\ x(n+L-1) \end{bmatrix}, \quad \hat{s}(n) = \begin{bmatrix} s(n) \\ s(n+1) \\ \vdots \\ s(n+L-1) \end{bmatrix}, \quad \hat{\omega}(n) = \begin{bmatrix} \omega(n) \\ \omega(n+1) \\ \vdots \\ \omega(n+L-1) \end{bmatrix} \tag{9}$$

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

$$\hat{R}_x\,(N_s) = \begin{bmatrix} \xi(0) & \xi(1) & \dots & \xi(L-1) \\ \xi(1) & \xi(0) & \dots & \xi(L-2) \\ \vdots & \vdots & \vdots & \vdots \\ \xi(L-1) & \xi(L-2) & \dots & \xi(0) \end{bmatrix} \tag{10}$$

where $\xi(l)$ is the sample auto-correlations of the received signal. It is described as:

$$\xi(l) = \frac{1}{N_{MED}} \sum_{m=0}^{N_{MED}-1} x(m)x(m-l)\,, l = 0,1,\dots, L-1 \tag{11}$$

where N_{MED} is the number of available samples. Based on RMT, the equation of the probability of false alarm for maximum eigenvalue detection is expressed as follow [11]:

$$P_{fa} \approx 1 - F_1\left(\frac{\lambda_{MED}\, N_{MED} - \mu}{\vartheta}\right) \tag{12}$$

where F_1 represents the Tracy-Widom cumulative distribution function of order 1 and μ and ϑ are given respectively by the following expressions:

$$\mu = \left(\sqrt{(N_{MED}} - 1\right) + \sqrt{L}\,)^2 \tag{13}$$

$$\vartheta = \left(\sqrt{(N_{MED} - 1)} + \sqrt{L}\right)\left(\frac{1}{\sqrt{(N_{MED}-1)}} + \frac{1}{\sqrt{L}}\right)^{1/3} \tag{14}$$

The threshold used to make a decision can be calculated for a given P_{fa}, N_{MED} and L using the formula above [14], [25]:

$$\gamma = \frac{(\sqrt{N_s}+\sqrt{L})^2}{N_s}\left(1 + \frac{(\sqrt{N_s}+\sqrt{L})^{-2/3}}{(N_s L)^{1/6}}\, F_1^{-1}(1 + P_{fa})\right) \tag{15}$$

where F_1^{-1} can be computed at certain points by means of Table 1.

Table 1. The Tracy-Widom distribution of order 1

t	-3.90	-3.18	-2.78	-1.91	-1.27	-0.59	0.45	0.98	2.02
$F_1(t)$	0.01	0.05	0.10	0.30	0.50	0.70	0.90	0.95	0.99

4. RESULTS AND ANALYSIS

The purpose of this section is to evaluate the proposed approach of spectrum sensing and compare it with the uniform sampling case. The block diagram of the simulation is shown in Figure 3. After digitizing the generated signal, we calculate all the frequencies of the multi-band signal and we select the band of interest using the SVD direct algorithm. We then analyze the occupancy of the radio frequency spectrum using the two-spectrum sensing studied methods (ED and MED). In order to characterize the detection performance of the receiver, we estimated the detection and the false alarm probabilities for band occupancy, by using Monte Carlo simulation. In this application, the test signal used is a multi-band signal which is composed of five carriers spaced by 80 Hz, modulated with QPSK and then filtered by a raised cosine filter with a rounding coefficient (roll-off) of 0.5. Each carrier has a symbol rate of R = 40 sym/s. The values considered are suitable for our compute power.

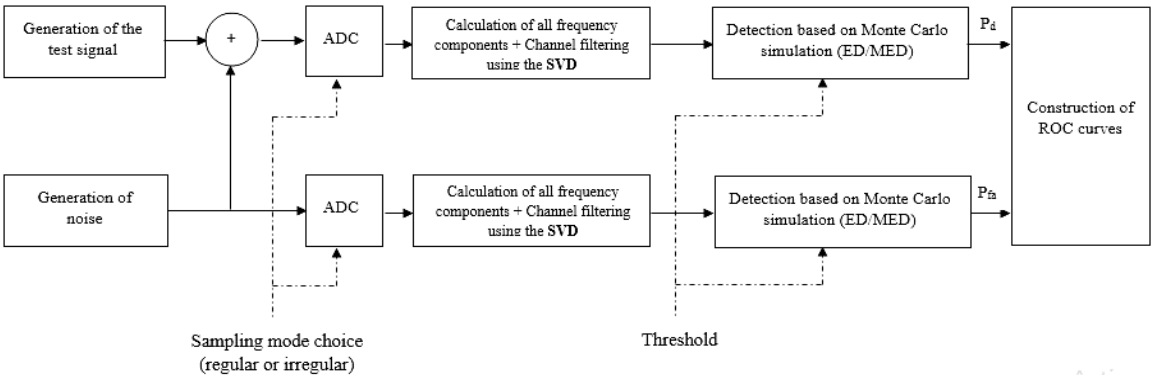

Figure 3. Block diagram of simulation

We evaluated the performance of the proposed approach in terms of Receiver Operating Characteristics curves (ROC) that plots the evolution of the probability of detection P_d as a function of the probability of false alarm P_{fa} for different threshold values, also in terms of P_d for different values of the SNR. In our tests, we considered two central frequency values which are as follows: a center frequency value within the allowed bands (AB) and a center frequency value within the forbidden bands (FB). The approach was tested by both modes of sampling: uniform sampling and random sampling to show the benefit and utility of the proposed approach. The AB is the band of sampling frequencies on which there is no spectrum aliasing [18].

The Figures 4 and 5 represent the ROC curves for both spectrum sensing methods ED and MED, using uniform sampling (Figure 4) as well as random sampling (Figure 5) for a SNR= -18db and a smoothing factor L= 8. From Figure 4, we can note that, in the case of uniform sampling, we have two cases of ROC curves:

- For a central frequency value that is inside the allowed bands, good performance is obtained as it is possible to find a trade-off between P_{fa} and P_d which explains the ROC curves form inside these bands.
- For a central frequency value that is inside the forbidden bands, a spectrum aliasing occurs within the channel of interest and hence a great energy is present within this channel even when this channel is free. This explains the obtained ROC curves which are reduced to a unique point ($P_d = P_{fa} = 1$), meaning that the two studied detectors do not work properly.

On the other side, by using the random sampling (Figure 5), we noticed that we have a good performance (the reconstruction process is efficient) regardless of the value of the central frequency. The use of the random sampling overcomes the constraint of the forbidden bands imposed in the uniform sampling case. This explains the obtained ROC curves which are almost similar for a same detector. We may also notice that the MED allows a good detection compared to the ED method [24].

As mentioned above, the performance of our proposed approach is also evaluated in terms of the detection probability as a function of the SNR, using both sampling modes and two central frequency values: a center frequency value within the allowed bands (AB) and a center frequency value within the forbidden bands (FB). The achieved results are presented in Figure 6 and Figure 7. From these figures, we can note that using a uniform sampling, for a center frequency value that is inside the forbidden bands, a spectrum aliasing occurs within the channel of interest. This explains that the detection probability is always equal to 1 even if this channel is free. This constraint is overcome by applying a random sampling mode. The detection probability curves are almost similar to the two chosen values of central frequencies and the probability of detection increases with increasing SNR.

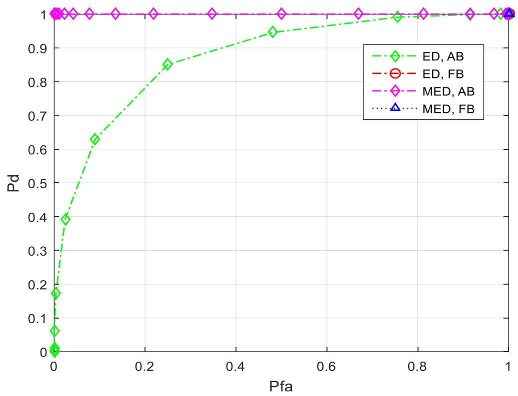

Figure 4. ROC curves of the studied methods using a uniform sampling mode at two different central frequency values

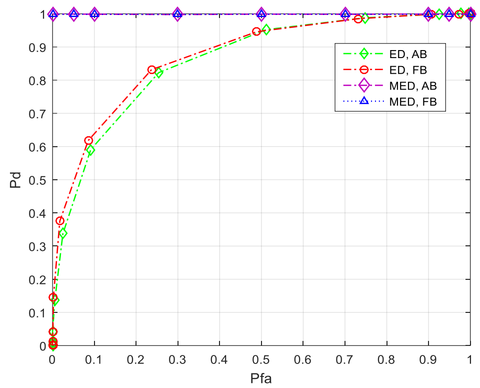

Figure 5. ROC curves of the studied methods using a random sampling mode at two different central frequency values

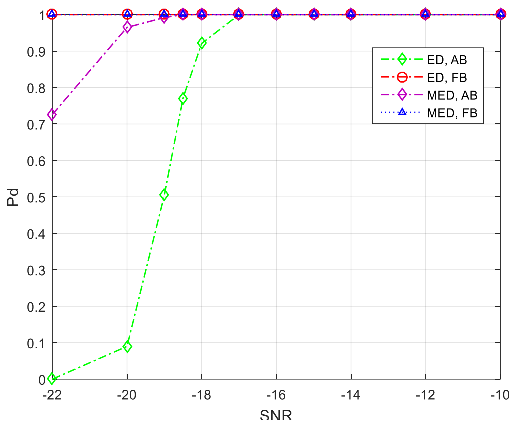

Figure 6. P_d vs. SNR of the ED and the MED methods using a uniform sampling mode

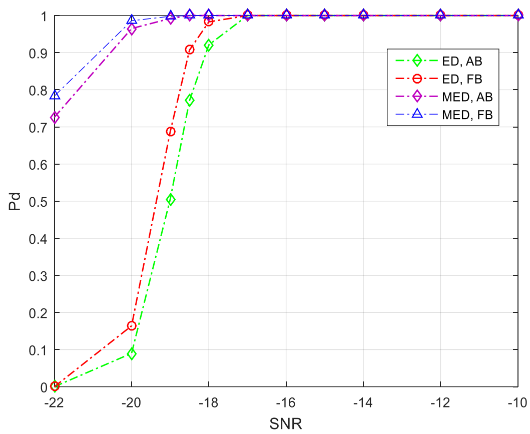

Figure 7. P_d vs. SNR of the ED and the MED methods using a random sampling mode

5. CONCLUSION

In this work, we were interested in spectrum sensing which is an important and crucial function in cognitive radio systems. We investigated the effect of random sampling on spectrum sensing. Two spectrum sensing approaches were considered: The energy detection (ED) method and the maximum eigenvalue detection (MED).

The obtained results show that random sampling makes it possible to overcome forbidden band restriction encountered with uniform sampling mode. Therefore, we can note that random sampling associated with the energy detector and the maximum eigenvalue detector represents an interesting solution in cognitive radio systems. This work is a theoretical part of a future work that will be a practical implementation to confirm these simulation results.

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This work is an extended version of our work entitled "Energy detection versus maximum eigenvalue-based detection: A comparative study" presented in the 14th International Multi-Conference on Systems, Signals & Devices (SSD'2017). This paper aims to illustrate the difference between random sampling and uniform sampling.

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