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Artificial Bee Colony Optimized Eigenvalue based Detection for Spectrum Sensing

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Abstract – **Energy detection based spectrum sensing method is the most common technique due to its simple operation and efficient detection rate for signals with higher SNR values. When the SNR level degrades, the performance of energy detector fails to give proper detection rate. This problem led towards development of an efficient spectrum sensing algorithm. In this regard, this paper includes the development of efficient and reliable spectrum sensing algorithm for cognitive radio network with the help of soft computing technique. An Artificial Bee Colony (ABC) optimized model of Eigen value based detection (EVD) for spectrum sensing algorithm has been presented. To estimate the performance of proposed scheme a simulation model is developed using MATLAB 2014a.**

Keywords –**ABC, ADC, CR, EVD, QoS, PU.**

I. INTRODUCTION

Cognitive radio (CR) has been proposed as a promising technique for future wireless communication systems. CR is able to fill in spectrum holes and serve its users (Secondary users) without causing harmful interference to the licensed user (PU). To do so, the CR must continuously sense the spectrum it is using in order to detect the reappearance of the PU. Once the PU is found to be active, the SU is required to vacate the channel. Therefore, spectrum sensing is of significant importance in CR networks. Moreover, periodic sensing is essential where the SU has to be aware of the channel status at all times. This is achieved by using a frame structure. In this structure, each frame consists of a sensing period and a transmission period. At the end of each sensing period, the SU transmission starts when the licensed channel is idle. Otherwise, the SU will wait until the next frame to sense the licensed channel again.

The rapid growth in wireless communications has contributed to a huge demand on the deployment of new wireless services in both the licensed and unlicensed frequency spectrum. However, recent studies show that the fixed spectrum assignment policy enforced today results in poor spectrum utilization. To address this problem, cognitive radio (CR) has emerged as a promising technology to enable the access of the intermittent periods of unoccupied frequency bands, called white space or spectrum holes, and thereby increase the spectral efficiency. The fundamental task of each CR user in CR networks, in the most primitive sense, is to detect the licensed users, also known as primary users (PUs), if they are present and identify the available spectrum if they are absent. This is usually achieved by sensing the RF environment, a process called spectrum sensing. The objectives of spectrum sensing are twofold: first, CR users should not cause harmful interference by either switching to an available band or limiting its interference with PUs at an acceptable level and, second, CR users should efficiently identify and exploit the spectrum holes for required throughput and quality-of-service (QoS). Thus, the detection performance in spectrum sensing is crucial to the performance of both primary and CR networks. The detection performance can be primarily determined on the basis of two metrics: probability of false alarm, which denotes the probability of a CR user declaring that a PU is present when the spectrum is actually free, and probability of detection, which denotes the probability of a CR user declaring that a PU is present when the spectrum is indeed occupied by the PU. Since a miss in the detection will cause the interference with the PU and a false alarm will reduce the spectral efficiency, it is usually required for optimal detection performance that the probability of detection is maximized subject to the constraint of the probability of false alarm. Many factors in practice such as multipath fading, shadowing, and the receiver uncertainty problem may significantly compromise the detection performance in spectrum sensing.

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The objective of this research is to utilization of the idle frequency band or unused spectrum holes which has the license to the PU is then assign to cognitive users or to the unlicensed users without any interference to the PU communication. So a good sensing algorithm is required. Energy detection method is an efficient spectrum sensing technique for high SNR environment but it gives poor performance under low SNR. So by applying some technique result can be improved. Therefore, in our report ABC optimized EVD using Hankel matric approach method is used, in order to obtain improved result, which does not require the knowledge of signal properties, channel and uncertainty noise parameter. Performance analysis and comparison of both techniques is carried out using MATLAB 2014a. This paper presented the performance of cognitive radio by archive large probability of detection in low SNR as compare to Energy detection additionally, the threshold computation of algorithm is irrespective to noise parameter.

II. PROPOSED METHODOLOGY

A. System Model

The purpose of signal detection is to test the existence of primary user's signal in receiver. For the signal detection, there are two kinds of hypothesis: H_0, which means primary user's signal does not exist; H_1, which means primary user's signal exists. The two hypothesis are given respectively by formula as follows:

$$H_0 : x(n) = \eta(n) \quad (1)$$

$$H_1 : x(n) = \bar{s}(n) + \eta(n) \quad (2)$$

Where $\bar{s}(n)$ is the received signal samples including the effects of path loss, multipath fading and time dispersion, and $\eta(n)$ is the received white noise assumed to be identically distributed signal, and with mean zero and variance σ_η^2.

The received signal at receiver can be given as:

$$x(n) = \sum_{j=1}^{P} \sum_{k=0}^{N_{ij}} h_j(k) s_j(n-k) + \eta(n) \quad (3)$$

Where, P is the number of source signals i.e. number of transmitters, $h_j(k)$ is channel response and N_{ij} is the order of the channel.

The detection techniques performance can determined through two probabilities: probability of false alarm (P_f) is probability of incorrectly detection of primary user in the frequency band that is case H_0 and probability of detection (P_d) is probability of correctly detection primary user in frequency band that is case H_1.

B. Energy Detection Technique

Energy detection is transmitter detection technique for spectrum sensing. It is used to detect the primary signal is exist or not in the frequency spectrum which is being sensed. The concept for energy detection of unknown signals is developed by Urkowitz in 1967. Although, in which the signal is actually unknown in detail, it's considered deterministic. Deterministic signal is assumed as the input with signal present is Gaussian but not zero mean. The spectral region is known and the noise is assumed to be Gaussian and additive with zero mean [1]. Energy detection method is, also, known as periodogram (PE) [2]. Basically, Energy detection is most common method of spectrum sensing is due to two reasons:

a) Receiver do not require any knowledge about primary user's signal

b) it have very low computation complexity

The energy detection can be performed in two ways, Time domain and frequency domain. There is no difference in evaluated result any domain can be used. Figure 1 shows the time domain representation of the energy detection method. To measure signal power in specific frequency band in time domain, bandpass filter of bandwidth W is used at input signal. ADC is used to convert one form to another for samples. A square and average device is used to obtain the receiver signal energy, and it compared with threshold to decide whether the signal is present or not.

H_o= Absence of user

H_1= Presence of user

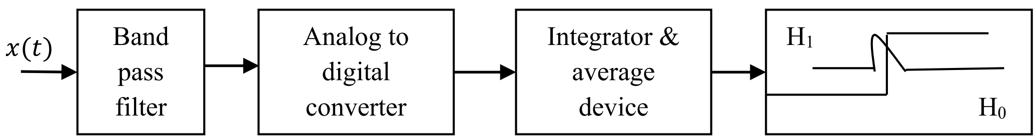

Figure 1: Block diagram of Energy Detection

For system model, a system is considered of one cognitive radio (CR), one primary user (PU) and fusion center (FC). When a signal from PU is transmitted, the received signal by the CR for the detection of PU can be modeled under two hypotheses (H_0 & H_1), is gives as follows

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$$H_0:\ y(k) = n(k): \text{PU is absent} \quad (4)$$
$$H_1:\ y(k) = h * s(k) + n(k): \text{PU is present} \quad (5)$$

Where y(k) the received signal by secondary users, s(k) is the transmitted signal of the primary user, h is the channel coefficient and n(k) is AWGN with zero mean and σ^2 variance (i.e. N $(0,\sigma^2)$). H_0 & H_1 are the sensing states for absence and presence of signal respectively.

The decision statics D, to check about the presence or absence is made by making the test on the received signal at cognitive radio receiver. The decision statics for energy detection is,

$$T = \sum_{k=0}^{L} |y(k)|^2 \quad (6)$$

Therefore, T is the summation of energy of y (k) over L samples via energy detection statics. Probability of detection P_d is used is defined as follows:

$$P_d = Pr\ \{T > \gamma | H_1\} \quad (7)$$

Probability of false alarm P_f is used is defined as follows:

$$P_f = Pr\ \{T > \gamma | H_0\} \quad (8)$$

In maximum a posteriori (MAP) detector is known to be optimal in CR. In MAP detection, the output of the integrator is called as the chi-square distribution [3]. Whenever number of sample is large, with central limit theorem, we will have to assume the chi-square distribution is approximate as Gaussian distribution [1];

$$T \sim \begin{cases} N(n\,\sigma_n^2, 2\,n\,\sigma_n^4) \\ N(L\,(\sigma_n^2 + \sigma_s^2), 2\,n\,(\sigma_n^2 + \sigma_s^2)^2) \end{cases} \quad (9)$$

Where L is the number of samples, variance of noise is σ_n^2, the is the variance of received signal is σ_s^2, As from the equation (9), $(\sigma_n^2 + \sigma_s^2)$, is the total variance of signal plus noise as σ_t^2 therefore,

$$\sigma_t^2 = \sigma_n^2 + \sigma_s^2 = \sigma_n^2(1 + SNR) \quad (10)$$

We know from the Nyquist sampling theorem, the minimum sampling rate should be 2W, therefore, L can be represent as 2 T_sW, where T_s is the observation time and W is the bandwidth, the probability of false alarm can be expressed in term of Q function as follows [4]:

$$P_f(W, T_s) = Q\left(\frac{\gamma - 2\,T_s\,W\,\sigma_n^2}{\sqrt{4\,Ts\,W\,\sigma_n^4}}\right) \quad (11)$$

The threshold value γ is controlled based on the noise variance (noise power). We can first set the false alarm probability P_f be a specific constant and P_f should be kept small to avoid underutilization of transmission opportunities, from equation (11), threshold value γ can be obtained.

$$\gamma = \sqrt{4\,Ts\,W\sigma_n^4}\, Q^{-1}(P_f) + 2\,T_s\,W\,\sigma_n^2 \quad (12)$$

Where Q represent the Q function, which is defined as the probability that standard normal random variable (zero mean, unit variance) exceeds x;

$$Q(x) = \frac{1}{\sqrt{2\,\pi}} \int_x^{\infty} e^{-\frac{t^2}{2}dt} \quad (13)$$

C. Maximum-Minimum Eigenvalue (MME) Detection

MME is used to perform signal detection without prior knowledge of signal or noise power. MME detection compares the threshold with the ratio of the maximum eigenvalue to the minimum eigenvalue [5].

Step 1: Compute the sample covariance matrix of the received signal:

$$R_x(N_s) = \frac{1}{N_s} \sum_{n=L-1}^{L-2+N_s} \hat{x}(n)\hat{x}^{\dagger}(n) \quad (14)$$

Where N_s is the number of collected samples.

Step 2: Obtain the maximum and minimum eigenvalue of the matrix $R_x(N_s)$, that is, λ_{max} and λ_{min}.

Step 3: Decision: if $\lambda_{max}/\lambda_{min} > \gamma_1$, signal exists ("yes" decision); otherwise, signal does not exist ("no" decision), where $\gamma_1 > 1$ is a threshold.

D. Threshold Determination using Artificial Bee Colony Algorithm

Random matrix theory based Eigen values detection provides two parameters namely decision threshold and probability of false alarm. Equation (15) shows ratio of maximum to minimum eigenvalues of the signal received for covariance matrix [6]:

$$T_Y = \lambda_{max}/\lambda_{min} \quad (15)$$

Above equation provides the essential statistics to attain the required probability of false alarm using the estimation of detection threshold (g). It is accomplished using the density of the test statistic (T_Y) [6].

The detection threshold in terms of anticipated probability of false alarm is considered by:

$$\gamma_{mme} = \left((\sqrt{N_s} + \sqrt{L})^2/(\sqrt{N_s} + \sqrt{L})^2\right) \times \left(1 + \frac{(\sqrt{N_s}+\sqrt{L})^{\frac{2}{3}}}{(N_s L)} . F_1^{-1}(1 - P_{fa})\right) \quad (16)$$

Where F_1^{-1} 1 represents the inverse of cumulative distribution function (CDF) of the Tracy-Widom distribution of order 1 [6].

The threshold definition is formulated based on deterministic asymptotic values of the minimum and maximum eigenvalues of the covariance matrix, R, when the number of samples, N_s is very large. As shown in the equation (16), it is defined only in terms of number of samples, N_s, level of covariance matrix, L and the desired probability of false alarm, P_{fa} [6].

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Threshold optimization is performed using Artificial Bee Colony (ABC) algorithm which is explained as follows.

Artificial Bee Colony (ABC)

The ABC algorithm is a swarm based, meta-heuristic method based on the model first proposed by [7] on the foraging behaviour of honey bee colonies. The model is composed of three important elements: employed and unemployed foragers, and food sources. The employed and unemployed foragers are the first two elements, while the third element is the rich food sources close to their hive. The two leading modes of behaviour are also described by the model. These behaviours are necessary for self-organization and collective intelligence: recruitment of forager bees to rich food sources, resulting in positive feedback and simultaneously, the abandonment of poor sources by foragers, which causes negative feedback [8].

The ABC consists of three groups of artificial bees: employed foragers, onlookers and scouts. The employed bees comprise the first half of the colony whereas the second half consists of the onlookers. The employed bees link to particular food sources. In other words, the number of employed bees is equal to the number of food sources for the hive. The onlookers observe the dance of the employed bees within the hive, to select a food source, whereas scouts search randomly for new food sources. Analogously in the optimization context, the number of food sources (that is the employed or onlooker bees) in ABC algorithm, is equivalent to the number of solutions in the population. Moreover, the position of a food source signifies the position of a promising solution to the optimization problem, whereas the value of nectar of a food source represents the fitness cost (quality) of the associated solution.

The search cycle of ABC consists of three rules:

1. Sending the employed bees to a food source and evaluating the nectar quality.
2. Onlookers choosing the food sources after obtaining information from employing bees and calculating the nectar quality
3. Determining the scout bees and sending them on to possible food sources.

The positions of the food sources are randomly selected by the bees at the initialization stage and their nectar qualities are measured. The employed bees then share the nectar information of the sources with the bees waiting at the dance area within the hive. After sharing this information, every employed bee returns to the food source visited during the previous cycle, since the position of the food source had been memorized and then selects another food source using its visual information in the neighbourhood of the present one. At the last stage, an onlooker uses the information obtained from the employed bees in the dance area to select a food source. The probability for the food sources to be selected increases with an increase in its nectar quality. Therefore, the employed bee with information of a food source with the highest nectar quality recruits the onlookers to that source. It subsequently chooses another food source in the neighbourhood of the one currently in her memory based on visual information (i.e. comparison of food source positions). A new food source is randomly generated by a scout bee to replace the one abandoned by the onlooker bees. This search process could be represented in ABC algorithm as follows:

Pseudo Code of the ABC Algorithm

1. Initialize the population of solutions x_{ij}
2. Evaluate the population
3. Cycle=1
4. Repeat
5. Produce new solutions (food source positions) v_{ij} in the neighbourhood of x_{ij} for the employed bees and evaluate them.
6. Put on the greedy selection process between xi and v_i
7. Compute the probability values p_i for the solutions x_i by means of their fitness values. In order to calculate the fitness values of solutions
$$\begin{bmatrix} \frac{1}{1+f_i} & if\ f_i \geq 0 \\ 1 + abs(f_i) & if\ f_i < 0 \end{bmatrix} \quad (17)$$
Normalize p_i values into [0, 1]
8. Produce the new solutions (new positions) v_i for the onlookers from the solutions x_i, selected depending on p_i, and evaluate them
9. Put on the greedy selection process for the onlookers between x_i and v_i
10. Determine the abandoned solution (source), if exists, and replace it with a new randomly produced solution xi for the scout using the equation
$$x_{ij} = min_j + rand(0,1) * (max_j - min_j) \quad (18)$$
11. Memorize the best food source position (solution) achieved so far
12. cycle=cycle+1
13. Until cycle= Maximum Cycle Number (MCN)

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III. SIMULATION AND RESULTS

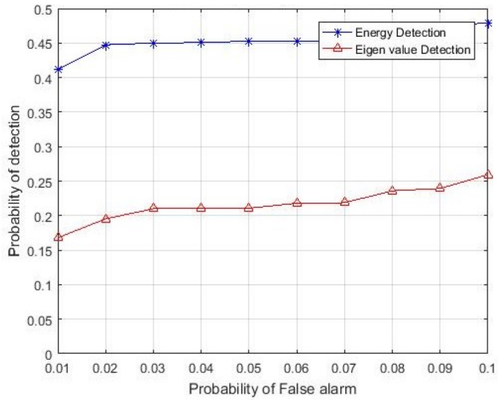

Figure 2: Comparison of Energy & Eigenvalue based detection using Probability of detection (P_d) Versus Probability of false alarm (P_f) at SNR is -4 dB

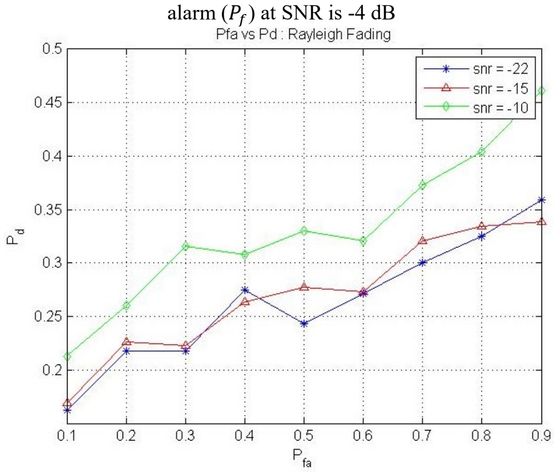

Figure 3: Probability of detection (P_d) versus Probability of false alarm (P_f) graph for ABC optimized eigenvalue based detection at different SNR values using Rayleigh fading channel

IV. CONCLUSION

This paper proposes the performance analysis of Eigen Value based Detection (SVD) using Artificial Bee Colony (ABC) for spectrum sensing. Here the ABC is used to select a value of smoothening factor with objective of highest probability of detection. The fitness function comprises of full scenario where we generate a random standard signal (modulated and filtered) and transmitted it to channel of defined SNR, we have taken lowest SNR value, signal received at each cognitive secondary user is collected and arranged in Hankel matrix with a random value of smoothening factor and detection probability has been calculated. Now this value of detection probability is analyzed by ABC and an update in the value of smoothening factor has been performed. With this update the whole process is repeated iteratively. At the end we get smoothening factor for which we are getting highest probability of detection

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