Single Threshold Spectrum Sensing Energy Detector using Whale Optimization

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Abstract:
Efficiency of spectrum sensing gets affects by less signal to noise ratio. To improve spectrum sensing performance, a single threshold determination approach based on the Whale optimization algorithm is proposed in this study. Spectrum sensing using Energy is being acceded. The simulation results showed that using the best threshold selection raised spectrum sensing performance. The performance has been raised by 30%.

Keywords: Spectrum sensing, Energy detection, Threshold, Whale optimization.

1. INTRODUCTION:

Current spectrum allocation policy, known as FSA, is a set policy (fixed spectrum allocation). The electromagnetic spectrum is separated into bands that are meant for different types of services under this policy. The authorization to utilize the electromagnetic spectrum has a set duration and is often provided based on the location of the transmitter system. Only the concessionaire or licensee to whom the authorization was issued has access to the electromagnetic spectrum resources within this region and for the period of validity of this authorization, even if the resource is underutilized over time. At first, the strategy was sufficient to avoid interference between the various systems that employed the electromagnetic spectrum, as well as to meet the need for information for wireless communication services.

The scenario of electromagnetic spectrum use has changed dramatically as a result of today's continual expansion of wireless communication technology. Despite attempts by business and research to improve the spectral efficiency of new communication systems, an increase in transmission rate requires an increase in the bandwidth required for transmission. The phenomenon known as spectral scarcity is caused by the increased demand for transmission frequencies combined with the fixed offer [1].

In addition to limiting the electromagnetic spectrum's availability, the policy that was formerly appropriate for the resource utilization profile is now ineffective. The spectrum cannot be reused by other systems because it is reserved and not used at particular periods of the day.

In this scenario, a new proposal for spectrum allocation, known as DSA (dynamic spectrum allocation), develops (dynamic spectrum access). This new strategy advises that the resource be used opportunistically, i.e., spectrum access would be depending on demand, and spectrum bands would no longer be completely protected for certain types of services.

Currently, the 2.4GHz band, an unlicensed usage band shared by wireless telephone, 802.11 WLAN, and Bluetooth devices [2], is an example of this form of allocation. The new policy recommends a significant shift in the architecture of receiving and transmitting devices, in addition to significantly modifying the way spectrum use is governed. The assurance that there will be no interference between the different systems is one of the primary barriers to the adoption of a dynamic spectrum access strategy. There will be no interest in changing the current strategy if it is not possible to ensure that the DSA network does not interfere with legacy FSA systems, as networks with both spectrum allocation policies must coexist.

Spectrum sensing appears as one of the key properties of DSA networks in this setting. Transmission possibilities, also known as spectrum holes, or sections of the electromagnetic spectrum that are not in use at any particular time, are found in this step. If spectrum sensing is ineffective, radios will be unable to recognize transmission opportunities, or, even worse, they will be unable to distinguish when spectrum is in use, leading to the misleading impression that spectrum is available when it is not.

For cognitive radio networks, the development of efficient approaches that can be applied in real time and can detect signals with a high probability is critical.

2. LITERATURE SURVEY:

A cognitive radio user is a system that monitors and determines whether or not the main user is present. The second user must use the free spectrum if the primary user (PU) is not accessible [3]. Due to key user recognition, this is not as dependable as many dimming and dimming alternatives for the average user [4]. The problem is caused by secondary user access to the primary user licensing range as a result of this issue. This topic was posed in order to increase detection accuracy and address issues with shared spectrum perception. The fundamental idea behind collaborative spectrum sensor performance is to empower secondary users to improve their own performance [5] [6].

Outside of the voting rule N, the cognitive recognition spectrum is specified. Secondary users point out primary users N with an external SU at the merging center [7]. Users increase their power usage within seconds to proclaim the Fusion Center's spectral sensitivity and sensitivity (FC). To raised efficiency of energy , storage solutions have been suggested [8] [9]. Spectrum allocation can minimize time and power usage if the SNR is too high or the primary user (PU) is too high. If this is not the case, the spectrum detection sensitivity will be employed again to increase performance. [10] [11] A strategy for reducing power consumption is provided, which includes time recording and transmission time. As a result, by eliminating interference, PU improves energy efficiency. In order to enhance energy efficiency, several well-known channels have been proposed for efficient input recognition [12].

Each secondary user knows the channel in some modes, yet the same second user FC and other secondary users can transmit the same message in others [13]. To increase spectral energy detection performance, [14] presents a dependable high energy threshold circuit. Based on the influence of the SU transmit power, the authors proposed the limitation as adaptive in [15]. The detection threshold is solely determined by the incoming signal's statistical features, as outlined by the authors in [16]. The authors get the appropriate threshold value in [17] by using the Lagrange multiplier approach. In [15], a two-threshold method is proposed, which differs from the traditional one-threshold design and enhances detection performance substantially. In [18], it takes longer to detect the spectrum before getting results, whereas in [19], the authors present a method for generating threshold value. The author specifies the maximum number of entries in [20]. The SU will switch to detecting a different spectrum if the quantity of spectrum detection time surpasses the upper limit.

Furthermore, all of the techniques have difficulty obtaining spectrum on the cognitive radio network. As a result, to avoid all shortcomings, this research presents a single threshold energy measurement technique.

3. PROPOSED METHODOLOGY:

3.1 Introduction:

Cooperative gain refers to the improvement in performance that occurs as a result of spatial variety. From the standpoint of sensor hardware, the cooperative gain can also be considered .Having low signal-to-noise ratio of the received primary signal as a result of multipath fading and shadowing, making detection challenging. Because receiver sensitivity refers to the receiver's capacity to detect weak signals, a strict sensitivity requirement will be imposed on the receiver, More crucially, when the signal-to-noise ratio of PU signals is below a particular level called as an SNR wall, the detection performance cannot be increased by raising the sensitivity. Fortunately, cooperative sensing can alleviate the sensitivity need as well as the technology limitations.

Cooperative sensing consists of Local sensing, reporting, and data fusion Other key components of cooperative sensing, in addition to these phases, are essential. The elements of cooperative sensing are what we term these basic but necessary components.:

3.2 Energy Detection Technique:

Energy detector method is the most widespread form of spectrum sensing, It can also be considered a coarse detection technique, as it does not provide detailed information about the signals occupying the spectrum. Detection is based on the test of two hypotheses:

$$H_0 : \; y(p) = z(p)$$
$$H_1 : \; y(p) = x(p) + z(p) \tag{1}$$

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

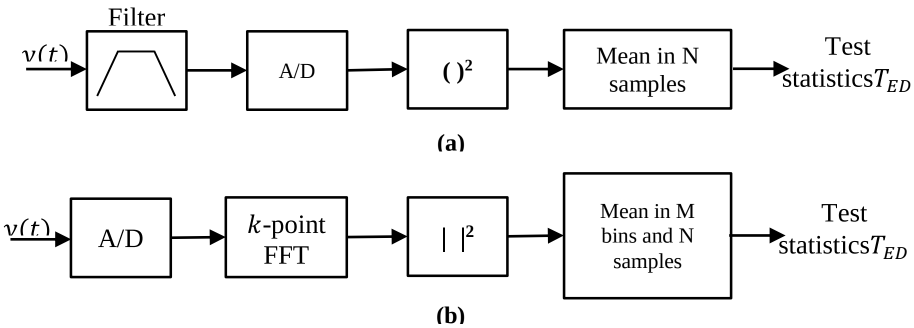


Figure 1: Energy detector implementation diagrams (a) in time and (b) in frequency

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-digital converter and a quadratic elevation device and only then the T_{ED} test statistic is calculated.

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

The second proposed architecture, shown in Figure 1 (b), proposes the processing of samples at frequency. In this architecture, there is the flexibility to process larger bands and multiple signals simultaneously, as the selection filter is replaced by the processing of the corresponding frequency ranges of the FFT, Fast Fourier Transform. Choose a fixed FFT size and the number of samples, N, becomes a parameter for improving the detection.

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 signal to noise ratio of the received signal, the technique's detection capability is impaired in scenarios where the noise is not stationary and varies rapidly.

In equation (2), T_{ED} is the summation of energy of $y(p)$ over L samples via energy detection statics. Probability of detection $P_d$is used is defined as follows:

$$P_d = P_r\{T_{ED} > \gamma | H_1\} \tag{3}$$

Probability of false alarm $P_{fa}$is used is defined as follows:

$$P_{fa} = P_r\{T_{ED} > \gamma | H_0\} \tag{4}$$

The chi-square distribution is the output of the integrator in MAP detection.

$$T\sim \begin{cases} N(n\,\sigma_n^2, 2\,n\,\sigma_n^4\,) \\ N(L\,(\sigma_n^2+\sigma_s^2), 2\,n\,(\sigma_n^2+\sigma_s^2)^2) \end{cases} \tag{5}$$

Where L is the number of samples, variance of noise isσ_n^2, the is the variance of received signal is σ_s^2,
As from the equation (18) , $(\sigma_n^2+\sigma_s^2)$, is the total variance of signal plus noise as σ_t^2 therefore,

$$\sigma_t^2 = \sigma_n^2 + \sigma_s^2 = \sigma_n^2(1+SNR) \tag{6}$$

The Nyquist sampling theorem states that the minimum sample rate should be 2W, therefore L can be written as 2 TsW, where Ts is the observation time and W is the bandwidth. The likelihood of false alarm can be stated using the Q function as follows:

$$P_{fa}(\mathrm{W}, \mathrm{T_s}) = \mathrm{Q}\ \left(\frac{\gamma - 2\ \mathrm{Ts\ W}\ \sigma_n^2}{\sqrt{4\,Ts\,W\,\sigma_n^4}}\right) \tag{7}$$

The threshold value γ is controlled based on the noise variance (noise power). We can first set the false alarm probability P_{fa}be a specific constant and P_f should be kept small to avoid underutilization of transmission opportunities, from equation (20), threshold value γ can be obtained.

$$\gamma = \sqrt{4\,Ts\,W\sigma_n^4}\,\mathrm{Q}^{-1}(\mathrm{P_f}) + 2\ \mathrm{Ts\ W}\ \sigma_n^2 \tag{8}$$

$$\mathrm{Q(x)} = \frac{1}{\sqrt{2\,\pi}}\int_x^{\infty} e^{-\frac{t^2}{2}dt} \tag{9}$$

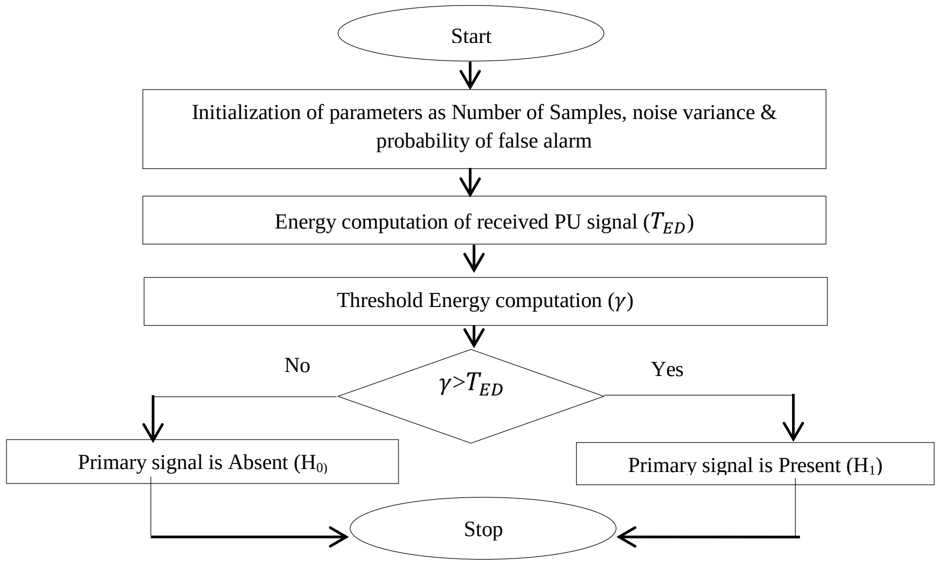


Figure 2: Flow chart of Energy Detector

3.3 Whale Optimization Algorithm (WOA):

WOA is a population-based algorithm Exploitation and exploration stages are balanced, it is considered a global optimizer. Furthermore, "B" associated with the search vector , exploration and exploitation: as the operator (|B |>=1) or phase (|B |<1). [21] [22].

3.3.1 Surround or Trap Prey:

The behavior represented mathematically as below:

$$\vec{E} = \left|\vec{D}.\vec{X}_p(x) - \vec{X}_w(x)\right| \tag{10}$$

$$\vec{X}_w(x+1) = \left|\vec{X}_p - \vec{B}\cdot\vec{D}\right| \tag{11}$$

Where X indicates the current iteration, D ⃗ and B ⃗ which are the coefficient vectors, X ⃗_ prey is the prey location vector and X ⃗_whales denotes the location vector of a humpback whale. The vectors D ⃗ and B ⃗ are calculated as follows:

$$\begin{cases} \vec{B} = 2b\cdot\vec{t} - \vec{b} \\ \vec{D} = 2\cdot t \end{cases} \tag{12}$$

Where b varies between 0 and 2 and $\vec{t}$ varies between 0 and 1.

3.3.2 Bubble Net Attack Strategy:

This behavior's mathematical model of Humpback whales swim is given below,

$$\vec{X}(x+1) = \begin{cases} \vec{X}^*(x) - \vec{B}\cdot\vec{E} & if\ s < 0.5 \\ \vec{E}'\cdot e^{bl}\cdot\cos(2\pi l) + \vec{X}^*(x) & if\ s \geq 0.5 \end{cases} \tag{13}$$

Where s is a randomly generated value in a range of [0,1].

3.3.3 Search for Prey (Exploration Phase):

The technique depend on the variation of the value A is employed in this stage. The whales, of course, wander about the search space at random, dependent on the positions of the other whales in the group.

Furthermore, the vector A is linked to the search vector's random value, which moves between [-1, 1] to drive the candidate agent to move away from a reference whale. As a result, the placements of search agents are updated depending on a previously established agent at random. Mathematically it is as given below:

$$\vec{E}' = \left|\vec{D} - \vec{X}_{rA} - \vec{X}\right| \tag{14}$$

$$\vec{X}_w(x+1) = \left|\vec{X}_p - \vec{A}\cdot\vec{E}\right| \tag{15}$$

Where $\vec{X}_{ra}$is a position vector

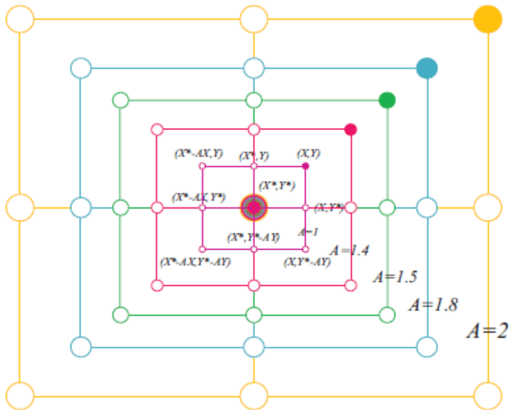


Figure 3:WOA Exploration [22]

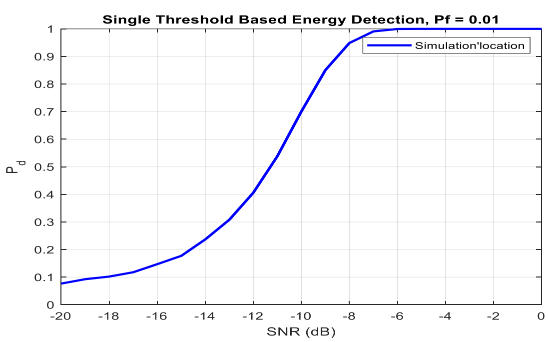
4. SIMULATION RESULTS:

Figure 4 shows SNR (dB) vs. P_d graph for single threshold based energy detection and comparative graph of SNR (dB) vs. P_d shows in figure 5

5. DISCUSSION ABOUT RESULTS:

Figure 4 shows SNR (dB) vs. P_d graph for single threshold based energy detection. It can be observed that probability of detection increases as the SNR value increases.

Figure 5 shows comparative graph of SNR (dB) vs. P_d it seems that probability of detection raise as the SNR value raise. It is clear from Figure 5 that the value of P_d in optimized threshold simulation is higher at -10dB SNR level when compared with theoretical and single threshold simulation which proves the good performance of proposed method at higher SNR.



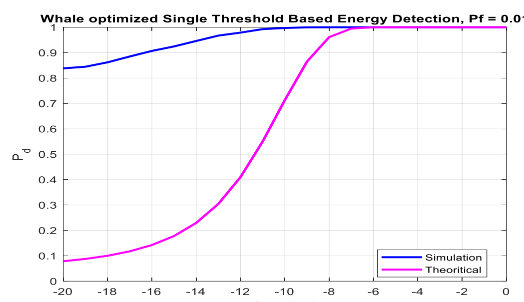


Figure 4: Graph of single threshold energy detection at P_f=0.01	Figure 5: Graph of single threshold based energy detection using whale optimization at P_f=0.01

6. CONCLUSION:

A single threshold detection model based on Energy detection is implemented. It raises the detection probability over the signal-to-noise ratio. Simulation result shows that proposed system can increase the probability of detecting and investigating spectral gaps in areas with a low signal-to-noise ratio.

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