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Evaluation of energy detection for spectrum sensing based on the dynamic selection of detection-threshold

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Abstract

Cognitive radios (CRs) have been proposed as a possible solution to improve spectrum utilization by enabling opportunistic spectrum sharing. The main requirement for allowing CRs to use licensed spectrum on a secondary basis is not causing interference to primary users. Spectrum sensing allows cognitive users to autonomously identify unused portions of the radio spectrum, and thus avoid interference to primary users. In this work, energy detection technique is considered for spectrum sensing, and the performance evaluation of an energy detector is presented. The process of threshold selection for energy detection is addressed by the Constant False Alarm Rate (CFAR) method and selection is carried out considering present conditions of noise levels. Our results show that if we dynamically adjust detection-threshold based to the noise level present during detection process, the detection probability will be higher than the one obtained when a fixed threshold value is considered.

Keywords: Cognitive Radio Networks; Spectrum Sensing; Energy Detection;Threshold Selection

1. Introduction

The convenience brought to people's lives by wireless products has motivated extensive development of wireless technologies and services. However, with most of radio spectrum already allocated to

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licensees, the compelling need for the radio spectrum to accommodate upcoming applications poses a serious problem for the future development of wireless communications [1].

Recent studies reveal that the usage of radio spectrum experiences significant fluctuations [2]. These studies conclude that heavy spectrum utilization often takes place in unlicensed bands (e.g., Industrial Scientific and Medical band, ISM), while licensed bands often experiences low (e.g., TV bands) or medium (e.g., cellular bands) utilization [1]. This sub-optimal spectrum utilization opens new ways to spectrum access by exploiting unused spectrum bands.

Cognitive radios (CRs) have been proposed as a possible solution to improve spectrum utilization by enabling opportunistic spectrum sharing. Their technological capabilities allow CRs to dynamically seek and access to unused portions of the radio spectrum, and thus improving spectral resources utilization [3]. The main requirement for CR to make use of spectral opportunities (also called spectrum holes [4]) is to protect licensed users from interference caused by secondary transmissions. In this sense, to opportunistically accessing into temporally and/or spatially unused licensed bands, efficient identification of spectrum holes is required.

Spectrum sensing allows secondary (cognitive) users to autonomously identify unused spectrum bands without the need of primary systems intervention. To this time, various methods have been proposed in literature for spectrum sensing. For example, matched filtering is optimal, in the sense that it maximizes SNR (Signal-to-Noise Ratio), and therefore minimizes detection time. However, synchronization with primary transmitter is required. Furthermore, it needs dedicated receiver circuitry for every band considered for secondary access, making secondary receiver complexity prohibitive [5]. Cyclostationary feature detection has the advantage of distinguishing between noise and primary signals, at the expense of extensive computational requirements; also it needs exact knowledge of primary signal parameters to correctly identify cyclic frequencies [6]. Other spectrum sensing techniques are also discussed in [5]. Of all this methods, energy detection is broadly considered due to its low computational complexity, and generic implementation.

When energy detection is considered for spectrum sensing, the energy contained over a spectrum band is measured and then compared with a threshold. If energy level is above the threshold, then the primary user is present, if the energy level is below the threshold, then the spectrum band is vacant. Even though energy detection is simpler than matched filtering and cyclostationary feature detection, it requires at least $\boldsymbol{O}(1/\mathrm{SNR}^2)$ samples for detection and it has several disadvantages. For example, energy detector performance is very susceptible to changing noise levels, and it cannot distinguish when energy comes from primary's transmission, interference, or noise [7].

Despite the drawbacks mentioned before, energy detection is the most studied technique for spectrum sensing. There are various proposals in literature to improve performance of energy detectors. For example, several authors have considered cooperation among secondary users to improve detection performance when energy detection is applied [8], [9], [10]. However, the most important process that defines performance for energy detection is the selection of detection threshold. Fading due to distance or shadowing may reduce primary signal intensity perceived by secondary receiver, and considering a high threshold value, may cause that secondary user will never detect the presence of the primary transmitter, and possibly interfere with primary transmissions. On the other side, if we set a threshold value too low, then detector will be very sensitive, and thus indicate the presence of primary users, even if they are not present. This may cause poor spectrum utilization by secondary users, even when opportunities are present.

Given the importance of detection threshold, there has been important research work in determining methods that improve "detection threshold" selection. In reference [11] a double threshold method is proposed to improve decision rule in a cooperative spectrum-sensing scheme. The results show that this method improves decision making at the fusion center, however the authors do not address how determine individual thresholds for cognitive users. Threshold adaptation to overcome noise variance estimation errors is considered in [12], here, authors take noise samples from a reference channel to estimate noise power, and take into account the estimation errors to determine detection threshold. An algorithm for selecting optimal threshold that minimizes probability of detection errors in a cooperative sensing scheme is proposed in [13]. In this work, the authors consider information of previous sensing frames for determining present threshold.

If we could define the optimal detection threshold for the present conditions of spectrum environment, then it would be possible to improve performance of energy detector, and thus increase spectrum efficiency. In this work we present preliminary results on the evaluation of energy detection performance, when the Constant False Alarm Rate (CFAR) method is considered for detection threshold selection. Unlike the works presented in [11], [12] and [13], the aim of our work is to identify the optimal detection threshold considering present conditions of noise and interference in the cognitive system. The results presented in this paper correspond to the first stage of the evaluation of energy detection applied for spectrum sensing.

The rest of the paper is structured as follows: Section 2 presents the definition of the spectrum sensing problem, the model of the system considered for the evaluation, and the theory related with energy detection. In section 3 the simulation setup is described and results are discussed. Finally, conclusions and future work are presented in section 4.

2. System model

The system considered is composed by a single primary user and a single secondary user. Secondary user applies energy detection for detecting primary user's transmissions. We assume that traffic pattern of primary user is slowly changing, i.e. primary user remains in a transmission state (busy/idle) for enough time to be observed in the same state through the entire detection process.

Spectrum sensing problem can be modeled as the binary hypothesis testing problem [10], where the state of primary user is defined by the following two hypotheses:

$$\begin{aligned} &\mathrm{H}_0: \quad y[n] = w[n] \qquad \text{(Primary user absent)} \\ &\mathrm{H}_1: \quad y[n] = s[n] + w[n] \qquad \text{(Primary user present)} \\ &\qquad n = 1, \ldots, N \end{aligned} \tag{1}$$

Where y[n] corresponds to the samples of the received signal, w[n] corresponds to the samples of the noise process, which is considered to be additive white Gaussian noise (AWGN), s[n] corresponds to the primary signal samples, and N is the length of the observation interval used to carry out the detection process.

The process for energy detection considered in this work is illustrated in figure 1. Here, detection process consists on the measurement of energy level contained over the band of interest, and the comparison of this measurement with some detection threshold. From this comparison, one of the hypotheses stated in (1) is chosen to be true, and based on the result of the test, the secondary user decides whether to access or not to the band.

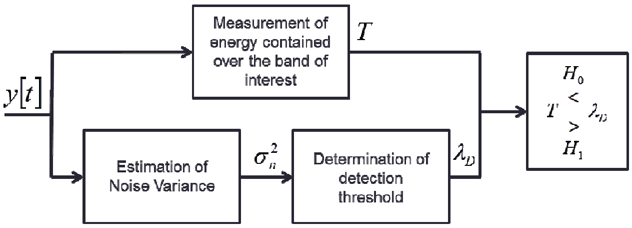

Fig. 1. Block diagram of energy detection process

2.1. Energy detection theory

The decision statistic for energy detection is [10]

$$T = \sum_{n=1}^{N} (Y[n])^2 \tag{2}$$

When the primary signal is absent, the decision statistic has a central chi square distribution with N degrees of freedom. When the primary signal is present, the decision statistic has a non-central chi square distribution with the same degrees of freedom [14]. If the number of samples used for detection is large enough (N > 250) we can make use of Central Limit Theorem to approximate the distribution of the test statistic as Gaussian, with mean and variance as stated in (3) for each of the hypotheses, where σ_w^2 is the variance of the noise process and σ_s^2 is the power of primary signal.

$$\begin{aligned} T &\sim N\left(N\sigma_w^2, 2N\sigma_w^4\right) \qquad \text{under } H_0 \\ T &\sim N\left(N\left(\sigma_s^2+\sigma_w^2\right), 2N\left(\sigma_s^2+\sigma_w^2\right)^2\right) \qquad \text{under } H_1 \end{aligned} \tag{3}$$

In testing H_0 versus H_1 there are two types of errors that can be made: H_0 can be falsely rejected or H_1 can be falsely rejected. The first of these two errors is called a False Alarm, and the second error is called a misdetection [15]. The performance of energy detector can be measured by the probability of occurrence of both types of errors, i.e., the probability of false alarm (P_{FA}) which describes the probability of erroneously decide that the band is occupied, when is actually not, and the probability of misdetection (P_{MD}), which is the probability of erroneously decide that the primary user is absent, when is actually present. Another form used to define performance is by the complement of the probability of misdetection, i.e., the probability of detection (P_D). The rest of this work will consider P_D instead of P_{MD} to describe performance. P_{FA} and P_D are statistically defined by:

$$\begin{aligned} P_{FA} &= \Pr(T > \lambda_D; H_0) \\ P_D &= \Pr(T > \lambda_D; H_1) \end{aligned} \tag{4}$$

Where T corresponds to the test statistic defined by (2) and λ_D is the threshold considered for determining the presence of primary users. Given that T can be approximately Gaussian distributed, the P_{FA} and the P_D can be evaluated by:

$$P_{FA} = Q\left(\frac{\lambda_D - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right) \quad (5)$$

$$P_D = Q\left(\frac{\lambda_D - N\left(\sigma_s^2 + \sigma_w^2\right)}{\sqrt{2N\left(\sigma_s^2 + \sigma_w^2\right)^2}}\right) \quad (6)$$

Where Q( ) stands for the Gaussian Q-Function. The design of a test for H_0 versus H_1 involves a trade-off between the P_{FA} and the P_D since a reduction on the P_{FA} will decrease the P_D, and an increment on the P_D will increase the P_{FA}. The Neyman-Pearson criterion for making this trade-off is to place a bound on the P_{FA} and then to maximize the detection probability within this constraint [15]. This criterion is also called Constant False Alarm Rate (CFAR). In this work we consider this approach for threshold selection, and evaluate detection performance through simulations. The threshold is obtained from (5) as:

$$\lambda_D = \sigma_w^2\left(Q^{-1}(P_{FA})\sqrt{2N} + N\right) \quad (7)$$

3. Performance evaluation

As commented in section 1, the evaluation presented in this paper is the initial stage of a more detailed characterization of energy detector. In this work, we wanted to evaluate detection performance when Neyman-Pearson criterion is used for threshold setting in energy detection.

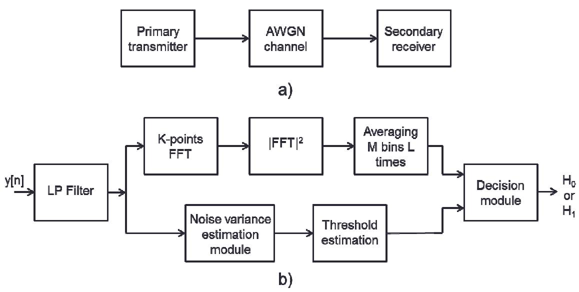

Fig. 2. a) General structure of simulation setup. b) Energy detector setup

For this purpose, we designed a simulation model using Simulink®. The results presented show the Receiver Operation Characteristics curves (ROC) of the secondary user for different SNR, and the P_D as a function of the sample number and SNR. The latter results will help us to identify the sample number required to obtain a particular P_D when the P_{FA} is set to a particular value. The results obtained for the ROC of the secondary user will help us as a reference for future evaluations.

3.1. Simulation setup

The model used for simulations consists of a primary signal generator, a communication channel and a secondary receiver. Energy detection is carried out at the secondary receiver. Simulation diagram and energy detector setup are shown in figure 2.

Given that we want to determine the P_D for a particular threshold value, we set a fixed P_{FA} to determine the threshold according to (5). Then we transmit continuously the primary signal, which is received, along with the noise produced by communication channel, at secondary receiver. We took N samples of the signal for processing at the energy detector.

As can be observed at figure 2b, the signal received at secondary receiver is filtered, and then fed to two sub-processes. The energy level of the signal received is estimated via magnitude square of the Fast Fourier Transform (FFT), the result of this sub-process is the test statistic (T, from eq. (2)). In parallel, noise variance is estimated at the second sub-process, and the threshold is determined based on the noise variance information obtained from the previous block. In order to obtain current noise levels, we estimate noise variance considering the median filter method presented in [16].

After the simulation has finished, P_D is obtained by:

$$\tilde{P}_D = \frac{number\ of\ detections}{number\ of\ observations} \tag{8}$$

3.2. Simulation results

The primary signal considered is a baseband QPSK modulated signal, with 4 MHz of bandwidth. A root raise cosine filter is considered for pulse shaping. The communication channel is Gaussian. The FFT length is 128 points, and the number of spectral averages used for energy estimation varies depending on the value of N. Primary signal power is varied from -75 dBm to -60 dBm, and power spectral density of noise is N_0 = -130 dBm/Hz. Thus SNR values ranging from -4 dB to -20 dB can be evaluated.

First, we measured how P_D scales as the sensing time, i.e., number of samples (N), increases. For all cases we set P_{FA} = 0.2. Figure 3 shows the achievable P_D for the QPSK signal when the number of samples, N, increases from 100 to 1000. If we set P_D to a limit of 0.9, then the energy detector with the characteristics considered here, may detect signal with power higher than -63 dBm (which corresponds to SNR = -8 dB or higher) with 1000 samples per detection period. The sensing time expended in sensing will depend on the sampling frequency of the analogic-to-digital (ADC) converter used at the secondary receiver. Also in this figure we observe that for SNR values below -16 dB, the P_D does not improve by increasing N.

Based on the results observed in figure 3, we set N = 1024 to obtain ROC curve for the SNR values aforementioned. ROC curves are presented in figure 4. In this case, we define a P_{FA} vector to determine λ_D and generate 1000 observations of the sensing process to obtain P_D in accordance to (8). In this case, λ_D is determined every observation based on the received samples of the signal, i.e. detection threshold is dynamically adapted to noise levels present during detection process.

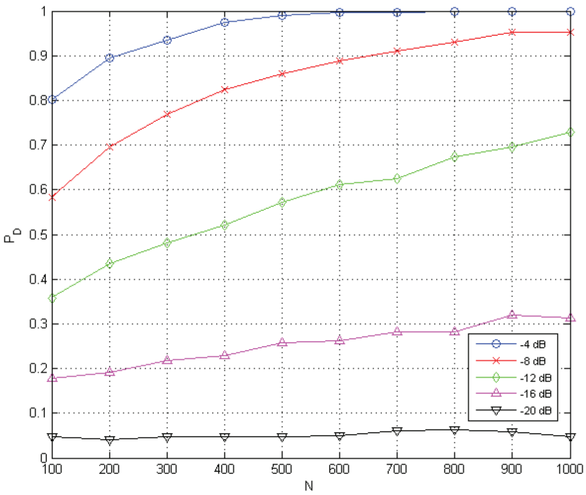

Fig. 3. Probability of Detection as a function of the number of samples for a $P_{FA} = 0.2$.

From figure 4 is possible to observe the trade-off between P_D and P_{FA}. Thus, this curve is helpful to determine the detection-threshold value for every (P_D, P_{FA}) pair we want to achieve, when the CFAR method is applied. As mentioned before, this curve will be considered as a reference for future evaluations, where other criteria may be considered for detection-threshold selection. As observed from figure 4, energy detection presents poor performance for the low SNR case, for example, if we set the $P_{FA} = 0.1$, and the $P_D \geq 0.9$, then energy detection could only detect signals with SNR grater or equal than -8 dB.

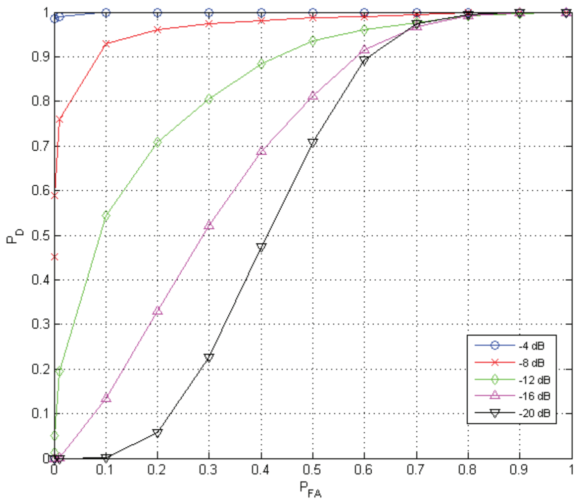

Fig. 4. ROC curve for energy detector with dynamic selection of detection-threshold

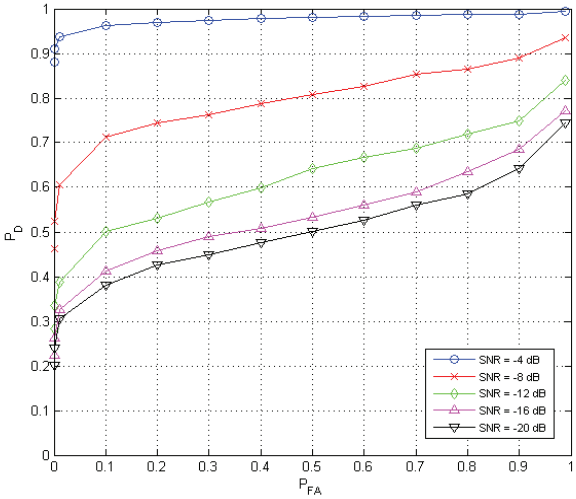

Fig. 5. ROC curve for energy detector with fixed threshold

For comparison purposes, ROC curve for energy detector considering a fixed value for detection-threshold was generated. In this case, noise variance could be obtained by a reference channel as done in [12], and the threshold corresponding to it used for the detection process. The resulting curves are presented in figure 5. By comparing figure 4 and figure 5, is possible to observe how dynamic selection of detection-threshold improves detection performance for SNR greater than or equal to -12 db. Particularly in the low P_{FA} region, which is where we are interested to design energy detectors.

4. Conclusions and future work

In this paper we present preliminary results on the evaluation of energy detection performance, when the detection-threshold is dynamically adapted to noise levels based on the Constant False Alarm Rate (CFAR) method. Our study includes theoretical description of energy detector and simulation results for the detection of QPSK modulated signals. Results obtained here will serve as a reference framework for future evaluations of energy detection in the next stage of our study. From this evaluation we can conclude than increasing sensing time would improve probability of detection; however, noise uncertainties and estimation errors impose a bound below which detection cannot be improved by increasing sensing time. Other important conclusion is that selecting dynamically the threshold used for detection, considering present conditions of the noise levels, would increase detection probability for the moderate SNR case (-12 dB and above). In the forthcoming stages of our work we want to consider different approaches for threshold setting, e.g. considering optimization methods for threshold selection, in order to define the optimal decision rule for the energy detector. Also we are considering experimental evaluations by the implementation of the energy detector on a hardware platform, such as a Field-Programmable Gate Array (FPGA)-based platform.

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