A Cooperative Spectrum Sensing Scheme using Particle Swarm Optimization and Cultural Algorithm

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Abstract – Cognitive radio is a software-based technology that provides dynamical access to unused or underused spectrum bands and enables spectrum sharing without causing any disadvantage among users. The performance of the cognitive radio in wireless communication networks depends on the accurate and fast detection of spectrum gaps.

The idea of Cognitive Radio is to share the spectrum between a so-called primary user and a so-called secondary user. The main objective of this spectrum management is to obtain a maximum rate of exploitation of the radio spectrum, for this cooperation between users is necessary. This paper provides a spectrum sensing approach using cooperation and competition to solve the spectrum allocation problem and thus ensure better management. The aim of spectrum detection is to detect spectrum gaps accurately and quickly. Therefore, the performance of cognitive radio networks largely depends on the spectrum sensing function. Particle Swarm Optimization (PSO) and Cultural Algorithm (CA) are proposed to increase spectrum detection performance in cognitive radio networks. The collaborative spectrum detection performance analysis of the proposed method was performed in Rayleigh fading channel in addition to the non-damped AWGN channel. As a result of simulation studies, it has been shown that a more effective perception can be made in cognitive radio networks by optimizing the threshold value expression from the historical data.

Keywords – Cognitive Radio, Cultural Algorithm, Particle Swarm Optimization, PU, Spectrum Sensing, SU, Wi-Fi.

1. Introduction

Through the great rise and popularity of wireless network technologies, third and fourth generation cellular networks (3G and 4G), as well as IEEE 802.11 home networks (Wi-Fi), are being increasingly adopted by a large portion of the population. Given the popularization of the Internet, the emergence of smartphones, mobile applications that use the global network, and the massification of social networks, the need to stay connected to the global network constantly appears as a worldwide trend today. Faced with this scenario, there are rising challenges in the area of wireless networks, among them the scarcity of resources, in view of the great competitiveness of access to such networks that arise in view of the massive amount of mobile devices concentrated in large urban centers.

The last decade has been marked by telecommunication systems which have evolved exponentially, all these new technologies have become essential, the growing demand from users of wireless technology is increasingly demanding, whether in terms of quality or well the availability of services.

However, this development is in the process of being blocked due to the scarcity of the spectrum, which has led to the search for a solution intended to solve this problem, thus a new technology called cognitive radio has emerged bringing with it dynamic management of the spectrum.

The scarcity of spectrum, given the various existing wireless network technologies, is a reality that arises from the increase in demand and the current model of use of this resource, adopted worldwide by the telecommunications regulatory agencies, which share the spectrum in two types: licensed and unlicensed. The spectrum of frequencies of the licensed type are those that are used only by devices that hold the license to use. This determination is given by the regulatory agency, which stipulates the use of technology, the operating parameters to be adopted by the licensed devices and the geographic space in which the license is valid. However, some bands of the licensed spectrum remain little used, or even unused, in several regions. Many are no longer used due to the disuse of technologies that have undergone evolutions, but that have stopped the use of parts of the spectrum, remaining with their exclusive operating licenses until today. Other licensed services use their spectrum slices on a temporary basis, due to their operating characteristics, making these slices remain temporarily idle. In addition to this temporal availability, there is also spatial availability, due to the existence of regions outside the coverage area of available services.

2. Literature Review

Wireless communication systems are rapidly changing and developing in order to meet the needs of users in all areas of life. Due to its flexible structure and high speed data transmission, the number of users using wireless transmission systems is increasing day by day. The variety of applications and the increase in the number of users made it necessary to use the spectrum, which is a scarce resource, efficiently. Studies by the Federal Communications Commission (FCC) have shown that most of the available spectrum bands are not effectively used by licensed users (PU) in time, frequency and geographic locations [1]. The cognitive radio model has been defined to ensure that unused or underused spectrum voids are used efficiently by secondary users (SU) in cases where they are not used by licensed users [2]. Cognitive radio is a software-based technology that performs spectrum sharing without causing any problems among users [3]. Since the priority of spectrum usage in cognitive radio networks belongs to PU, fast and accurate detection of spectrum gaps by SUs is important in terms of communication quality and sustainability. In cognitive radio networks, spectrum sensing performance decreases considerably due to hidden terminal problems, shading, noise uncertainty, multipath fading, and changes in the channel over time [4].

A collaborative spectrum sensing (CSS) model has been proposed to overcome the difficulties encountered in the spectrum sensing problem and to increase the perception performance [5] - [8]. The CSS model has a two-stage structure. In the first stage, spectrum detection function is performed by local SUs. In the second stage, each SU reports the data it obtains to a decision making center. The spectrum detection reports collected in this decision making center are combined according to a fusion rule and the final decision is made regarding the presence of PU [9] - [12]. When the literature is examined, the most popular method among spectrum sensing techniques is the energy-based sensing method because it does not need preliminary information about PUs and its mathematical complexity is low [13] - [15]. In energy-based sensing, the test statistic value calculated for a specific frequency band and the noise-dependent threshold value expression are compared to decide the presence or absence of PU. With appropriate threshold value selection, an increase in sensing performance and an improvement in sensing time can be achieved [16] - [18]. In [16], local threshold value expression is calculated based on the possibility of false alarms. An autocorrelation detector was utilized to decide the existence of PU, and the test statistics sent to the fusion center using a local threshold expression were restricted. As a result, an increase in spectrum sensing performance was achieved. System models using double thresholds for energy detection are proposed in [17] and [18]. It was found that the double threshold approach enhances the duration and detection performance of the model. In recent years, machine learning algorithms are one of the techniques widely used in the solution of spectrum detection problems. Thanks to the advanced estimation, estimation and classification capabilities of machine learning methods, spectrum detection performance has been shown to be better than traditional methods [19] - [21]. In [19], it was shown that the spectrum detection performance can be increased by analyzing the first and second types of statistical errors related to the hypotheses created to finalize the absence or presence of PU. In [20] and [21], spectral perception performance in cognitive radio networks was analyzed using a teaching-learning based optimization method (TLBO). An improvement in detection time and accuracy has been shown as a result of optimizing the threshold value expression. The cooperative spectrum sensing is also elaborated by using optimal linear framework [22], particle swarm optimization [23], multi-objective evolutionary algorithms and fuzzy decision making [24], artificial bee colony algorithm [25], hybrid invasive weed optimization and PSO [26].

In this study, the spectrum detection performance of AWGN fading channels of cognitive radio networks is analyzed using the Particle Swarm Optimization and Cultural algorithm. In addition, in order to increase spectrum detection performance, false alarm and false detection possibilities have been minimized in total and optimum threshold value expression has been redefined. The second section of paper provides the detailed methodology for proposed spectrum sensing method. Section three presents MATLAB based simulation results and finally the section four provides the general conclusion along with future perspectives.

3. Proposed Methodology

A. Proposed Energy Detector

The energy detector is the most used in real scenarios due to its low complexity. From samples of the received signal and a binary hypothesis test, the secondary user decides the channel's occupation status.

To make a decision, a binary hypothesis test is used, which is equivalent to dividing the (n-dimensional) observation space into two regions determined by the decision threshold, as defined in [27] and manifested in equation (1):

$$\mathrm{x(k)} = \begin{cases} \mathrm{n(k)} & \mathrm{H_0} \\ \mathrm{hs(k) + n(k)} & \mathrm{H_1} \end{cases} \quad \mathrm{k} = 1, \ldots, \mathrm{N} \tag{1}$$

Where $\mathrm{x(k)}$ represents the signal received by the CR, $\mathrm{n(k)}$ represents white Gaussian noise with mean zero and variance σ_n^2, s(k) represents the sample of the transmitted primary user signal and h is the gain of the observed channel. This type of detector can be used in the domain of time and frequency and its operation is shown in the block diagram in Figure 1. In the figure the received signal passes through the block that represents the bandpass filter, the output of the filter $\mathrm{x(t)}$ passes through an analog / digital converter whose output $\mathrm{x(k)}$ is the input of the block that accumulates the signals of each user, obtaining the u value that will be evaluated in the decision block to establish the corresponding hypothesis.

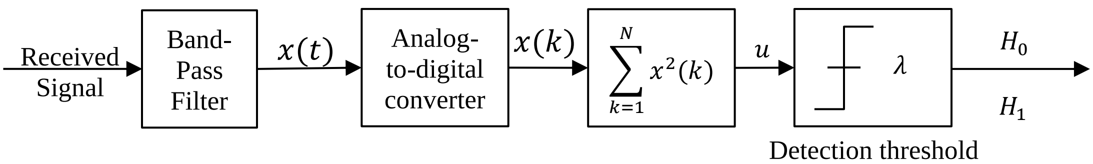

Figure 1: Energy detector block diagram

The energy detector uses the Neyman-Pearson theorem that defines the test statistic or metric as the likelihood ratio test (LRT) presented in the equation (2) and in [28].

$$\mathrm{u_{LRT}} = \frac{\mathrm{p}(\mathbf{x}|\mathrm{H_1})}{\mathrm{p}(\mathbf{x}|\mathrm{H_0})} \tag{2}$$

According to the theorem, the LRT ratio is used to maximize the probability of detection for a given false alarm rate once the distributions from **x** to H_0 and H_1 are known a priori. Observing the equation (1) it is possible to notice that the distribution from **x** to H_0 depends only on the noise distribution. On the other hand, the distribution from **x** to H_1 is related to the wireless channel, the signal transmitted by the PU and the noise distribution.

Bearing in mind that for this work, white Gaussian noise was considered, and also considering that when the channel is active H_1 (busy), the samples transmitted by the PU signal will be independent, and with their constant channel gain (value of one), in this way it is possible to (2) obtain the expression of the density function of **x** for each hypothesis presented in equations (3) and (4).

$$p(\mathbf{x}|H_0) = \prod_{k=1}^{N} p(x(k)|H_0) \qquad (3)$$

$$p(\mathbf{x}|H_1) = \prod_{k=1}^{N} p(x(k)|H_1) \qquad (4)$$

Assuming the noise sample is independent and equally distributed with Gaussian distribution, the likelihood test becomes the Estimator-Correlator (EC), which uses the energy of the signal samples received by the CR to detect some PU's activity.

$$u = \mathbf{x}^T\mathbf{x} = \sum_{k=1}^{N} x^2(k) \qquad (5)$$

It is important to note that EC detectors usually require a covariance matrix between the source signal and the noise, but when the presence of the PU signal is unknown it is impossible to know it, and that is why the PU signal is modeled as a process Random Gaussian with independent and identically distributed variables.

In the detector's block diagram, it is possible to observe how the bandpass filter removes signals that are not in the desired range, which is centered on frequency f_c and has a bandwidth W. The signal x(t) received after filtering is digitized by an analog-digital converter and a simple device that squares and allows to obtain the average energy contained in the N samples of $x(k)$. The decision metric is then compared with a detection threshold λ to decide whether the band is free (H_0) or busy (H_1).

The performance of the energy detector is characterized by the probability of false alarm and the detection probability, respectively, which are presented in equations (6) and (7). As the name implies, the false alarm is defined as the decision that the channel is busy when it is actually inactive. The probability of detection is associated with the correct decision about the occupation of the channel by a primary user transmitting information.

$$P_{fa} = P_r(\text{Detected Signal}|H_0) = P_r(u > \lambda|H_0) = \int_{\lambda}^{\infty} f(u|H_0)du \qquad (6)$$

$$P_d = P_r(\text{Detected Signal}|H_1) = P_r(u > \lambda|H_1) = \int_{\lambda}^{\infty} f(u|H_1)du \qquad (7)$$

B. Threshold Optimization

The performance of the energy-based detection method used in the solution of the spectrum detection problem varies depending on the threshold value expression defined according to the noise power. As a result of analyzing the first and second types of statistical errors obtained due to false alarm and detection probabilities in the spectrum sensing function, the optimum threshold value expression is defined as follows:

$$\lambda = \lambda_i \pm p_i \left[\frac{\min(\text{energy}_i)+\max(\text{energy}_i)}{2}\right] \qquad (8)$$

Here, p_i is the improvement factor.

In this section, a model in which the optimum threshold value expression with the best detection performance is obtained with two methods; Particle Swarm Optimization and Cultural Algorithm.

i. Particle Swarm Optimization

The PSO is based on a set of individuals originally randomly and homogeneously arranged, which we call particles from now on, which move in the research hyper-space and constitute, each one, a potential solution.

Each particle has a memory of its best solution visited and the ability to communicate with the particles that surround it. From this information, the particle will follow a tendency made, on the one hand, of its will to return towards its optimal solution, and on the other hand, of its mimicry compared to the solutions found in its neighborhood.

From local and empirical optima, the set of particles will normally converge to the optimal overall solution of the problem being addressed.

A particle swarm is characterized by [23]:

- The number of particles of the swarm is nb.
- The maximum speed of a particle is $\vec{v}_{max}$.
- The size and topology of the neighborhood of a particle that defines its social network.
- The inertia of a particle, noted Ψ.
- The confidence coefficients, denoted ρ_1 and ρ_2, which weight the conservative behavior (the tendency to return to the best solution visited) and the overreaction (the tendency to follow the neighborhood)

A particle is characterized at time t by:

- $\vec{x}_i(t)$: position in the search space.
- $\vec{v}_i(t)$: its speed.
- $\vec{x}_{pbest_i}(t)$: the position of the best solution by which it has passed.
- $\vec{x}_{vbest_i}(t)$: the position of the best-known solution of its neighborhood.
- pbest_i: the fitness value of his best solution.
- vbest_i: the fitness value of the best-known solution of the neighborhood.

PSO Algorithm

INPUTS: $0 < \rho < 1$
repeat
for $i = 1$ up to nb do
if $F(\vec{x}_i) > \mathrm{pbest}_i$ then
$\mathrm{pbest}_i = F(\vec{x}_i)$
$\vec{x}_{pbest_i} = \vec{x}_i$
end if
$\vec{v}_i = \vec{v}_i + \rho(\vec{x}_{pbest_i} - \vec{x}_i)$
$\vec{x}_i = \vec{x}_i + \vec{v}_i$
end for
until (one of the convergence criteria is reached)

ii. Cultural Algorithm

Cultural algorithm (CA) was initially developed as an extension of evolutionary algorithms. Its operation, represented in Figure 2, is explained in the following model.

CA have a basic functioning in which two main components are described: Population Space and Space of Beliefs. It is important to note that it is not necessary that all the properties described are implemented, but they will be presented in order to maintain completeness.

The two main components of a cultural algorithm are detailed below:

- Population Space: set of solutions that can be modelled using any computational intelligence technique that makes use of a population of individuals;
- Belief Space: Place where storage and representation of knowledge (experience or individual mappas) acquired throughout the evolutionary process occurs. It is from this stored knowledge that individuals are guided in the direction of the best regions of the search space.

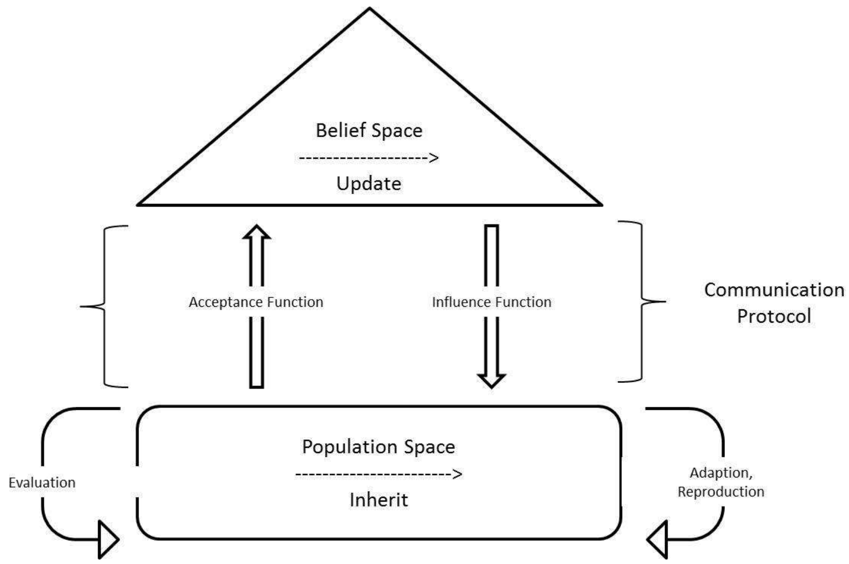

Figure 2: Basic functioning of a cultural algorithm [29]

Individuals are described by a set of characteristics and behaviours and by a map that generalizes the knowledge and experiences acquired by that individual. These characteristics and behaviours are modified by genetic operators that can be influenced socially. In the same way, knowledge and experiences are joined and modified to form the space of beliefs. These unification of modifications are also made through special operators.

The symbols used to represent knowledge in the space of beliefs can be modified over generations. In this way it is possible to remove or add new features and forget or acquire knowledge through the experiences acquired by the population.

With each new generation of individuals, an assessment is made and the knowledge of the best individuals may or may not be part of the Belief Space. The new population to be generated is influenced by the knowledge previously stored through operators.

Both the space of belief and the individuals of a population can be influenced by what are called Intercommunication Protocols. The communication between the individuals of a generation and the Space of Beliefs is given by a protocol called the Acceptance Function. It is already the interaction of the Belief Space with the population of individuals and it is called the Influence Function [29].

The basic pseudo code is given below [29]:

Initializes the population
Initializes the belief space
Repeat
    Assess the population
    Adjusting the space of beliefs through the acceptance function
    Manages the next population from the current considering the influence function
Until the termination condition is achieved

4. Simulation Results

The graphs below represent the results obtained:

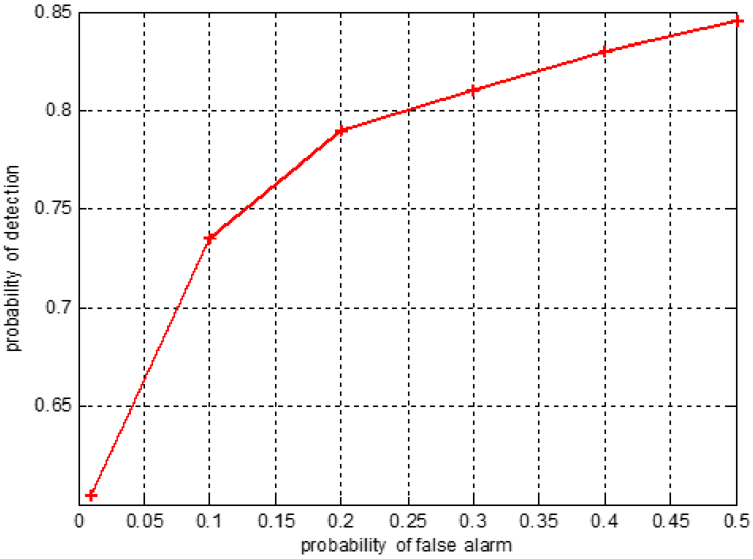

Figure 3: P_f vs P_d graph

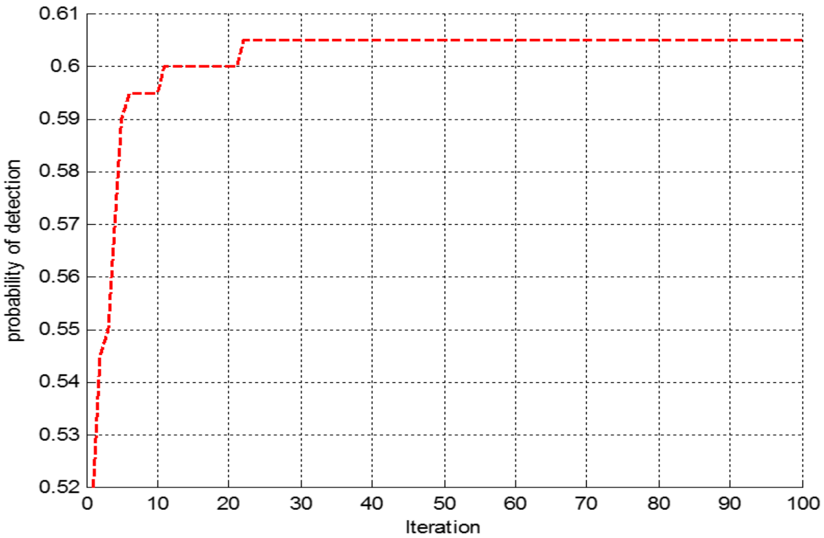

Figure 4: Probability of detection at probability of false alarm=0.01

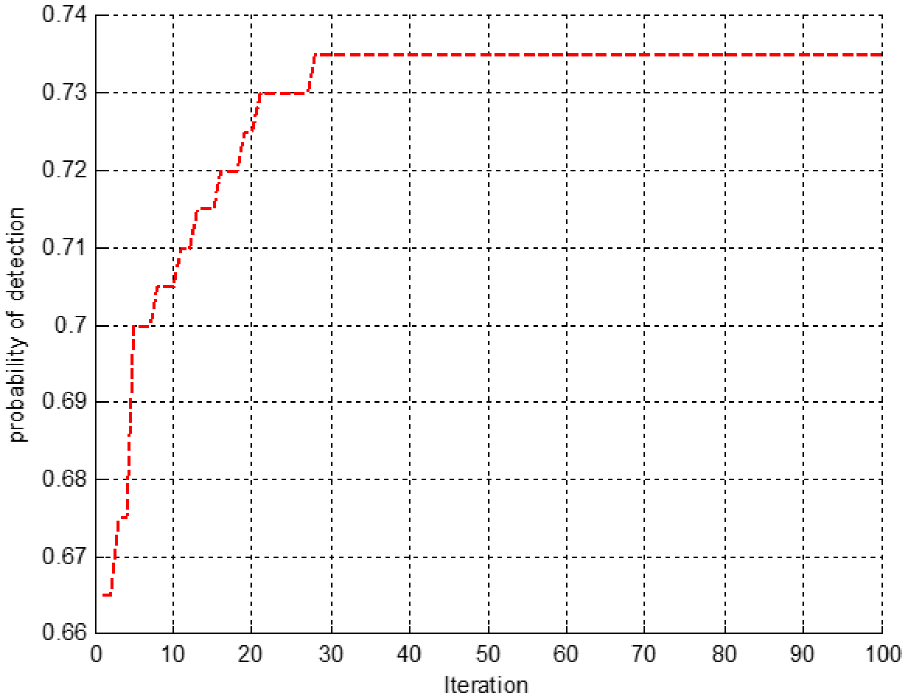

Figure 5: Probability of detection at probability of false alarm=0.1

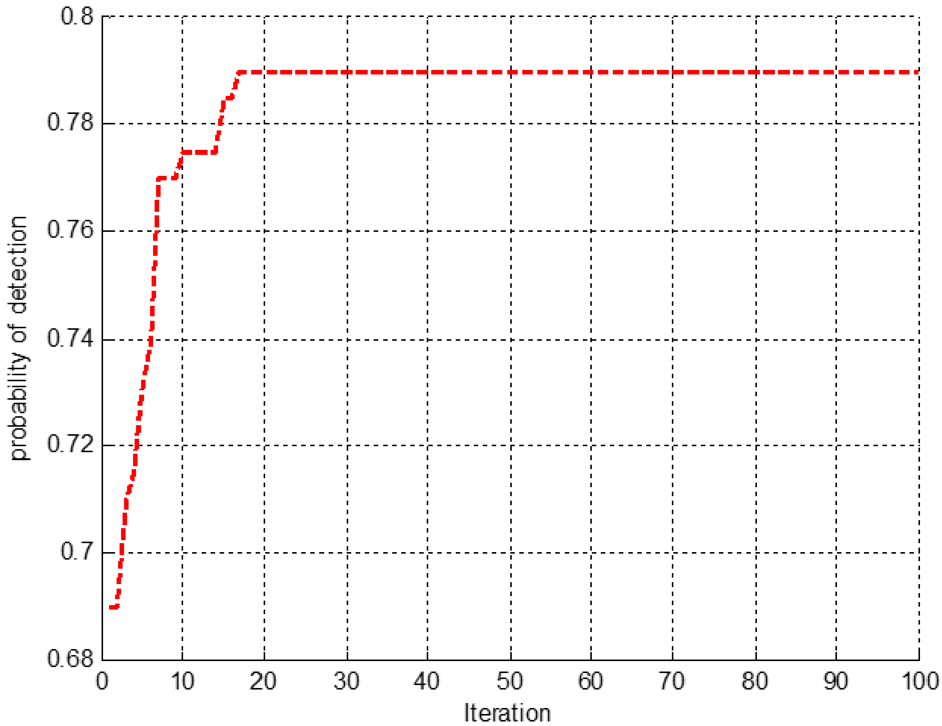

Figure 6: Probability of detection at probability of false alarm=0.2

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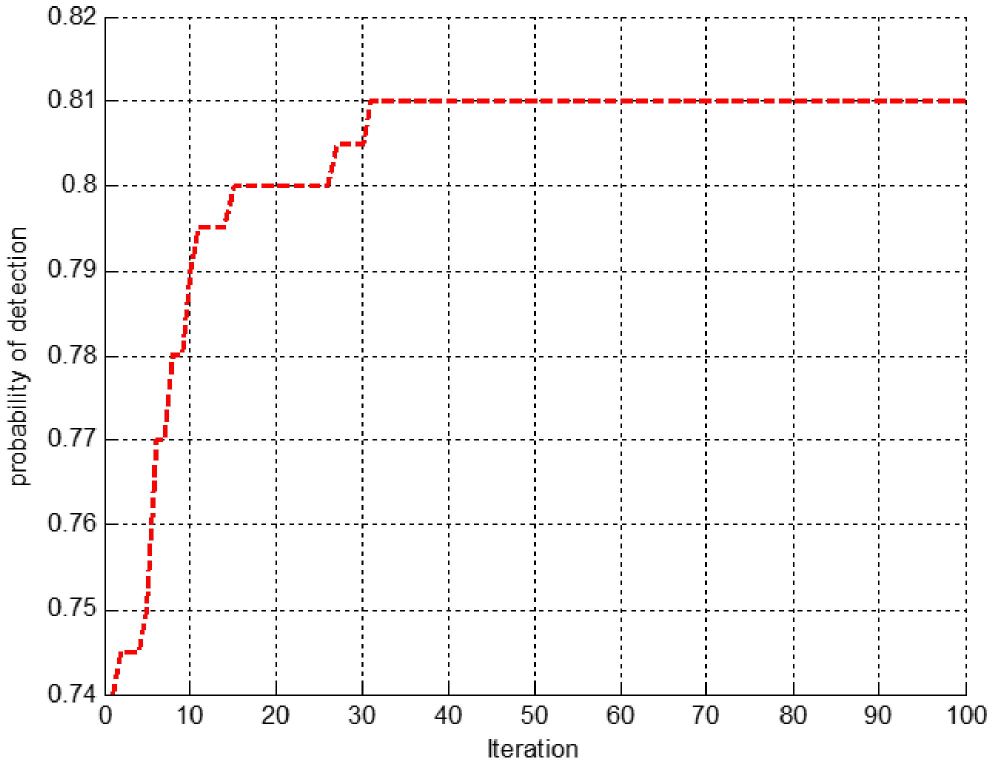

Figure 7: Probability of detection at probability of false alarm=0.3

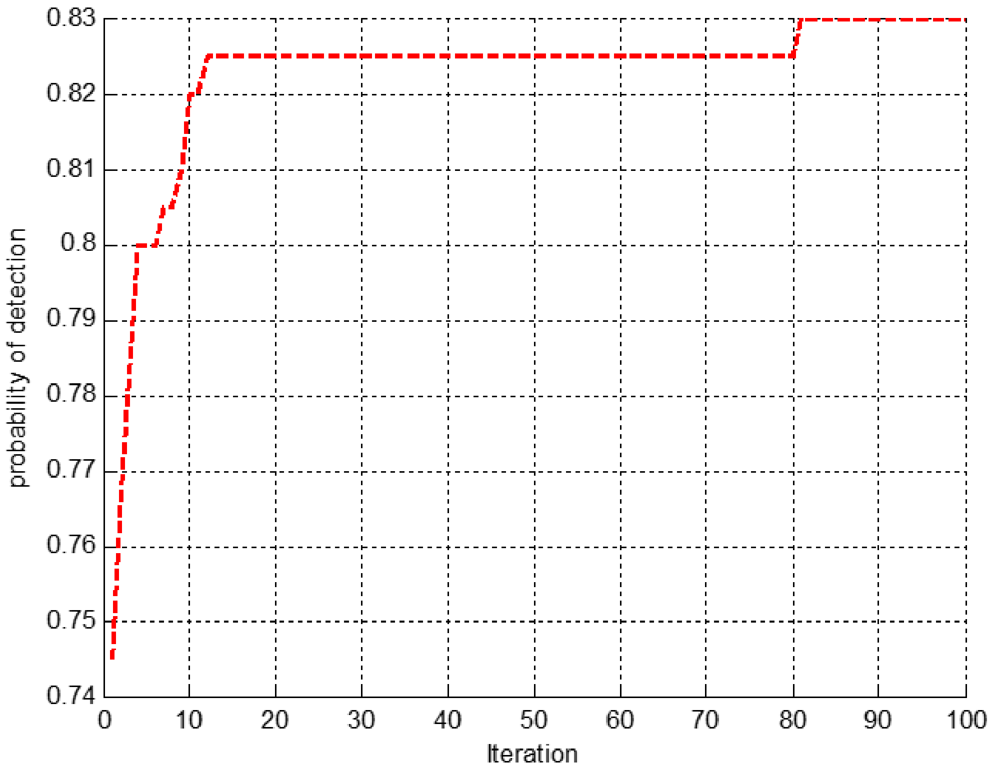

Figure 8: Probability of detection at probability of false alarm=0.4

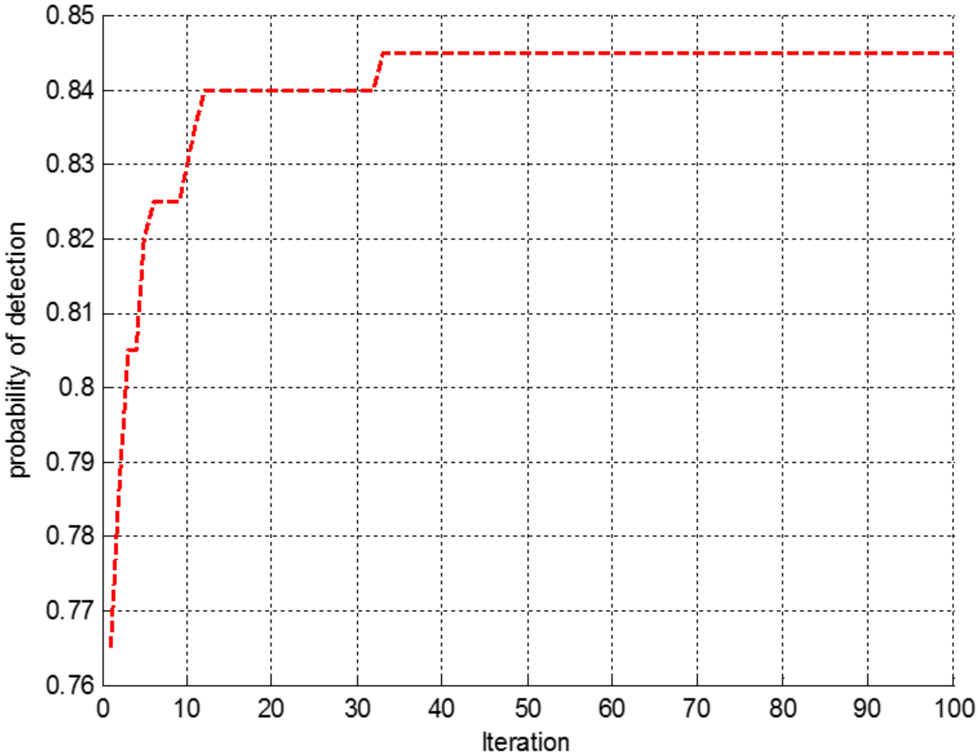

Figure 9: Probability of detection at probability of false alarm=0.5

5. Conclusion

Cognitive radio is a technology that has revolutionized the world of telecommunications, its capacity for interaction and adaptation allow it to widen its field of operability, and ultimately guarantee a wider bandwidth for radio users cognitive through dynamic spectrum access techniques. Cognitive radio thus allows the existing wireless spectrum to be exploited opportunistically, and solves the problems of current wireless networks resulting from the limitation and inefficient use of the spectrum. All these techniques must be coordinated with highly sophisticated algorithms in order to have the most successful technology possible.

Metaheuristic algorithms are robust procedures to solve optimization problems, thanks to their different operations, they allow to quickly provide solutions close to the optimal solution.

Thus in our study, we focused on a solution that could nevertheless give a better performance to this negotiation, our work is built the metaheuristics which allow to obtain quickly good results. Two metaheuristic PSO and Cultural Algorithm that represent the optimization methods. Other metaheuristic based method can also be used in future to enhance the performance. In perspective, we propose to extend the approach to other layers of CR such as the application layer. Take into account other functions such as spectral efficiency, interference. And finally, evaluate and test other techniques of artificial intelligence.

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