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Performance of Cognitive Spectrum Sensing Based on Energy Detector in Fading Channels

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Abstract

Spectrum scarcity and the inefficient use of the electromagnetic spectrum motivated the development of Cognitive Radio (CR), which aims to extend the spectral efficiency, with opportunistic access to the available frequency bands. Energy Detection (ED) is the most adopted spectrum sensing technique for cognitive radio applications due to its simplicity. However, fading effects are usually simplified or discarded when evaluating the energy detector performance in spectrum sensing. This paper presents the performance evaluation of cognitive spectrum sensing, based on energy detector, for fading channels. The objective is to analyze how the use of various fading models affect the spectral detection in cognitive networks. Rayleigh, Rice, Nakagami-m and Lognormal fading channels are considered, and the results favor the use of ED when the channel is subject to Lognormal fading.

Keywords: Cognitive Radio; Spectrum Sensing; Energy Detector; Fading Channels.

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1. Introduction

Cognitive radio is a technique that enables users to analyze the electromagnetic spectrum to opportunistically transmit in available frequency bands. Spectrum sensing is the step responsible for evaluate frequency bands that can be used by non-authorized users[1].

Several spectrum sensing methods were proposed. Among them, Energy Detection is the most popular due to its simplicity of implementation. Although, it demands a better signal to noise ratio to perform properly[2]. The problem of how fading and multipath affect the transmission of a signal in a wireless channel is complex. Consequently, several researchers tend to minimize or even discard fading effects over wireless communications.

The research presented in this paper consider the effects caused by fading over cognitive transmissions. Specifically, the performance of the energy detector for cognitive spectrum sensing is investigated when fading effects are taken in account. Rayleigh, Rice, Nakagami and Lognormal fading models are evaluated and its effects over the detection of a cognitive user are presented via simulation.

In this context, this article is organized as follows: Section 2 presents the concepts of cognitive radio and spectrum sensing; spectrum sensing based on energy detector is detailed in Section 3; fading models and its characteristics are highlighted in Section 4, while the effects of different fading models over energy detection are evaluated via simulation and the results discussed in Section 5. Finally, the conclusions of the paper are presented in Section 6.

2. Cognitive Radio

Cognitive radio is a recent wireless technique that modifies transmission parameters through the interaction of the radio with the environment[3]. CR evaluates the momentarily occupation of the frequency bands in a region. This task is performed by spectrum sensing. When a spectral opportunity is identified (also known as a spectrum hole), the radio adapts its transceivers to operate in that frequency channel[4].

Spectral sensing evaluates if any Primary (or Licensed) Users (PUs) are operating in the scanned licensed bands. If no PU is detected, the spectral holes are identified and the Secondary (or Cognitive) Users (SUs) are allowed to operate temporarily in that channel. Spectrum holes can be detected in time, frequency or space dimensions [5].

The sensing should be dynamic and meet acceptable interference levels. If a band is temporarily available, cognitive users can transmit in that channel; otherwise, if a priority user is detected, cognitive users should not operate in that frequency band[6].

The detection problem can be evaluated as a binary hypothesis model, defined as[2]:

$$y[n] = \begin{cases} w[n], if\ H_0 \\ w[n] + h.x[n], if\ H_1 \end{cases} \tag{1}$$

in which *y[n]* is the signal detected by the CR during the observation time; *x[n]* is the transmitted signal from the primary user; *w[n]* is additive white Gaussian noise (AWGN) with zero mean and variance σ^2; and *h* corresponds the channel gain due to the fading that affects the channel[2].

H_0 refers to the lack of primary signal in the channel, while H_1 indicates that the spectrum is occupied by a signal (this occupancy can refer to a PU or to a SU). Based on these hypotheses, the probability of detection is defined as $P_d = \mathrm{Prob}(\text{signal detected}|H_1)$; the probability of false detection is $P_f = \mathrm{Prob}(\text{signal detected}|H_0)$; and the probability of missed detection (which is the complement of P_d) is $P_{md} = 1 - P_d = \mathrm{Prob}(\text{signal not detected}|H_1)$. The objective is to maximize P_d while minimizing P_f [7].

2.1. Spectrum Sensing Methods

Several spectrum sensing techiques are described in literature to detect spectrum holes. The main criterion for diferentiate the spectrum sensing methods is the previous knowledge (a priori) of the transmitted signals' features. Spectrum sensing methods can be classified as[2]:

- Non-blind sensing: the characteristics of the transmitted signal are known, as well as the noise power. The spectrum sensing technique has total knowledge of the monitored signal;
- Semi-blind sensing: the detector previously knows only the noise variance estimation;
- Blind sensing: no information about the transmitted signal or the noise that affects the channel is known a priori. Many practical detectors are categorized as blind sensing due to the lack of information about the transmitted signal.

Some of the most adopted spectrum sensing techniques for cognitive radio are described above[8]:

- Energy Detection (ED): when the level of energy measured in the channel is below a predetermined threshold, the channel is considered free or non-occupied by licensed users. The simplicity of this technique and its low signal processing demands are the positive aspects. However, energy detection demands longer measurments periods(consequently energy consumption is higher). The effect of fading channels in the detection scheme is a remarkable issue in this problem[9].
- Matched Filtering detection (MF): the best technique when the licensed user characteristics are known a priori; this knowledge optimizes the filtering.
- Cyclostationary (or Feature) Detection (CD): this detection technique is adopted when some characteristics of the primary user are known a priori (as modulation strategy or carrier frequency). It requires extra computational complexity.
- Interference Temperature: sensor nodes calculate the level of interference they would cause at the PU receiver and should adjust their transmission power to not exceed a specific interference temperature level[10].
- Other techniques are well described in technical literature. Also, the combination of two or more spectrum sensing techniques can be investigated to obtain better results when compared to these techniques individually. This approach is known as hybrid sensing techniques[11].

3. Spectrum Sensing Based on Energy Detector

Energy Detection (ED) is the most used technique for the detection of signals. Also referred as radiometry[12], ED is vastly adopted in scenarios which cognitive user do not know the features of the transmitted signal. Although it is simple to implement, ED requires a good signal to noise relation to perform reliable detection[6].

Energy detector measures the received energy in a finite time interval, and then compares the acquired measurement with a predetermined threshold. Considering the noise that disturbs a channel is an AWGN with zero mean and variance σ^2, the measured signal y[n] is also estimated as a random gaussian process with zero mean and variance σ_y^2.

Signal to noise ratio is an important parameter that affects the decision threshold when the signal is unknown. If the noise level that disturbs the channel is high, the noise energy can distort the ED measurements and leads to false detections (cognitive user do not differentiate between the transmitted signal and the noise)[8].

Energy detection is normally used in time domain or in frequency domain. In both cases the goal is to compare the signal energy with a predefined sensing threshold[13]. The estimate of the energy detector is defined as the mean of the energy of the N gathered samples:

$$\mathrm{Y_{DE}} = \frac{1}{N}\sum_{n=1}^{N} |\mathrm{y}[\mathrm{n}]|^2 \tag{2}$$

After gathering the N samples from the primary signal, a Fast Fourier Transform (FFT) processing is executed over the samples. The amount of samples considered in the processing is an important parameter due to the computational processing time required[14].

A posteriori, the result of the FFT point-processing is squared and the decision about the energy of the detected signal can be taken through the comparison with the threshold λ. If $\mathrm{Y_{DE}} \geq \lambda$ the receiver selects the hypothesis H_1

(which means that the primary user is transmitting over the channel, and the cognitive user can not opportunistically operate). If $Y_{DE} \prec \lambda$ the channel is considered idle, the cognitive user is allowed to occupy the channel[8].

Detection probability and false alarm probability verifies if the decision taken by the energy detector is correct, and these probabilities can be expressed in terms of the relation between Y_{DE} and λ[8]:

$$P_d = \mathrm{Prob}(Y_{DE} \geq \lambda | H_1) \quad (3)$$

$$P_f = \mathrm{Prob}(Y_{DE} \geq \lambda | H_0) \quad (4)$$

The performance of the detector would be optimized by maximizing P_d and minimizing P_f; however, these probabilities are related to the same problem and thus are not independent. The best alternative to optimize the spectral detection is to fix one of the probabilities in a specified value and try to maximize (or minimize) the other probability[14].

4. Fading

Wireless communications channels are affected by different effects due to the multipath of the electromagnetic waves. Through the wireless channel, transmitted signal can be penalyzed with multiple reflections, scattering or difractions – characterizing multipath effects. Also, shadowing and propagation loss can disturb the signal in these channels[15].

Fading provokes aleatory fluctuations in phase and amplitude of the signals in a wireless channel. These effects lead to degradation in the performance of communication systems due to the increase of error rates[16]. Several propagation models aim to well characterize the amplitude variations suffered by the signals when traveling between the transmitter and the receiver. Statistical behavior of the channel is modeled under specific conditions, which leads to different fading models. The fading models analyzed in this research are described below[15,16]:

- Rayleigh: Rayleigh distribution is commonly selected to model variations in the signal amplitude when no line-of-sight exists between the transmitter and the receptor. The channel fading amplitude x has the probability density function (PDF):

$$p_X(x) = \frac{2x}{\Omega} exp(\frac{-x^2}{\Omega}) \text{, where } \Omega = E[X^2]. \quad (5)$$

- Nakagami-m: this distribution models multipath propagation for mobile communication and ionosferic communication radio link. The PDF for the Nakagami-m distribution is:

$$p_X(x) = \frac{2m^m x^{2m-1}}{\Gamma(m)\Omega^m} exp(\frac{-mx^2}{\Omega}) \text{,} \quad (6)$$

where $\Omega = E[X^2]$ and m is the fading figure given by:

$$m = \frac{\Omega^2}{E[(X^2-\Omega)^2]} \text{, with } m \geq 0.5. \quad (7)$$

- Nakagami-n (Rice): this distribution is adopted for propagation models with a strong direct line of sight and several weak aleatory components. If X_1 and X_2 are two independent Gaussian random variables with equal variance σ^2 and means μ_1 and μ_2, respectively, the Rice random variable $X = \sqrt{X_1^2 + X_2^2}$ has the PDF:

$$p_X(x) = \frac{x}{\sigma^2} I_0(\frac{sx}{\sigma^2}) e^{-(\frac{x^2+s^2}{2\sigma^2})} \text{,} \quad (8)$$

Where $s = \sqrt{\mu_1^2 + \mu_2^2}$ and $I_0(x)$ is the Bessel function.

- Lognormal: this distribution is applied for modeling shadowing effects of the signal caused by large obstructions (for example, tall buildings) in mobile communications. If the random variable has a normal distribution with mean μ and variance σ^2, the PDF of a Lognormal distribution is:

$$p_X(x) = \frac{1}{x\sqrt{2\pi\sigma^2}}\, e^{-(\ln x - \mu^2)/2\sigma^2} \tag{9}$$

5. Effects of Fading Over Energy Detection

Recent investigations are dealing with fading effects over cognitive transmissions[17]. An energy detector and different spectrum detection techniques are considered regarding to the influence of fading in its detection metrics[18]. Rayleigh and Rice fading models are investigated for signals with complex envelope; the proposed method is based on Bartlett estimator[13].

The performance of adaptive modulation applied to cognitive networks under Nakagami fading is detailed in[19]. A statistical model for the cognitive transmission is proposed based on experimental measurements. Empiric data was collected; fading model considered is Nakagami[20].

Although, for the best of the author's knowledge, the performance comparison of different fading models over an energy detector has never been directly evaluated before. In this context, the simulation of energy detection over different fading scenarios is proposed.

To evaluate the effects of fading over the performance of an energy detector, simulation efforts were conducted. A BPSK signal transmission over a wireless channel with AWGN was simulated. Simulations compared the detection probability when no fading disturbed the AWGN channel, and when different fading models affect the transmission. Selected fading models were Rayleigh, Rice, Nakagami-m and Lognormal.

100 samples were transmitted and simulated over 500 Monte Carlo simulations for each fading model. Different false alarm probability values were fixed: $P_f = 0.01$, $P_f = 0.05$ and $P_f = 0.1$.

5.1. Simulation Results

The results of the simulation of an energy detector over different fading models is presented below. Obtained curves present the performance of the detection probability P_d in terms of the signal to noise relation in the receiver. Theoretical probabilities of detection for different false alarm probabilities ($P_f = 0.01$, $P_f = 0.05$ and $P_f = 0.1$) were calculated via CFAR (Constant False Alarm Rate) method[8]: the false alarm probability is fixed in a small value and the detection probability should be maximized. Detection probabilities are calculated via the ratio of the performed detection number and the total Monte Carlo simulation repetitions.

Fig.1 presents theoretical curves for the detection probability compared to the values of P_d calculated via simulation for Rayleigh fading channel. One can verify that P_d converges to unity in around 0dB for the three considered theoretical P_f. Although, when fading effects are considered as depicted in the figure, the performance of the detector is penalized (in around 15dB if compared to the theoretical curves). P_d simulated with Rayleigh fading converges to unity in around 15dB while theoretical values converged to $P_d = 1$ in around 0dB.

Additionally, energy detector presents a reduced detection probability in all cases analyzed over small SNR values; these signal to noise ratios implicate in a low P_d. Otherwise, when SNR is increased the performance of the detector improves until converge to $P_d = 1$.

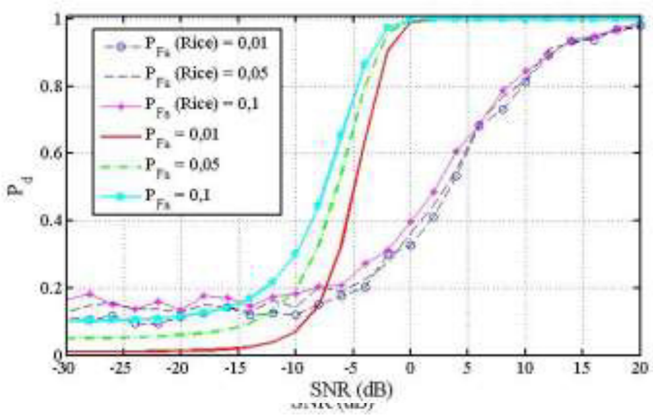

Fig. 1. Detection probability as a function of the SNR for energy detector subject to Rayleigh fading (500 Monte Carlo simulations and 100 samples).

Fig.2 shows theoretical curves for the detection probability compared to the values of P_d calculated via simulation for Nakagami-m fading channel. Nakagami-m parameter selected was m = 0.5. One can verify that P_d converges to unity in around 0dB for the three considered theoretical P_f. Although, when Nakagami-m fading effects are considered, the performance of the detector is significantly affected (P_d did not converge to unity even with the increase of the SNR).

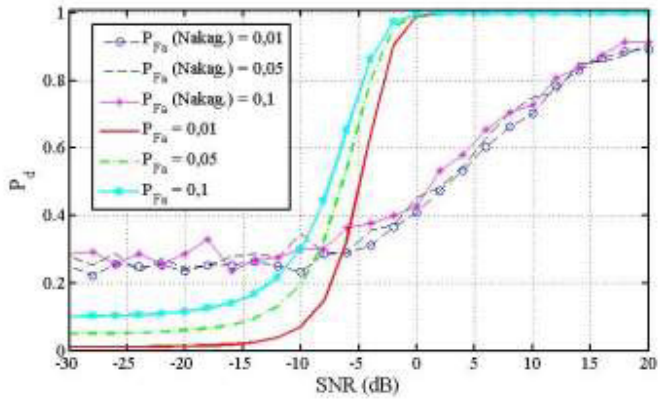

Fig. 2. Detection probability as a function of the SNR for energy detector subject to Nakagami-m fading (500 Monte Carlo simulations and 100 samples).

In Fig.3 the detection probability for the energy detector is computed for Rice fading and AWGN. It can be observed that in the absence of fading the curves are similar to the ones presented in Figures 1 and 2. However, when Rice fading affects the transmission, the detection probabilities converge to unity at 20dB. It means that Rice fading decreases the performance of the energy detector in 20dB.

Fig.4 highlights theoretical curves for the detection probability compared to the values of P_d calculated via simulation for Lognormal fading channel. One can verify that P_d converges to unity in around 0dB for the three considered theoretical P_f, as observed in Fig.1, 2 and 3. When considering Lognormal fading effects, the performance of the detector is decreased. P_d converges to 1 in about 12dB.

When comparing the four fading models applied to energy detector, it can be verified that ED performed better under Lognormal fading. In the sequence, Rayleigh, Rice and Nakagami-m performed with larger SNR, respectively.

Fig. 3. Detection probability as a function of the SNR for energy detector subject to Rice fading (500 Monte Carlo simulations and 100 samples).

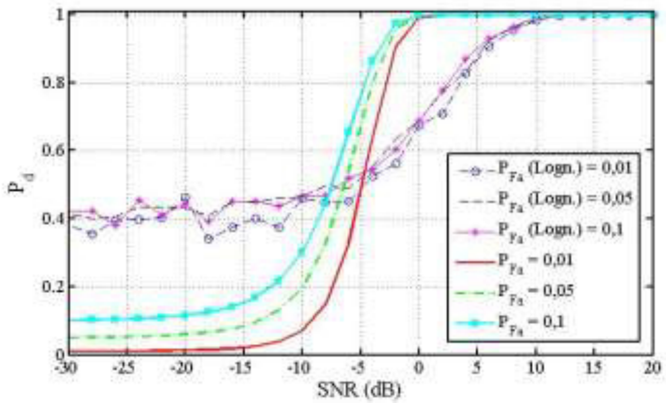

Fig. 4. Detection probability as a function of the SNR for energy detector subject to Lognormal fading (500 Monte Carlo simulations and 100 samples).

6. Conclusions

Cognitive spectrum sensing, based on energy detector, was analyzed for channels that are subject to fading. Simulation results indicated that, despite the best detection probability performance for energy detectors (ED), when compared to other spectrum techniques, fading will degrade the energy detector measurements.

The Rayleigh, Nakagami-m, Rice and Lognormal fading models were simulated during the research. The performance of energy detectors was penalized in all scenarios, although the best performance has been observed for Lognormal fading. Additional Monte Carlo simulations (with more samples) will be performed in the continuation of this article to verify the fading effects on the energy detection.

One can conclude that cognitive spectrum detection based on energy detector (and other spectrum sensing techniques) must consider the effects of fading to improve the performance, independently of the fading model considered. The suppression of fading effects on energy detection leads to imprecise detection probability and the consequence is that the false alarm probability can increase (degrading the overall performance of the spectrum detection).

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