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Implementation of Particle Swarm Optimization Technique for Spectrum Sensing in Cognitive Radio Networks

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Abstract

Cognitive Radio has a fixed time frame to sense its environment and to transmit the data. If the sensing time of the CR is more, then there will be less time for transmission i.e. throughput will be small and if the transmission time is more, then there will be interference to the Primary user. Hence, there is a compromise between sensing time and transmission time. An algorithm called Particle Swarm Optimization (PSO) is used to find the optimal sensing time at which there will be maximum possible throughput provided that there will be required Quality of Service to the Primary user. In this paper, we compare the optimal (PSO) with non-optimal (Maximum Likelihood) technique and a graph is generated between P_d and P_f. For PSO, graph between throughput and P_f is also generated.

Keywords: Cognitive Radio (CR); Probability of detection (P_d); Secondary user (SU); Throughput; Primary user (PU); Probability of false alarm (P_f).

INTRODUCTION

As now days, users are increasing at a very high rate and we have a limited spectrum resources, so spectrum should be used very efficiently. Cognitive Radio's are used for this purpose. There are two types of users-Primary user and secondary user. Primary user has a license of the spectrum and secondary user has no license of the spectrum. When the spectrum of the PU is idle, SU can utilize the spectrum of primary user until the PU is inactive but if the PU becomes active then SU must immediately vacate the spectrum of the primary user [1]. The spectrum which is idle at a particular time is called a spectrum hole [2]. Cognitive Radio senses its radio frequency environment to detect the idle spectrum and to detect whether the PU is active or inactive. Cognitive Radio has a fixed time frame in which sensing of the environment and transmission of the data has been done [3]. Now, if the sensing time of the CR will be more, then there will be less time for data transmission which and there will be less throughput. On the other hand, if the transmission time will be more, then there is a possibility that CR will not detect the active user and there will be interference to the primary user, with which there will be low Quality of Service. Hence, transmission time and sensing time has a tradeoff [4]. There should be some optimal sensing time at which CR can achieve maximum possible throughput provided there is a sufficient quality of service to the primary user i.e. there is no interference to the primary user. Particle Swarm Optimization (PSO) is used to find this optimal sensing time [3].

Particle Swarm Optimization (PSO) is an algorithm to solve optimization problems. In Particle Swarm Optimization, there are lot of particles in the search space having some randomly assigned initial position and velocity. Each particle is known as an individual and population of all the particles is known as swarm. The main aim is to find the best solution for the given problem. A point in the search space will give the optimal solution. Every particle is moving with some speed in some direction in the search space. The velocity and position of the particles will be updated after every iteration. At any point of time, every particle has its own personal best position and a global best position of the swarm. Particles will move towards to the global best position of the swarm. Global best position of the population will be updated if any particle's position will be more close to the best solution. Now, this particle's position will become the global best position and all the particles will start moving towards this updated global position. This process will continue until all the particles converges at one point of the search space. The point at which all the particles converges is the optimal solution of the given objective function.

Let ith particle's position at iteration t is $ps_i(t)=\{ps_{i1}(t),ps_{i2}(t),\ldots,ps_{iD}(t)\}$. Let $pb_i(t)=\{pb_{i1}(t),pb_{i2}(t),\ldots,pb_{iD}(t)\}$ be the ith particle's personal best position at iteration t and global best position is the best position in the swarm at iteration t and is denoted as $gbp(t)=\{gbp_1(t),gbp_2(t),gbp_3(t),\ldots,gbp_D(t)\}$.

Let ith particle's velocity at iteration t is $vl_i(t)=\{vl_{i1}(t),vl_{i2}(t),\ldots\ldots,vl_{iD}(t)\}$. Following equations update the velocity and position of the particles :

$$vl_{id}(t+1)=IWvl_{id}(t)+A_1r_1(+)[pb_{id}(t)-ps_{id}(t)]+A_2r_2(t)[gb_d(t)-ps_{id}(t)] \quad (1)$$

$$ps_{id}(t+1)=ps_{id}(t)+vl_{id}(t) \quad (2)$$

where $d=\{1,2,3,4,\ldots\ldots,D\}$ is the dimension of the search space, IW is the inertia weight and A_1,A_2 are the acceleration constants. r_1,r_2 are the two random numbers in the range[0,1]. (vl_{min},vl_{max}) is the range of the particle's velocity. A_1 gives move to each particle towards its best position and A_2 gives move to each particle towards the global best position of the swarm [1].

The paper is organized as follows. Section II represents the system model. Section III gives the algorithm and flowchart of PSO. Simulation & Results are discussed in Section IV. Finally Section V gives the conclusion of the paper.

1. SYSTEM MODEL

In Cognitive Radio Networks, there are two types of sensing. One is wideband sensing and the other one is in-band sensing. Wideband sensing is used to identify the spectrum holes in the network. It is also known as preliminary coarse sensing [8]. Once the spectrum holes are identified, CR senses its environment to detect whether the PU is active or not. This is known as in-band sensing or fine sensing [9], [10]. If the PU becomes active, then SU must vacate the frequency band so that there is no interference to the Primary user. There are strict Federal Communications Commission guidelines for the protection of the primary user. There is a fixed time frame in which the secondary user should sense its environment and transmit the data. Let D_f is the duration of the frame, D_s is the duration of sensing and D_t is the transmission duration, then [3]

$$D_f = D_s + D_t \quad (3)$$

There are two hypothesis for the signal, S[n] sensed by the CR:-

H_0 : S[n] = N[n] ; when primary user is not present.

H_1 : S[n] = gS[n] + N[n] ; when primary user is present.

Where g is the channel gain. For H_0, its value is 0 and for H_1, its value is 1. n =1,2,….ss. ss is the no. of signal samples and N[n] is the noise. The energy detector combines all the samples of the signal and gives the output Z, which is used for the decisions [11].

$$Z=\frac{1}{ss}\sum_{n=1}^{ss}(S[n])^2 \quad (4)$$

P_d is the probability of detection and P_f is the probability of false alarm such that [12],

$P_d = P(Z>\mu|H_1)$, $P_f = P(Z>\mu|H_0)$ (5)

Where μ is the threshold value to assume the sensed signal as the primary signal.

Number of samples of the sensed signal i.e. ss is given as:

$$ss=\frac{1}{SNR^2}\left(Q^{-1}(P_f)-Q^{-1}(P_d)\sqrt{2SNR+1}\right)^2 \quad (6)$$

where SNR is the signal to noise ratio, Q(.) is the standard Gaussian's complementary distribution function.

If the sampling time is S_t, then sensing time, $D_s = S_t \times ss$.

When PU is not present and there is no false alarm , the achievable throughput is as follows [4] :-

$$T_0 = \frac{D_f - D_s}{D_f}(1-P_f)B_0 \quad (7)$$

When PU is present and SU does not detect it, the achievable throughput is as follows [4] :-

$$T_1 = \frac{D_f - D_s}{D_f}(1-P_d)B_1 \quad (8)$$

Where B_0 and B_1 is the throughput of the SU in the absence and presence of the PU respectively.

The average throughput that can be achieved by the SU is as [13] :-

$$T = P(H_0)T_0 + P(H_1)T_1 \quad (9)$$

As $B_0>B_1$, the first term will dominate in the above equation and the simplified equation will be as follows:-

$$T = P(H_0)T_0 \quad (10)$$

As the aim is to maximize the throughput such that there is no interference to the PU, the optimization problem can be expressed as:-

$$\{\max P(H_0)T_0$$

$$\text{s.t. } P_d \geq TP_d\} \quad (11)$$

where TP_d is the target for the probability of detection to protect the PU from the interference.

2. ALGORITHM OF PSO

Initial Parameters for PSO are set as:

Maximum no. of Iterations($Iteration_{max}$) = 500;

No. of Particles = 30;

Dimension (D) = 1;

Inertia weight (IW) = 2;

Maximum Inertia Weight (IW_{max}) = 0.9;

Minimum Inertia Weight (IW_{min}) = 0.4;

Acceleration constant (A_1) = 2;

Acceleration constant (A_2) = 2;

Maximum velocity (vl_{max}) = 6;

Initial velocity $vl_{i,d}(0) = 0$;

Initial position $ps_{i,d}(0) = 0$;

Following Parameters are evaluated at each iteration of the PSO algorithm :

Personal Best position of every particle;

Global Best position of the population;

Inertia Weight (IW)=(IW_{max}-1)*((IW_{max}-IW_{min}) / $Iteration_{max}$);

Velocity of each particle i.e. $vl_{i,d}(t+1)$ using equation (1);

Position of each particle i.e. $ps_{i,d}(t+1)$ using equation (2);

Fitness function evaluation using equation (11);

Flowchart of the PSO algorithm is shown in Fig. 1.

3. SIMULATION AND RESULTS

MATLAB is used to run the algorithm. We have generated the graphs between P_f and P_d, P_f and throughput. Simulation Parameters are as follows:

Region of Interest(ROI)=1000;

Grid Size = 1;

Number of Sensors = 50;

Transmit Power of the Emitter (in watts) = 1;

Assumed Transmit Power (in watts) = 1;

Actual Path Loss Exponent = 3.5;

Assumed Path Loss Exponent = 3.5;

Receiver Sensitivity (in watts) = -∞;

Signal Spread values = 0-10;

4.1 Graph between P_f and P_d

In this graph , there is a comparison between PSO (optimal) and Maximum Likelihood (non-optimal) technique by calculating the mean estimation error for both the techniques. Mean estimation error is calculated as the difference between the actual distance of the PU and the estimated distance of the PU from the SU. This graph shows that the performance of PSO is much better than the non-optimal technique as P_f is lower and P_d is higher for PSO than the non-optimal technique. The x-axis of the graph is the P_f and y-axis is the P_d. The upper curve in the graph is of the PSO technique(optimal) and the lower curve is of the Maximum Likelihood (non-optimal) technique. The generated graph is shown in Fig 2.

The values of mean estimation error for PSO and Maximum Likelihood technique is shown in Table 1.

Table 1. Mean Estimation Error

Spectrum Sensing	For PSO (Mean Estimation Error in distance(meters))	For Maximum Likelihood (Mean Estimation Error in distance(meters))
0	1.1911e-012	5.8961e-013
2	42.0149	73.6522
4	108.8895	164.8123
6	207.7874	313.0992
8	408.4061	504.335
10	761.7611	944.2664

4.2 Graph between P_f and throughput for PSO

The graph generated between P_f and throughput for PSO (optimal) is shown in Fig 3. The x-axis of the graph is the P_f and y-axis is the throughput of the secondary user. Red line depicts the ideal relationship between probability of false alarm and throughput, blue line depicts the relationship between probability of false alarm and throughput with PSO.

4. Conclusion

Particle Swarm Optimization (optimal) technique is better approach than non-optimal technique to calculate the optimal sensing time as it has low mean estimation error i.e. P_f is smaller and P_d is higher than non-optimal technique. Regarding the future work, Hybridization of the PSO with Ant Colony technique can be done to further enhance the results of the PSO.

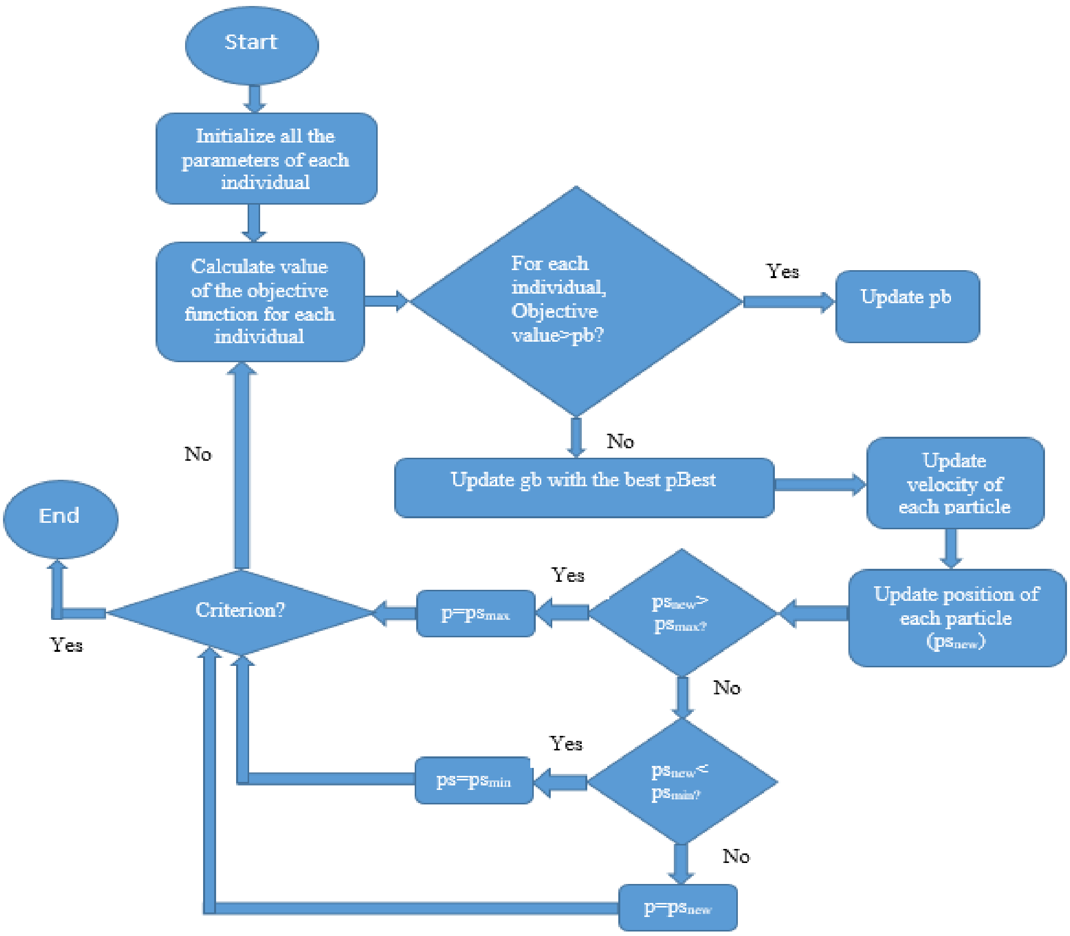

Figure. 1. Flowchart of PSO algorithm.

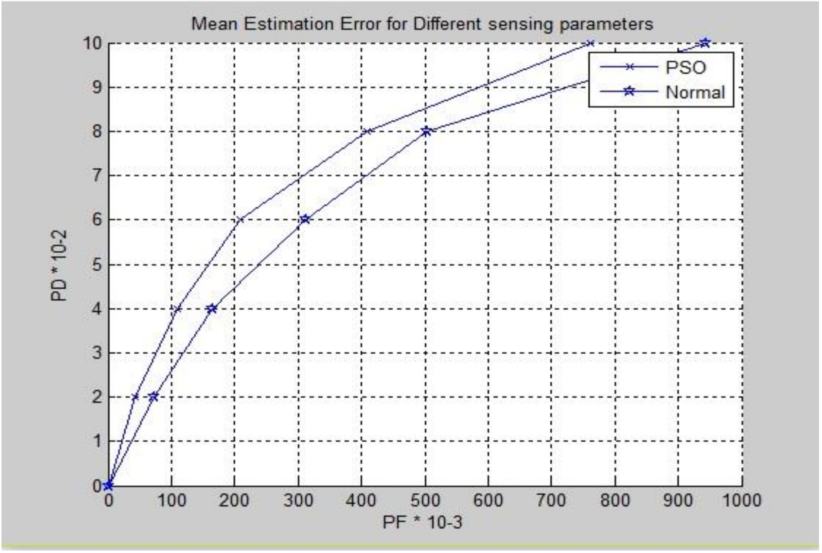

Figure. 2. Graph between P_f and P_d.

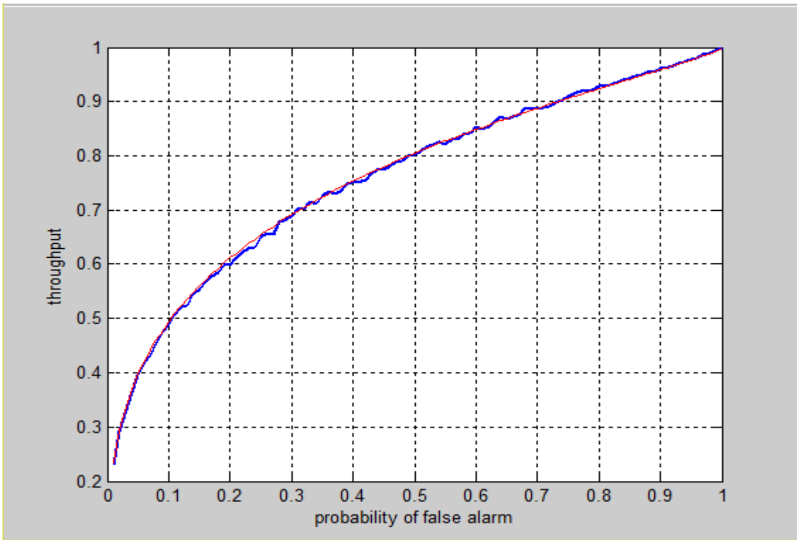

Figure. 3. Graph between P_f and throughput for PSO.

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