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Cognitive Radio Spectrum Sensing using Hybrid MME and Energy Double Thresholding Optimized with Weighted Chimp Optimization Algorithm

Mr. Raghavendra L. R.[1], Dr. Manjunatha R. C.[2]

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Abstract: The detection of free frequency bands for use by cognitive radio networks without disrupting primary users is essential, making spectrum sensing a crucial technology. The adaptive double-threshold technique modifies the upper and lower thresholds for energy detection, depending on the cognitive nodes' SNR. To calculate the thresholds' weighting coefficient, the SNR of all cognitive nodes in the network is considered. This paper proposes the WCOA based approach for weighting coefficients calculation, which is used to adjust the upper and lower thresholds accordingly. Specifically, when multiplying the weighting coefficient of the upper threshold by a scaling factor to obtain the new upper threshold, and further multiply the weighting coefficient of the lower threshold by another scaling factor to obtain the new lower threshold. The scaling factors are used to ensure that the new thresholds are within a reasonable range and to prevent them from being too sensitive to small changes in the weighting coefficients. The suggested double-threshold algorithm based on a hybrid of Energy and maximum-minimum Eigenvalue (MME), further enhanced with the Weighted Chimp algorithm (WCOA), can efficiently solve the issue of inadequate detection performance encountered by the conventional double-threshold energy detection method, especially at low SNR. By collaborating, cognitive nodes can enhance their detection accuracy, resulting in a shorter spectrum sensing period and a higher probability of detection.

Keywords: *Chimp Optimization Algorithm, Cognitive Radio, Energy Detection, Maximum-Minimum Eigenvalue, Spectrum Sensing.*

1. Introduction

Coordination of the use of the electromagnetic spectrum, at an international level, is carried out by the ITU (International Telecommunications Union), the United Nations agency responsible for technological, information and telecommunications matter. The control over the use of this resource, however, is done sovereignly by each country through its regulatory agencies, such as the FCC, which regulate the use of this scarce resource.

Currently, the spectrum allocation policy adopted is a fixed policy, known as FSA (fixed spectrum allocation). In this policy, the electromagnetic spectrum is subdivided into bands that are intended for different types of services. Authorization to use the electromagnetic spectrum has a fixed term and, in general, is issued according to the region where the transmitter system is installed. Within this region and during the period of validity of this authorization, only the concessionaire or licensee to which the authorization was issued must have access to the resources of the electromagnetic spectrum, even if the resource is underused over time. Initially, the policy adopted was sufficient both to avoid interference between the different systems that used the electromagnetic spectrum, and to meet the demand for wireless communication services.

The utilization of the electromagnetic spectrum has significantly transformed due to the persistent development of wireless communication technologies today. While the industry and researchers strive to enhance the spectral efficiency of new communication systems, the rising transmission rate is still correlated with an amplified bandwidth requirement for transmitting information. This escalating demand for transmission frequencies and a limited supply generates the phenomenon acknowledged as spectral scarcity [1].

In addition to restricting the offer of the electromagnetic spectrum, the policy that was once adequate to the resource usage profile is currently not efficient. Despite being reserved and not used at certain times of the day, the spectrum cannot be reused by other systems.

In this context, a different proposal for spectrum allocation emerges, the dynamic allocation known as DSA (dynamic spectrum access). This new policy suggests that the resource be used in an opportunistic way, that is, access to the spectrum would be based on the demand for its use and the spectrum bands would no longer be totally reserved for certain types of service. Currently, an example of this type

1Research Scholar, Department of ECE
Global Academy of Technology
Bengaluru, Karnataka, India-560098
raghavendra.lr52@gmail.com
2Associate Professor, Department of ECE
Global Academy of Technology
Bengaluru, Karnataka, India-560098
manjunathrc84@gmail.com

of allocation exists in the 2.4GHz band, an unlicensed usage band shared by wireless telephone, 802.11 WLAN and Bluetooth systems [2]. In addition to radically changing the way spectrum use is regulated, the new policy suggests a substantial change in the design of receiving and transmitting devices. One of the main restrictions to the adoption of a dynamic spectrum access policy is the guarantee that there will be no interference between the different systems. If it is not possible to guarantee that the DSA network does not interfere with the legacy FSA systems, there will be no interest in changing the current policy, as networks with both spectrum allocation policies must coexist.

In this context, spectrum sensing emerges as one of the main features of DSA networks. In this step, transmission opportunities are identified, or spectrum holes, portions of the electromagnetic spectrum that are not used at a given time. If spectrum sensing is not efficient, radios will not be able to perceive transmission opportunities, or worse, they may not be able to identify when spectrum is used, which would give the false idea that spectrum is available when it is not used.

The significance of implementing a hybrid MME and EDT algorithm optimized with the Weighted Chimp algorithm for spectrum sensing can be condensed as follows:

- Improved precision and dependability: The hybrid algorithm amalgamates MME and EDT's benefits to enhance the spectrum sensing's precision and dependability. Further, optimizing the algorithm's parameters with the Weighted Chimp algorithm boosts its performance.

- Reduced false alarms and missed detections: The optimization process using the Weighted Chimp algorithm aims to reduce false alarms and missed detections, which are important factors in cognitive radio systems. This can improve the overall efficiency of spectrum utilization and reduce interference with other wireless networks.

- Increased spectrum utilization: Spectrum sensing using the hybrid MME and EDT algorithm can identify idle or underutilized spectrum bands, which can be used for dynamic access by cognitive radio devices. This can increase the overall spectrum utilization and provide more opportunities for wireless communication.

- Compatibility with different signal types: The MME technique can be used to detect a wide range of signal types, while the EDT technique is effective in detecting signals with varying levels of energy. This makes the hybrid algorithm suitable for spectrum sensing in diverse environments and applications.

The utilization of the hybrid MME and EDT algorithm for spectrum sensing, optimized with the Weighted Chimp algorithm, is a noteworthy advancement in cognitive radio technology. This technological approach can advance spectrum utilization's accuracy, reliability, and efficiency, while empowering cognitive radio devices to dynamically access the radio spectrum.

The following is an outline of the remaining sections in this paper. Section II contains a literature review of the relevant field, while Section III describes the recommended methods for hybrid threshold-based energy detection. Section IV presents the simulation results obtained using MATLAB. Finally, the paper concludes with a summary of the findings in Section V.

2. Literature Review

The technology of cognitive radio user enables the detection of the availability of the main user in the spectrum. In case the primary user (PU) is not available, the secondary user may use the free spectrum [3]. However, the reliability of this approach for an average user is not high due to key user recognition issues [4]. This issue leads to the problem of secondary user accessing the primary user's licensed spectrum. To address this issue and improve detection accuracy, collaborative spectrum sensors are employed, allowing secondary users to enhance their performance [5] [6].

The spectrum of cognitive recognition is defined beyond the N voting rule. At the center of fusion, where a minimum of N primary users is identified by secondary users with an external SU [7]. Within seconds, users boost their power consumption to report their spectral sensitivity and Fusion Center's (FC) sensitivity. Storage schemes have been proposed to enhance energy efficiency [8] [9]. If the SNR or primary user (PU) is too high, spectrum allocation can minimize time and power consumption. Otherwise, the spectrum detection sensitivity will be employed again to improve performance. A framework for optimizing power consumption by recording the time and transmission time is proposed [10] [11]. This enhances energy efficiency by reducing interference. To improve energy efficiency, various well-known channels have been suggested for optimized input recognition [12].

While some secondary users may be aware of the channel, the Fusion Center (FC) and other secondary users may still transmit the same message [13]. To enhance spectral energy detection performance, a reliable high-energy threshold circuit is presented in [14]. In [15], the authors proposed an adaptive limitation based on the influence of the secondary user (SU) transmit power. The detection threshold, as described by the authors in [16], relies solely on the statistical properties of the received signal. The ideal threshold value is achieved using the Lagrange multiplier method, as shown in [17]. An algorithm based on two thresholds is presented in [15], which improves detection performance significantly by deviating from the conventional one-threshold design. In [18], a longer time is required to detect the spectrum before obtaining results, while in [19], the authors propose a method for determining an adaptive threshold value for an unlicensed 2.4 GHz WLAN channel that can be applied practically, especially with cellular sensors. Finally, in [20], the maximum number of entries is defined, and if the spectrum detection time exceeds the upper limit, the SU will switch to detecting a different spectrum.

To overcome the difficulties in acquiring spectrum on the cognitive radio network encountered by all existing methods, this study puts forward a hybrid threshold that combines MME with energy measurement techniques.

3. Material and Methods

Cognitive radio systems use spectrum sensing to detect available frequency bands or channels for wireless communication. To improve spectrum sensing, this study proposes a hybrid technique combining maximum-minimum eigenvalue (MME) and energy double thresholding optimized with the Weighted Chimp algorithm. Hybrid MME estimates the number of signals present in a frequency band by calculating the eigenvalues of the signal's covariance matrix and comparing them to a threshold. This method is combined with energy double thresholding (EDT), which compares the received signal's energy with two predefined thresholds to detect signals. The Weighted Chimp algorithm optimizes hybrid MME and EDT by mimicking natural selection to find the optimal threshold values for the spectrum sensing process. By searching a population of candidate threshold values, the algorithm selects the ones that improve spectrum sensing performance. This combination of techniques can enhance spectrum sensing in cognitive radio systems.

3.1 MME Based Spectrum Sensing Scheme

The Maximum-Minimum Eigenvalue (MME) detection technique is a signal processing approach used for spectrum sensing in cognitive radio networks. The mathematical formulation of the MME detection technique considering the given expressions is as follows:

1. ***Acquisition of Received Signal Samples:*** The received signal at the secondary user (SU) is sampled over N_s time instances to obtain a set of received signal samples. These samples are denoted as $x(n)$, where n is the sample index.
2. ***Formation of the Received Signal Covariance Matrix, R_x:*** To obtain the received signal covariance matrix, R_x, the sample covariance of the received signal samples is taken into account. The resulting matrix is expressed as follows:

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

Where $x \dagger (n)$ denotes the Hermitian transpose of $x(n)$, N_s is the no. of samples used to estimate the covariance matrix, and L is the index of the first sample.

3. ***Calculation of the Eigenvalues of R_x :*** The Eigenvalues of the received signal covariance matrix, R_x, denoted as $\lambda_1, \lambda_2, \ldots, \lambda_N$, where N is the number of antennas at the SU, are calculated. These Eigenvalues can be obtained by solving the following equation:

$$R_{xv} = \lambda_v \qquad (2)$$

Where v is the corresponding Eigenvector.

4. ***Calculation of Maximum and Minimum Eigenvalues:*** The maximum and minimum Eigenvalues of R_x , denoted as λ_{max} and λ_{min} , respectively, are calculated. They can be obtained by:

$$\lambda_{max} = \max(\lambda_1, \lambda_2, \ldots, \lambda_N) \qquad (3)$$

$$\lambda_{min} = \min(\lambda_1, \lambda_2, \ldots, \lambda_N) \qquad (4)$$

5. ***Comparison with Threshold Value:*** The ratio of the maximum and minimum Eigenvalues, denoted as max/min, is compared to a pre-defined threshold value, γ. The decision rule for signal detection is:

$$if max/min > \gamma, signalexists;$$

$$otherwise, signaldoesnotexist. \qquad (5)$$

MME detection is a simple and effective technique that can be used for spectrum sensing in cognitive radio networks. However, it has some limitations such as the need for a large number of samples to estimate the covariance matrix accurately, and it is sensitive to noise and interference. These limitations can be addressed by using advanced signal processing techniques such as cooperative sensing, multiple antenna systems, and advanced detection algorithms.

3.1.1. Probability Parameters and Threshold Value for MME Detection

The Maximum-Minimum Eigenvalue (MME) detection technique relies on probability parameters and threshold values to determine whether a primary user (PU) signal is present or absent. The mathematical representation of these crucial parameters in MME detection is expressed as follows:

1. ***False Alarm Probability*** (P_f)***:*** The probability of false alarm, denoted as P_f, is defined as the probability of wrongly detecting a primary user (PU) signal when it is not present. When no signal is present, this probability can be computed using the cumulative distribution function (CDF) of the ratio of maximum and minimum Eigenvalues, which is denoted as $\rho = \lambda_{max}/\lambda_{min}$. Assuming that the received signal samples are Gaussian distributed, the CDF of ρ can be approximated as:

$$F_\rho(\rho) = e^{-\alpha N_s(\rho - \gamma)} \quad (6)$$

Where, α is a constant related to the noise power, N_s is the number of samples used to estimate the covariance matrix, and γ is the threshold value. The false alarm probability can be obtained by integrating the CDF over the threshold value, γ, to obtain:

$$P_f = \int_\gamma^\infty F_\rho(\rho)d\rho = e^{-\alpha N_s(\gamma - \gamma)} = 1 \quad (7)$$

This implies that the false alarm probability is always 1 when the threshold value is set to the maximum value of ρ, which leads to a high probability of false alarm.

2. ***Detection Probability*** (P_d) ***:*** The detection probability, P_d , is defined as the probability of correctly detecting a PU signal when it is present. It can be calculated using the CDF of ρ when a signal is present. Assuming that the received signal samples are Gaussian distributed, the CDF of ρ can be approximated as:

$$F_\rho(\rho) = e^{-\alpha N_s(\rho-\gamma)} + Q\sqrt{(\alpha N_s)(\rho - \gamma - \Delta)} \quad (8)$$

Where, $Q(x)$ is the complementary error function, and Δ is a constant related to the signal-to-noise ratio (SNR). The detection probability can be obtained by integrating the CDF over the threshold value, γ, to obtain:

$$P_d = \int_\gamma^\infty F_\rho(\rho)d\rho = e^{-\alpha N_s(\gamma-\gamma)} + Q\sqrt{(\alpha N_s)(\gamma - \gamma - \Delta)} \quad (9)$$

This implies that the detection probability increases with increasing SNR and decreasing false alarm probability.

3. ***Threshold Value*** (γ)***:*** The threshold value, γ, is a critical parameter in MME detection, which determines the decision on the presence or absence of a PU signal. The threshold value can be set based on the required detection probability and false alarm probability. A common approach is to set the threshold value such that the detection probability is maximized while maintaining a specified false alarm probability. The threshold value can be obtained by solving the following equation:

$$P_d(\gamma) = 1 - P_f \quad (10)$$

Where $P_d(\gamma)$ is the detection probability as a function of the threshold value, γ. The threshold value can be obtained by numerical methods such as bisection or gradient search.

The false alarm probability, detection probability, and threshold value are important parameters in MME detection, which can be used to make a decision on the presence or absence of a PU signal. These parameters depend on the number of samples, noise power, SNR, and threshold value, which can be optimized based on the required performance. In this paper, the threshold optimization is achieved by using chimp optimization algorithm which is described in the following subheading.

3.2 Chimp Optimization Algorithm (COA)

Chimpanzees, like dolphins, have a brain-to-body ratio close to humans, and their DNA is quite similar to our DNA. The chimp optimization algorithm is an innovative heuristic approach that draws inspiration from the personal intelligence and sexual drive of chimpanzees when they hunt in teams and exhibit herd intelligence. This algorithm differs from previous predator-inspired algorithms. The authors of [21] suggested COA in 2020. There are four sorts of chimps in the COA to represent varied intelligences: aggressor, barrier, predator, and driver. Hunting consists of four major steps: chasing, blocking, attacking, and driving [21].

- Drivers chase after their prey without trying to catch it.
- Trees are used to create obstacles that impede the progress of the prey.
- The hunters quickly move to capture their prey.
- Conversely, the predators anticipate that the end of the hunt will lure their targets towards them.

Equations (11) and (12) illustrate the mathematical methodology used to update the location of chimps (12).

$$X_1(t+1) = X_{offensive}(t) - a_1 \cdot d_{offensive} \quad (11)$$

$$X_2(t+1) = X_{barrier}(t) - a_2 \cdot d_{barrier} \quad (12)$$

$$X_3(t+1) = X_{hunter}(t) - a_3 \cdot d_{hunter} \quad (13)$$

$$X_4(t+1) = X_{driver}(t) - a_4 \cdot d_{driver} \quad (14)$$

$$X_{chimp} = \frac{X_1+X_2+X_3+X_4}{4} \quad (15)$$

In the formulations, t denotes the current number of iterations. This iteration updates dependent on where the chimp is. The dynamic coefficient is indicated by a , whereas the vector is denoted by d.

$$a_1 = 2.f_1.r_1 - f_1, d_{offensive} = \left|c.X_{offensive}(t) - m.X(t)\right| \quad (16)$$

$$a_2 = 2.f_2.r_1 - f_2, d_{barrier} = |c.X_{barrier}(t) - m.X(t)| \quad (17)$$

$$a_3 = 2.f_3.r_1 - f_3, d_{hunter} = |c.X_{hunter}(t) - m.X(t)| \quad (18)$$

$$a_4 = 2.f_4.r_1 - f_4, d_{driver} = |c.X_{driver}(t) - m.X(t)| \quad (19)$$

The coefficient f drops non-linearly from 2.5 to 0 as the iteration in the following equations continues. $c = 2r_2.r_1$ is a random value between c and r_2 [0,1]. m is a chaotic vector [22].

When $\mu \geq 0.5$, the chaotic model is utilised for position update for a random number between [0,1] of probability discovered in the procedure, as indicated in Equation (20). When $\mu < 0.5$, Equation (15) is still utilised.

$$X_{chimp}(t+1) = chaotic\_value \quad (20)$$

Attackers are rewarded with a greater chunk of meat after successful hunting than other chimps because they attempt harder to foresee the prey's future actions. This significant function is related to age, IQ, and physical ability. Chimpanzees might switch between responsibilities while hunting or stay with the same duties the entire time.

3.3 Energy Detection Technique

Due to its low complexity in implementation, energy detection is the most commonly used method of spectrum sensing. However, this technique is a rough form of detection, as it does not furnish detailed information regarding the signals that are present in the spectrum. Detection is based on the test of two hypotheses:

$$H_0 : y(n) = z(n)$$
$$H_1 : y(n) = x(n) + z(n) \quad (21)$$

In hypothesis H_0, the signal is not present and the received signal $y(n)$ is formed only by $z(n)$ noise samples. In hypothesis H_1, the signal of interest $x(n)$ is present together with the noise.

The energy detector can be implemented in two main ways, exemplified in Figure 1. In the first form, Figure 1 (a), a filter is used to select the band of interest. The filter must be centered on the frequency of interest, fc, and preferably, have a bandwidth equal to the channel of interest. In the case of spectrum sensing in a wide range of frequencies, for a better estimate of the occupation of the selected band, it is interesting that the sweep filter has a narrow band. Another possible hypothesis is the existence of a narrowband filter bank. After the input filter, the signal passes through an analog-to-digital converter and a quadratic elevation device and only then the T_{ED} test statistic is calculated.

$$T_{ED} = \frac{1}{L}\sum_{n=1}^{L}|y(n)^2| \quad (22)$$

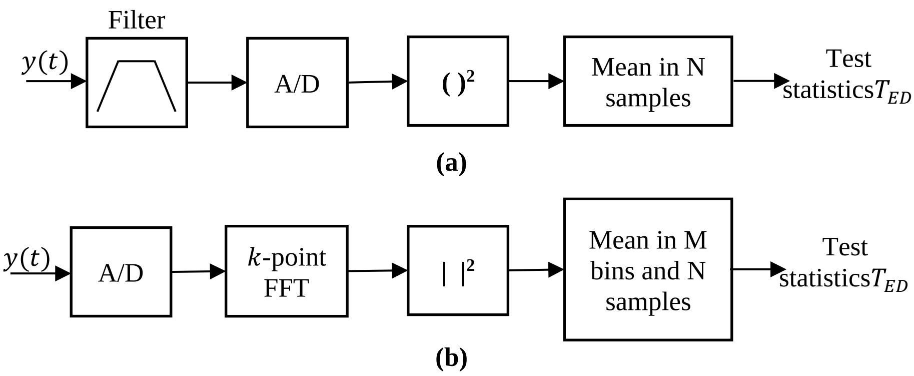

Fig. 1 Energy detector implementation diagrams (a) in time and (b) in frequency

The second proposed architecture, shown in Figure 1 (b), proposes the processing of samples at frequency. This design offers the capacity to handle multiple signals and larger frequency bands simultaneously by processing the corresponding frequency ranges of the fast Fourier transform, which replaces the selection filter. Within this structure, there are two detection variables: the frequency resolution of the FFT and the number of samples, N, utilized to compute the average. Typically, a constant FFT size is selected, while the number of samples, N, is adjusted to enhance the detector's performance.

In both forms of implementation, the T_{ED} test statistic is compared with a threshold λ_{ED} to choose between the two hypotheses. As the detection threshold depends on the SNR of the received signal, the technique's detection capability is impaired in scenarios where the noise is not stationary and varies rapidly.

The main advantage of the energy detection method is its low implementation complexity, while its main disadvantage is the low accuracy in situations of non-stationary noise and low SNR.

In equation (22), T_{ED} is the summation of energy of $y(n)$ over L samples via energy detection statics. The detection probability P_d is used is defined as follows:

$$P_d = P_r\{T_{ED} > \gamma | H_1\} \quad (23)$$

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

$$P_f = P_r\{T_{ED} > \gamma | H_0\} \quad (24)$$

The maximum a posteriori (MAP) detector is acknowledged as the optimal choice for CR. During MAP detection, the chi-square distribution is referred to as the integrator output. As the sample size becomes increasingly large, the central limit theorem necessitates approximating the chi-square distribution with the Gaussian distribution.

$$T \sim \begin{cases} N(n\sigma_n^2, 2\, n\sigma_n^4) \\ N(L(\sigma_n^2 + \sigma_s^2), 2\, n(\sigma_n^2 + \sigma_s^2)^2) \end{cases} \quad (25)$$

Where L represent the number of samples, σ_n^2 denote the variance of the noise, and σ_s^2 stand for the variance of the received signal.

As from the equation (25), $(\sigma_n^2 + \sigma_s^2)$, is the total variance of signal plus noise as σ_t^2 therefore,

$$\sigma_t^2 = \sigma_n^2 + \sigma_s^2 = \sigma_n^2(1 + SNR) \quad (26)$$

According to the Nyquist sampling theorem, the minimum sampling rate should be $2W$. Therefore, we can express L as $2\, T_s W$, where T_s represents the observation time and W represents the bandwidth. The false alarm probability can be defined in terms of the Q-function:

$$P_f(W, T_s) = Q\left(\frac{\gamma - 2\text{ Ts W}\sigma_n^2}{\sqrt{4\, TsW\sigma_n^4}}\right) \quad (27)$$

The noise variance (or power) regulates the threshold value, γ. Initially, we may set the false alarm probability, P_f, to a constant, ensuring it is kept to a minimum to prevent the underutilization of transmission opportunities. From equation (27), we can determine the threshold value, γ.

$$\gamma = \sqrt{4\, TsW\sigma_n^4}\, Q^{-1}(P_f) + 2T_s W\sigma_n^2 \quad (28)$$

The Q-function is denoted by Q and defined as the probability of a standard normal random variable (having zero mean and unit variance) exceeding x.

$$Q(x) \frac{1}{\sqrt{2\,\pi}} \int_x^\infty e^{-\frac{t^2}{2}} dt \quad (29)$$

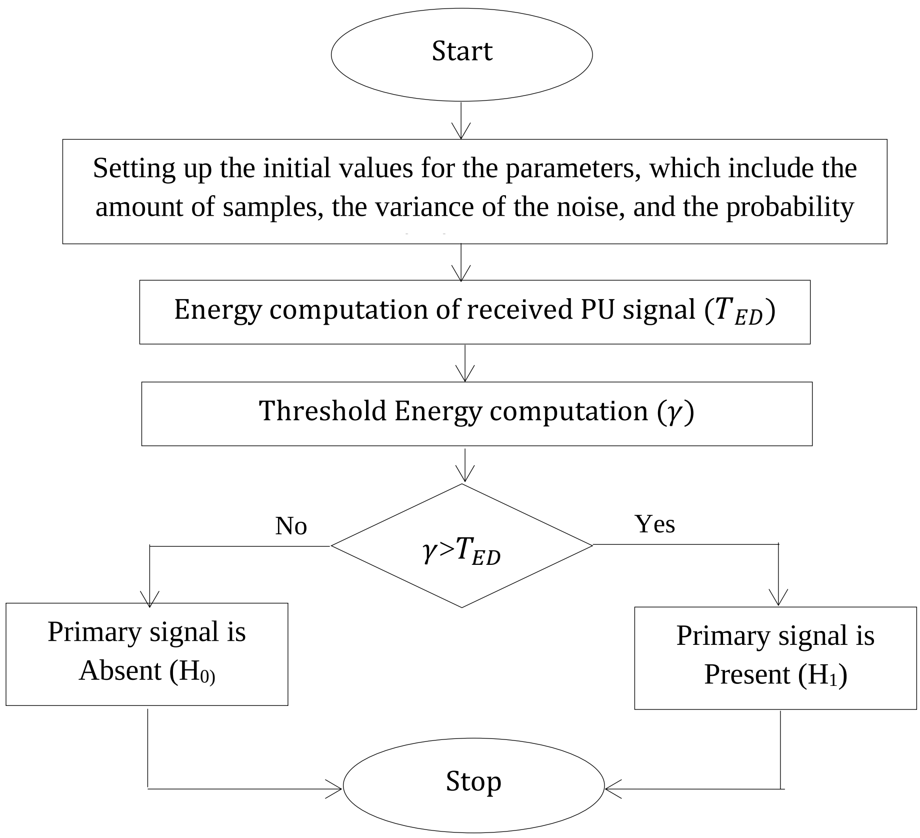

Fig. 2 Energy Detection Flowchart

3.4 Proposed Methodology

The Weighted Chimp Optimization Algorithm (WCOA) is a metaheuristic optimization algorithm that takes inspiration from the social conduct of chimpanzees. It is capable of addressing various optimization issues, including those related to cognitive radio energy detection. The mathematical representation of WCOA in the context of cognitive radio energy detection is as follows:

Consider a set X that comprises N potential solutions to the energy detection problem. Each solution can be expressed as a vector $x_i = [x_{i1}, x_{i2}, \dots, x_{iD}]^T$, where D denotes the dimensionality of the problem. The energy detection problem can be framed as a binary classification problem aimed at identifying the presence or absence of a signal in a particular frequency band. The energy detector function can be represented using the following equation:

$$f(x_i) = \frac{1}{N_t}\sum_{n=1}^{N_t} y_n h_n^T x_i \quad (30)$$

Where, N_t is the number of samples, y_n is the received signal at time n, h_n is the channel gain at time n, and x_i is the weight vector of the energy detector.

The optimization problem is to find the optimal weight vector x^* that maximizes the energy detector function $f(x_i)$, subject to the constraint that $||x_i||_2^2 = 1$, where $||x_i||_2^2$ is the L2-norm of x_i.

The WCOA algorithm can be summarized as follows:

1. Initialize the population of chimpanzees with N solutions randomly generated within the constraints of the problem.
2. Evaluate the fitness of each chimpanzee using the energy detector function $f(x_i)$.
3. Sort the population in descending order of fitness.
4. Select the top $k\%$ of the population as the elite group and assign them higher weights.
5. Randomly select the remaining population and assign them lower weights.
6. Generate a new population by iteratively applying the following operations:

a. Randomly select two chimpanzees from the population, x_i and x_j, and combine them to produce a new solution x_k using crossover and mutation operations.

b. Evaluate the fitness of x_k using the energy detector function $f(x_i)$.

c. Replace a randomly selected chimpanzee from the population with x_k if it has higher fitness than the selected chimpanzee.

7. Continue executing steps 3-6 until the stopping criterion is achieved (such as reaching the maximum number of iterations or observing convergence in the fitness values).

The weights assigned to each chimpanzee in step 4 are used to bias the selection process in step 6, such that the elite group has a higher probability of being selected for reproduction than the remaining population. This approach helps to prevent premature convergence and encourages exploration of the search space.

3.4.1. Hybrid Threshold Based Energy Detection

In this model there is addition of one more threshold to single threshold, represented as λ_{th1} and λ_{th2}. If $E > \lambda_{th2}$, it implies that the channel is employed by the PU. If $E < \lambda_{th1}$, it means the channel is available. If $\lambda_{th1} < E < \lambda_{th2}$, spectrum sensing is executed once more.

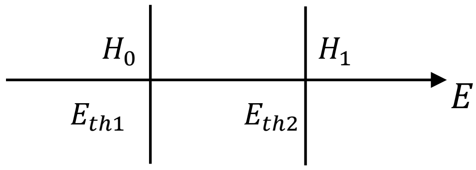

Fig.3 Double threshold model

The detection threshold is given by:

$$\lambda_D = \frac{\frac{2}{N}\ln(\lambda) + \ln(1+\gamma)}{\frac{\gamma}{\sigma_u^2(1+\gamma)}} \quad (31)$$

And the received instantaneous SNR is given by:

$$\gamma = \frac{\sigma_s^2}{\sigma_u^2} \quad (32)$$

For double threshold,

$$\lambda_{th1} = m\lambda_D$$
$$\lambda_{th2} = n\lambda_D \quad (33)$$

This method was used to minimize the collision between primary and secondary user. And check probability of detection at low SNR values. At high SNR signal performance is good but at low SNR performance degrades. Using hybrid threshold there is increase in probability of detection and collision rate is minimized. Monte Carlo simulations were carried out taking, N (number of samples=1000), Pf=0.01 and $m ==$ 1, n=0.25.

Here the double threshold is also optimized by chimp optimization algorithm, described in previous headings.

The fitness function for cognitive radio energy detection using WCOA depends on the specific problem and design constraints. However, a general mathematical formula for the fitness function can be expressed as:

$$FitnessFunction = F(P_d, E) \quad (34)$$

Where P_d is the probability of detection and E is the energy consumption. The goal is to maximize PDR while minimizing E.

A common approach to implement the fitness function is to assign weights to P_d and E, which can be tuned based on the importance of each objective. For example, if energy consumption is a critical constraint, the weight of E in the fitness function can be higher than that of P_d.

The fitness function F can be defined as a weighted sum of P_d and P_f:

$$F = w_1 P_d - w_2 E \quad (35)$$

Where w_1 and w_2 are the weights assigned to P_d and E, respectively. The values of w_1 and w_2 can be determined based on the trade-off between P_d and E.

The goal of the WCOA is to find the optimal threshold value T that maximizes the fitness function F. This can be achieved by iteratively generating a population of candidate solutions, evaluating their fitness using the above formula, selecting the best individuals, and applying genetic operators such as mutation and crossover to generate new offspring. The optimal threshold value T can then be used to determine the presence or absence of a signal on each channel, and allocate the available spectrum accordingly.

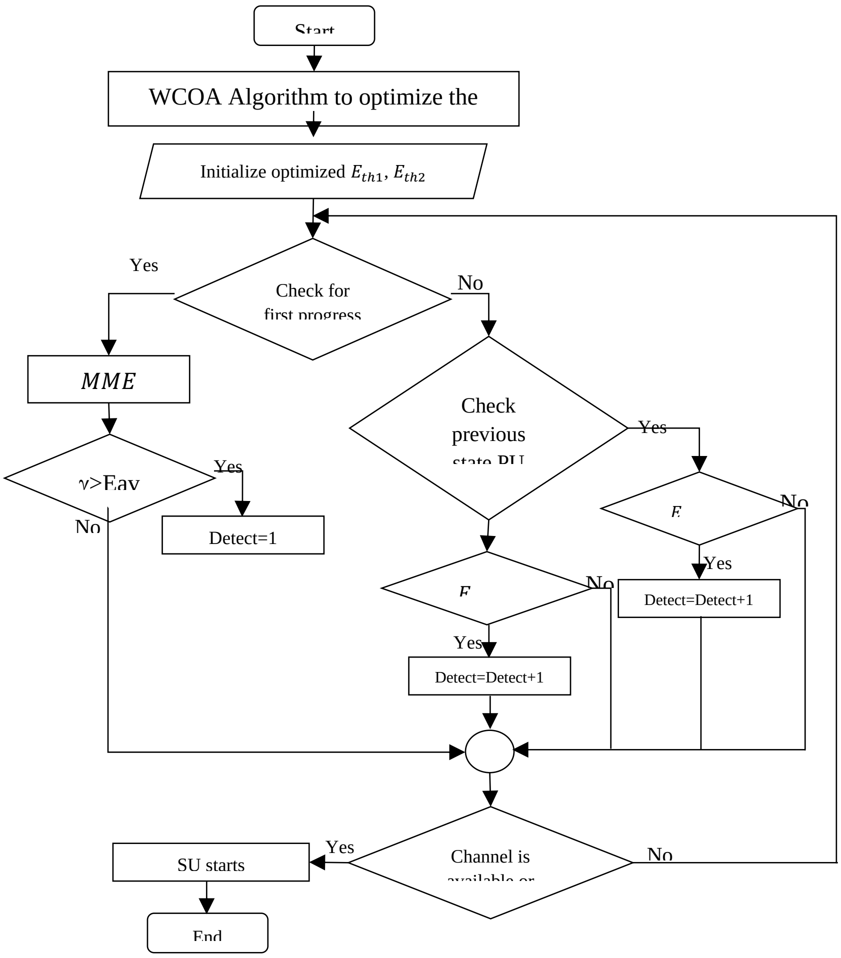

Fig. 4 Flowchart of double threshold-based energy detection

4. Simulation and Results

Figure 5 shows comparative graph of SNR (dB) vs. P_d for single threshold-based energy detection scheme using chimp optimization at P_f=0.01.

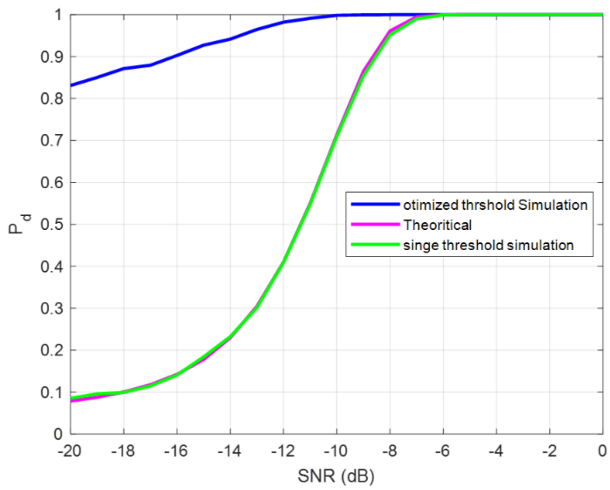

Fig. 5 Probability of detection graph for single threshold based energy detection using chimp optimization at P_f=0.01

The relationship between the probability of detection and SNR can be observed to be direct, i.e., as SNR increases, the probability of detection also increases. Figure 5 demonstrates that in the optimized threshold simulation, the value of P_d is notably higher at -10dB SNR level in comparison to theoretical and single threshold simulation, indicating the superior performance of the proposed method at higher SNR.

Figure 6 shows that the chimp optimization algorithm performs well by providing a higher probability of detection at various SNR values.

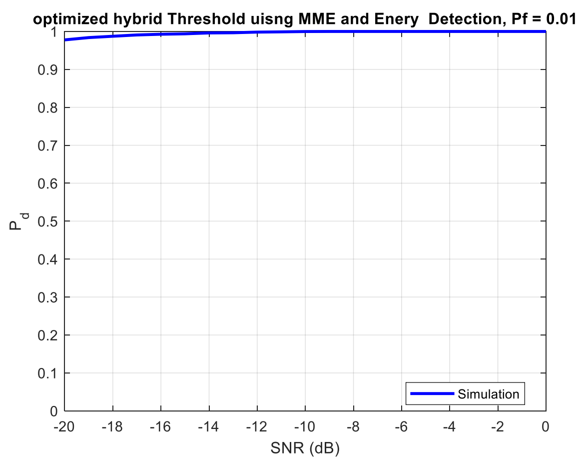

Fig. 6 Probability of detection graph for MME and Energy detector based hybrid threshold with chimp optimization at P_f=0.01

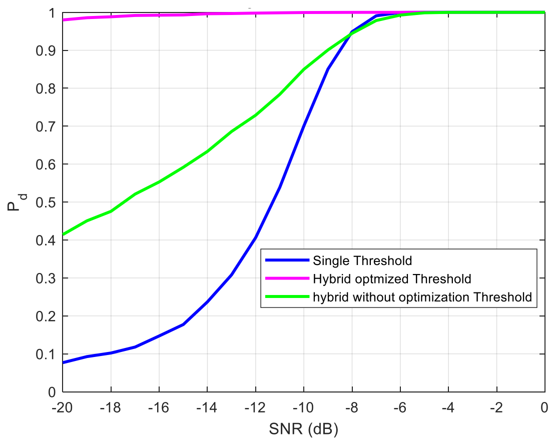

Fig 7 Comparative graph for probability of detection

A graph in Figure 7 illustrates the relationship between SNR (dB) and P_d for three different methods: single threshold, hybrid threshold without optimization, and COA-optimized hybrid threshold. As expected, the probability of detection increases with an increase in SNR value. The graph reveals that the probability of detection in the hybrid threshold is higher than the single threshold, while the COA-optimized hybrid threshold shows the best performance among the three methods, with the highest probability of detection at any SNR value.

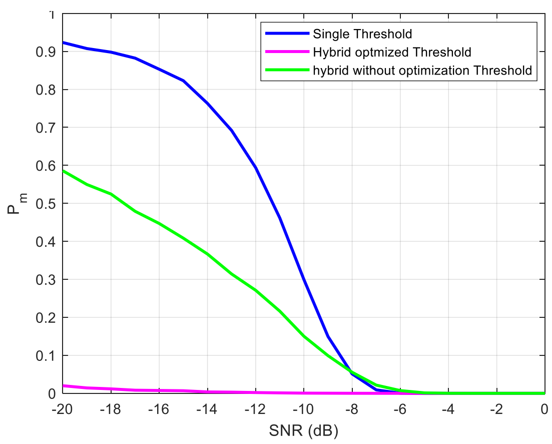

Fig 8 Comparative graph for probability of misdetection

The graph in Figure 8 provides a comparison of SNR (dB) versus P_m for single threshold, hybrid threshold without optimization, and COA-optimized hybrid threshold. As the SNR value increases, the probability of misdetection decreases. The hybrid threshold shows a lower value of P_m than the single threshold, whereas the COA-optimized hybrid threshold outperforms the other two methods by displaying a lower probability of misdetection at any SNR value.

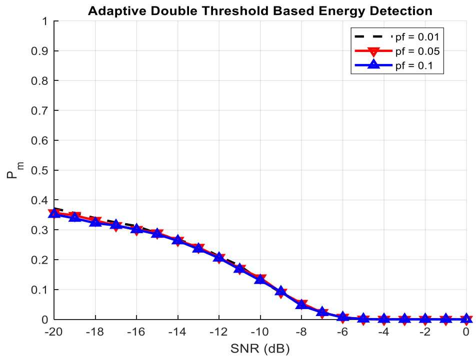

Fig. 9 Comparative graph for probability of misdetection at various values of P_f

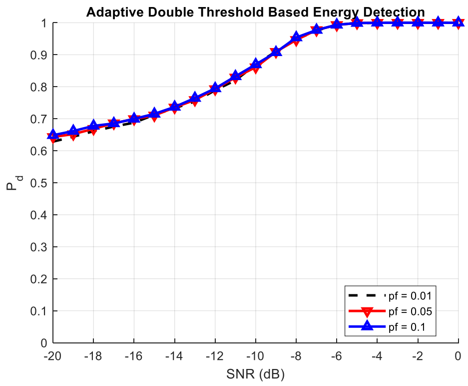

Fig. 10 Probability of detection graph for MME and Energy detector-based hybrid threshold without optimization at various values of P_f

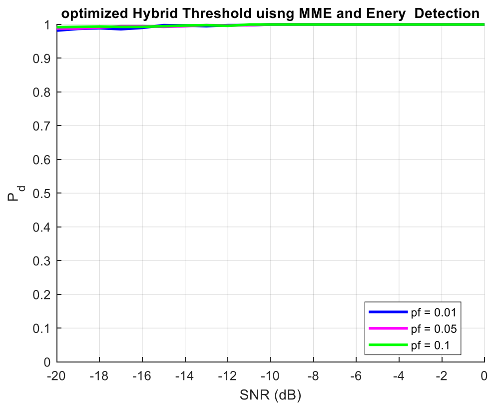

Fig. 11 Probability of detection graph for MME and Energy detector-based hybrid threshold with chimp optimization at various values of P_f

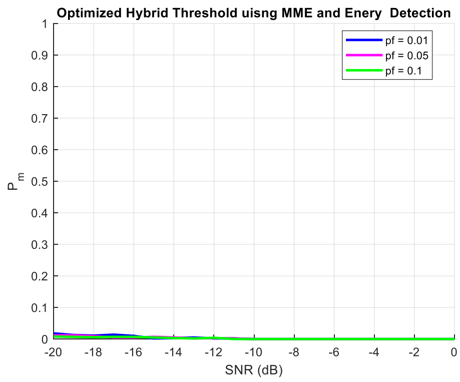

Fig. 12 Probability of misdetection graph for MME and Energy detector-based hybrid threshold with chimp optimization at various values of P_f

At different values of P_f, Figure 11 and Figure 12 illustrate the graphs of the probability of detection and the probability of misdetection, respectively, for the hybrid threshold based on the proposed MME and Energy detector with chimp optimization. These two graphs confirm the superiority of proposed hybrid approach while comparing with the simulation results of Alom et al. [15] and Sarala et al., [23].

Table 1. Probability of detection under different probability of false alarm

SNR(dB)	Probability of detection at $P_f = 0.01$	Probability of detection at $P_f = 0.05$	Probability of detection at $P_f = 0.1$
-20	0.978	0.984	0.989
-19	0.987	0.99	0.987
-18	0.99	0.986	0.986
-17	0.991	0.987	0.993
-16	0.993	0.993	0.995
-15	0.992	0.996	0.996
-14	0.993	0.998	0.997
-13	0.997	0.996	1
-12	0.997	0.996	0.997
-11	1	1	0.999
-10	1	1	1
-9	1	1	1
-8	1	1	1
-7	1	1	1
-6	1	1	1
-5	1	1	1
-4	1	1	1
-3	1	1	1
-2	1	1	1
-1	1	1	1
0	1	1	1

Table 2. Comparative analysis of various methods for detecting the probability in the presence of uncertain noise

SNR (dB)	Probability of detection [20]	Probability of detection [23]	Probability of detection [24]	Probability of detection [25]	Proposed
-20	0.2	0.3	0.4	0.1	0.978
-15	0.6	0.5	0.7	0.5	0.992
-10	0.8	0.7	0.9	0.6	1
-5	0..8	0.8	1	0.8	1

WCOA, is able to perform well even under challenging conditions, such as a low false alarm probability (pf=0.01). This is achieved by dynamically determining thresholds for energy detection based on the level of noise uncertainty, which allows for optimal extraction of trusted nodes to make accurate decisions.

Moreover, the assertion implies that other methods are inferior to the WCOA approach in achieving higher detection probability, even when subjected to the same false alarm probability. This demonstrates that the WCOA method is proficient in detecting desired signals while minimizing false alarms.

The findings from [20] suggest that the single threshold adaptive spectrum sensing approach is limited in its ability to achieve a high probability of detection at low SNR. In contrast, the work presented in [24] outperforms the method described in [25] at -20dB SNR. The proposed scheme is able to achieve the same level of sensing performance with fewer samples than the other methods, especially in low SNR conditions. For example, at SNR = -10 dB, the proposed scheme yields a probability of detection of 1, whereas the other methods do not. Therefore, the proposed scheme provides a significant complexity advantage over the other methods, as using a large number of samples is not preferred in cooperative spectrum sensing design due to its potential impact on spectrum efficiency.

5. Conclusion

This study introduces a novel approach to spectrum sensing in cognitive radio systems with uncertain noise, which is based on a hybrid threshold detection model using MME and energy detection. The proposed model offers an adaptive double threshold method that considers the trade-off between detection probability and error rate to improve sensing performance in low SNR conditions. The results obtained from the simulation demonstrate that the proposed model performs better than the current methods. At low SNR values of -18 dB and -20 dB, the detection probability (PD) is improved by 39.63% and 27.22%, respectively, in comparison to the existing double threshold method. Additionally, uncertain noise does not affect the optimal threshold expression, which is capable of reducing the probability of error for SNR values below -5 dB. Notably, the derived optimal threshold expression is shown to achieve the minimum error rate of 0.3 at an optimal threshold for uncertain noise at SNR = 20 dB.

Furthermore, the proposed model reduces the number of required samples for accurate sensing, depending on the SNR and noise level uncertainty. The simulation results demonstrate that the proposed system effectively detects and investigates spectral gaps in areas with low signal-to-noise ratio, outperforming previous research works [15] [23] in terms of probabilities of detection and misdetection.

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