



Enhanced Particle Swarm Optimization assisted Cooperative Spectrum Sensing in Cognitive Radio under Rayleigh Fading Scenario

R.Harikrishnan, V.Padmamathilgam

Abstract: When performing cooperative spectrum sensing by using Soft Decision Fusion (SDF), the weighting coefficients play a major role in the detection performance. In this work, by utilizing the Enhanced Particle Swarm Optimization (EPSO) is optimization of the weighting coefficient vector is carried out. The EPSO selects the best weighting coefficients from the weighting coefficient vector. The detection accuracy of the EPSO technique is evaluated and contrasted with traditional PSO, GA (Genetic Algorithm) and also with traditional Soft-Decision Fusion (SDF) methods by using MATLAB simulations. From simulation results, it is inferred that the proposed technique outperforms all other Soft-Decision methods over Rayleigh channel. An increased detection performance is obtained as inferred from the results.

Index terms: Cooperative spectrum sensing, Rayleigh fading channel, Soft decision fusion, Particle Swarm Optimization, Enhanced particle swarm optimization, weighting coefficient vector.

I. INTRODUCTION

Nowadays, a tremendous demand for spectrum has been greatly observed due to an exponential growth of wireless communication devices. But, the shortage of spectrum creates a barrier to establish new communication. So demand for spectrum is becoming more in current scenario. A survey was undertaken by Federal Communication Commission (FCC), to examine the utilization of spectrum in time and geographical domain. This survey concludes that present licensed spectrum is mostly not well utilized. The efficient utilization of spectrum, Cognitive Radio (CR) is the well known expertise to use the spectrum when it is free [1, 2].

Among all functionalities used in CR, the spectrum sensing becomes initial step to identify the status of the spectrum, which are in use or free. In reality, the frequent change of signal strength results in misinterpreted conclusion regarding status of the spectrum due to shadowing and fading nature of Radio Frequency (RF) environments. The shadowing and fading effects are frequently observed in local spectrum sensing by single SU (Secondary User) [3, 4, and 5].

To alleviate the fading and shadowing effects the collaborative spectrum sensing is addressed. The fusion centre is the main controller for generating the status of spectrum, which are based on the two technique soft decision and hard decision method [6]. By utilizing, Maximal Ratio Combining (MRC) and Equal Gain combining (EGC) and the process of the weighting the coefficients vector of all CR users. However, these methods are not optimal as EGC method allocates weights the different users equally, which leads to less performance. Likewise, in MRC technique weights the coefficients vector based the signal with highest SNR from the obtained signal [8]. And, also the weighting the coefficient in Modified Deflection Coefficient (MDC) and Normal Deflection Coefficient (NDC), methods lead to only sub-optimal results, which impose some performance deteriorations [10].

In [11, 12 and 13], by applying the PSO optimizing technique to the soft decision based collaborative spectrum sensing, to optimize the weighting the coefficients, but it take some time to convergences. The slow convergences of this scenario due to, it's dependent of binary encoding process. So in this work, an Enhanced Particle Swarm Optimization (EPSO) algorithm is introduced to optimizing the weighting coefficient vector, which selects the best weighting coefficient vector form all. The inertia weight vector has been implemented to weights the coefficient vector. This inertia weight vector prevents PSO technique to stuck into local or global minimum in search space. And thus EPSO is considered to be upgraded version of PSO for its offering the best solution to optimization problems and fast convergence rate.

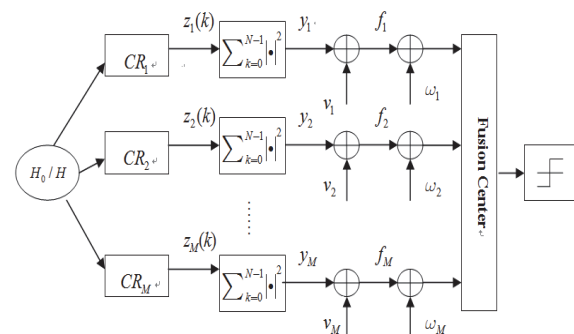


Fig.1: Scheme of Cooperative spectrum sensing in cognitive radio.

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* Correspondence Author

R.Harikrishnan*, Ph.D. Department, Electronics and Communication Engineering, Annamalai university, chidambaram

Dr.V.Padmamathilgam, Associate Professor, Electrical Engineering in Annamalai university, chidambaram

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II. SYSTEM MODEL FOR COLLABORATIVE SPECTRUM SENSING

When performing spectrum sensing, the initial stage of binary hypothesis testing at the secondary users at the given time instant k is put forward as

$$\begin{aligned} H_0: z_l[k] &= r_l(k) \\ H_1: z_l[k] &= S(k) + r_l(k) \end{aligned} \quad (1)$$

where $l=1,2,\dots,M$, $S(k)$ is denotes the primary signal, h_l is the channel gain, $z_l[k]$ the additive white Gaussian sensing noise with zero mean and variance σ_l^2 . Here, the hypotheses H_0 signifies the absence of primary signals, and the hypotheses H_1 signifies the presence of primary signals.

From Figure 1, the test statistics y_l of at the l -th cognitive user is given as

$$y_l = \sum_{k=1}^N z_l[k] \quad l=1, 2, \dots, M. \quad (2)$$

Where, N is the number of observation made. By applying the central limit theorem, the statistical distribution of y_l is $y_{lH_0} \sim N(\mu_{H_0}, \sigma_{H_0}^2)$ under H_0 or $y_{lH_1} \sim N(\mu_{H_1}, \sigma_{H_1}^2)$ under H_1 with means and the variances is defined as

$$\begin{cases} \mu_{H_0} = N\sigma_l^2, & \sigma_{H_0}^2 = 2N\sigma_l^2 & H_0 \\ \mu_{H_1} = (N + \eta_l)\sigma_l^2, & \sigma_{H_1}^2 = 2(N + \eta_l)\sigma_l^2 & H_1 \end{cases} \quad (3)$$

Where, $\eta_l = \frac{E_s |h_l|^2}{\sigma_l^2}$ is the local SNR and E_s is the signal energy. $\sum_{i=1}^M w_i = 1, 0$

$\sum_{k=0}^{N-1} |S(k)|^2$ is the obtained signal.

The fusion center measures the summary statistics from the l -th cognitive user. According to the theory, $\{f_1\}$ are normally distributed with means

$$f_1 = \begin{cases} N\sigma_l^2 & H_0 \\ (N + \eta_l)\sigma_l^2 & H_1 \end{cases} \quad (4)$$

and variance.

$$\text{Var}(f_1) = \begin{cases} N\sigma_l^4 + \delta_l^2 & H_0 \\ 2(N + \eta_l)\sigma_l^4 + \delta_l^2 & H_1 \end{cases} \quad (5)$$

Therefore, the overall summary statistics at the fusion center is represented as

$f_c = \sum_{i=1}^M w_i f_i = w^T f$, where

$W = [w_1, w_2, \dots, w_M]^T$, $w_i > 0$, is the weight vector and $f = [f_1, f_2, \dots, f_M]^T$. Thus, the mean and variance of f_c as follows

$$\bar{f}_c = \begin{cases} N\sigma^2 w & H_0 \\ (N + E_s h)^T w & H_1 \end{cases} \quad (6)$$

$\text{Var}(f_c)$

$$= \begin{cases} \sum_{l=1}^M (2N\sigma_l^4 + \delta_l^2) = w^T K_{H_0} w & H_0 \\ \sum_{l=1}^M (2N\sigma_l^4 + \delta_l^2 + 4\eta_l \sigma_l^4) = w^T K_{H_1} w & H_1 \end{cases} \quad (7)$$

By the principle of the energy detection, the decision rule at the fusion center is denoted as

$$f_c \underset{H_0}{\overset{H_1}{\gtrless}} \gamma_c \quad (8)$$

Where γ_c is the decision threshold. Therefore, the false alarm probability P_f and the detection probability P_d of the fusion center are given by

$$P_f = P(H_1/H_0) = Q\left(\frac{\gamma_c - \bar{f}_{cH_0}}{\sqrt{\text{var}_{f_{cH_0}}}}\right) = Q\left(\frac{\gamma_c - N\sigma^2 w}{\sqrt{w^T K_{H_0} w}}\right) \quad (9)$$

$$P_d = P(H_1/H_1) = Q\left(\frac{\gamma_c - \bar{f}_{cH_1}}{\sqrt{\text{var}_{f_{cH_1}}}}\right) Q\left(\frac{\gamma_c - (N\sigma + E_s h)^T w}{\sqrt{w^T K_{H_1} w}}\right) \quad (10)$$

The values of P_f and P_d highly depends on the weighting matrix W and the applicable threshold γ_c . The detection threshold at fusion centre is derived from equation (9) as

$$\gamma_c = Q^{-1}(P_f) \sqrt{w^T K_{H_0} w} + N\sigma^2 w \quad (11)$$

The detection probability (P_d) is written as

$$P_d = Q\left(\frac{Q^{-1}(P_f) \sqrt{w^T K_{H_0} w} - E_s h^T w}{\sqrt{w^T K_{H_1} w}}\right) \quad (12)$$

The optimal weight vector w is necessary for solving (12). Since, $Q(x)$ is a decreasing function, and then the minimization of $p(w)$ is always equal to maximization of P_d . The Cooperative spectrum sensing optimization problem in mathematical equation given as

$$\text{Min } P(w) = \frac{Q^{-1}(P_f) \sqrt{w^T K_{H_0} w} - E_s h^T w}{\sqrt{w^T K_{H_1} w}} \quad (13)$$

III. COOPERATIVE SPECTRUM SENSING TECHNIQUE BASED ON THE ENHANCED PSO

The traditional PSO based method offers a less optimal solution to the weight coefficient vector, also its shows slow convergence rate and relying on support from binary encoding for its operation. To increase the convergence rate and optimal selection of the weighting coefficient vector is necessary in such scenario; the EPSO may be a possible solution for this problem. So in this work, by utilizing the EPSO algorithm, the optimization of the weighting coefficient vector is done to enhance the detection performance.

A. The Core Theme of Particle Swarm Optimization Technique

In 1995, James Kennedy and Russell Eberhart developed Particle swarm optimization (PSO) technique for optimizing the certain problems and generate good solutions to that problem. Generally PSO is based on real world scenario; the group of birds is search for food its sources for daily needs is the main inspired theme. Here each birds is consider to be a candidate solution to the problems and finding the optimal food sources is the final optimized result to that problem. The search mechanism is simply vets on optimal solution by obtained information between the particles and take the global search method with respect to the swarms. Based on the system model, the mathematical formulation is given as follows for a minimization problem (12). Each and every member of the swarm is the right possible solution of the minimization problem, the weight vector w .

The four major vector notations used in the PSO algorithm

$$(i) \quad x_n^t = [x_{n1}^t, x_{n2}^t, \dots, x_{nj}^t]^T, x_{nj}^t \in [0,1], \text{ is the position of the particle at the } t - \text{th step}$$

$$(ii) \quad v_n^t = [v_{n1}^t, v_{n2}^t, \dots, v_{nj}^t]^T, v_{nj}^t \in [-V_{max}, +V_{max}], \text{ is the velocity of the particle at the } t - \text{th step}$$

$$(iii) \quad p_n^t = [p_{n1}^t, p_{n2}^t, \dots, p_{nj}^t]^T, p_{nj}^t \in [0,1], \text{ is best position obtained by the particle at the } t - \text{step};$$

$$(iv) \quad p_g^t = [p_{g1}^t, p_{g2}^t, \dots, p_{gj}^t]^T, p_{gj}^t \in [0,1], \text{ the best global position obtained by the particle at the } t - \text{step};$$

The adjustments equation for PSO for its position and velocity is given by

$$\begin{cases} v_{nj}^t = \Psi v_{nj}^{t-1} + C_1 (p_{nj}^{t-1} - x_{nj}^{t-1}) + C_2 (p_{gj}^{t-1} - x_{nj}^{t-1}), \\ x_{nj}^t = x_{nj}^{t-1} + v_{nj}^t, \end{cases} \quad (14)$$

Where, c_1 and c_2 are represented as the learning factor and Ψ is the inertia weight. For PSO, c_1 and Ψ are constants, and given as in $c_1 = c_2 = 2$, $\Psi = 1$ [14].

B. The Proposed Method Based on Adaptive inertia weight with PSO.

The constant inertia weight is mainly used in the conventional PSO. The concept of the linear decreasing inertia weight is introduced in the enhanced version of PSO to solve the optimization problem. Consider the inertia weights are varies from $[\Psi_{min}, \Psi_{max}]$. Then inertia weight Ψ is represented in the Enhanced PSO as follows.

$$\Psi_{nj}^t = \Psi_{max} - \frac{\Psi_{max} - \Psi_{min}}{\Gamma} \times t \quad (15)$$

Where, Γ is representing the number of iterations. Every particle is a right weight vector, i.e. $x_n = w_l$. From (14), the adjustments equation for EPSO for its position and velocity is given by

$$\begin{cases} v_{nj}^t = \Psi v_{nj}^{t-1} + C_1 (p_{nj}^{t-1} - w_{nj}^{t-1}) + C_2 (p_{gj}^{t-1} - w_{nj}^{t-1}), \\ w_{nj}^t = w_{nj}^{t-1} + v_{nj}^t. \end{cases} \quad (16)$$

C Enhanced PSO Algorithm for cooperative spectrum sensing

(1) Assign the value of the number of particle S and the maximum amount of iterations has to be done.

(2) Set t as 0 and random generation of w_{n1}^t and v_{n1}^t , where, $w_{n1}^t \in [0,1]$, $1 \leq n \leq M$, $1 \leq n \leq S$, $v_{n1}^t \in [-V_{max}, +V_{max}]$.

(3) Normalization of the weight vector $w_{n1}^t = w_{n1}^t / \sum_{l=1}^M w_{nl}^t$. Then compute the fitness value $P(w)$ of every particle. set $P_n^t = [w_{n1}^t, w_{n2}^t, \dots, w_{nM}^t]^T$ and $P_g^t = [w_{g1}^t, w_{g2}^t, \dots, w_{gM}^t]^T$.

(4) Set $t=t+1$, generate the inertia weight Ψ_{nm}^t from (15), then updating v_{nm}^t and w_{nm}^t from (16), and normalization of the weight vector w_{n1}^t i.e., $w_{n1}^t = w_{n1}^t / \sum_{l=1}^M w_{nl}^t$.

(5) Compute, the fitness value $P(w)$, and set $P_n^t = [w_{n1}^t, w_{n2}^t, \dots, w_{nM}^t]^T$ for particle n . The Fitness value is larger than that of fitness value of P_n^{t-1} , then set $P_n^t = [w_{n1}^t, w_{n2}^t, \dots, w_{nM}^t]^T$, then set $P_n^t = P_n^{t-1}$. When the

fitness value of particle n is larger than that of P_g^{t-1} , then set $P_g^t = [w_{n1}^t, w_{n2}^t, \dots, w_{nM}^t]^T$. if not then set $P_g^t = P_g^{t-1}$.

(6) When the number of iterations equal to the predetermined max value of Γ , then conclude the algorithm; if not, then go for step (4).

IV. RESULTS AND DISCUSSIONS

In this paper, the cooperative spectrum sensing under Rayleigh fading channel is designed for $M=25$ users. The detection technique for cooperative spectrum sensing based on EPSO and other traditional optimization technique such as PSO and GA and other conventional Soft Decision Schemes (SDF) are done. In EPSO, the optimization of a weighting coefficient vector is performed to generate the best solution to the problems. The primary signal used for this detection process is Quadrature Phase Shift Keying (QPSK) signal. The threshold setting at each user is set as the probability of false alarm=0.01. The above-mentioned parameters are simulated in MATLAB tool for about 1000 Monte Carlo simulation over the Rayleigh fading channel.

CR and channel parameters	
Number of users M	20
Bandwidth B	6 MHz
Signal type	QPSK
Sensing time T_s	30 msec
SU transmit power	30 dbm
PU transmit power	35 dbm
PU-SU channel noise	$20 \leq w \leq 30$ dBm
SU-FC channel noise	$20 \leq w \leq 30$ dBm
Channel model	Rayleigh fading
Pf	0.01
Numbers of Monte Carlo simulation	1000

Table 2. Parameter value setting for EPSO, PSO and GA.

Optimal parameter values					
GA		PSO		EPSO	
Population size	20	Population size	20	Population size	20
Mutation rate	0.1	Learning coefficient	2	Learning coefficient	2
Crossover rate	0.9	R1 and R2	2	R1 and R2	2
No of iteration	15	No of iteration	15	No of iteration	15

The various parameters for different optimization algorithms used in this work as EPSO, PSO and GA as follows. The population size is common to all algorithms is about 20. The learning coefficient for PSO and EPSO is 2 and the mutation rate for the genetic algorithm is 0.1. The value of R1 and R2 is 2 for PSO and EPSO respectively and the crossover rate for GA is 0.9. Finally, no of iteration is to perform in all algorithms are commonly set as 15.

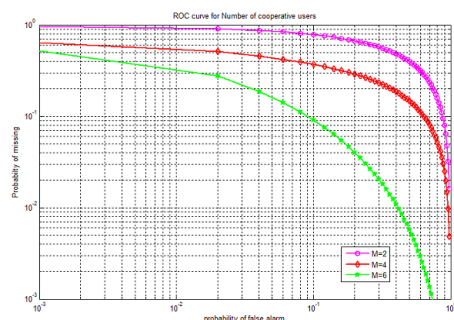


Fig. 2 ROC curves for pm vs. pf when no of cooperative user at M=2, M=4 and M=6.

From fig.2 it is clarified that when increasing the number of cooperative users then, decreased missing probabilities is obtained. It is concluded that when the situation of severe fading or shadowing the single secondary user is sense to identify the channel is not possible. To mitigate these effects switch over of single user to multiple users (cooperative user) is a possible solution.

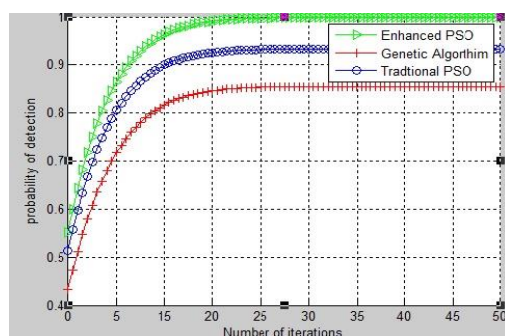


Fig.3 plot of probability of detection vs. Number of iterations for EPSO, PSO and GA.

Fig.3 shows the convergence curve of the probability of detection vs. number of iterations for EPSO, PSO and GA. It is noted that EPSO based method converges fast at 13 iterations than traditional PSO converges at 16 iterations and genetic algorithm (GA) converges at 20 iterations. The EPSO technique converges fast and achieves 0.97 of detection probability which is higher than the other two techniques. Traditional PSO method achieves detection probability about 0.90 and GA achieves 0.81 of detection probability respectively. Finally, it is concluded that Enhanced PSO generates better optimal solutions than other optimization algorithm.

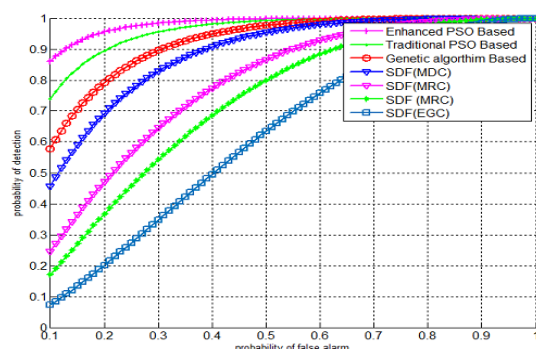


Fig.4 ROC curves for Pd vs. pf for EPSO, PSO and GA and other SDF conventional schemes.

Fig.4 shows the ROC curve for detection probability (Pd) and the probability of false alarm (Pf) for proposed EPSO technique, PSO, GA and other conventional SDF techniques. From the simulated curve, it is shown that EPSO shows good detection performance with $P_d=0.97$, which is highest among all other implemented techniques under Rayleigh fading channel.

V. CONCLUSION

To mitigate the fading effect of Rayleigh fading channel a cooperative sensing scheme based on is carried out. The generated result from MATLAB shows that the proposed EPSO has better detection performance than other implemented conventional schemes. The proposed EPSO is achieving about $P_d=0.97$ rate of detection probability at the minimum number of iteration is about 13. When weighting the vector coefficient for decision schemes are the EPSO generates best optimal than other methods. In addition to that EPSO needs less adjusting parameter than another prime reason for the faster convergences rate. And lastly, it is concluded that the proposed cooperative spectrum sensing based on EPSO could be a possible solution for when the cognitive user experiences severe fading.

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AUTHORS PROFILE



R. Harikrishnan, pursued Bachelor of Engineering from Vel High Tech Engineering, Chennai, Tamil Nadu in 2011 and Master of Engineering from KSR College Of Engineering in year 2015. He is currently pursuing Ph.D. in Department of Electronics and Communication Engineering, Annamalai University, Chidambaram since 2015. His main research work

focuses on cognitive radio network, spectrum sensing and wireless communication based application.



Dr. V. Padmathilagam, pursued Bachelor of Engineering and Master of Engineering from Annamalai University, Chidambaram in year 1993 and 2005. And Ph.D. in Electrical Engineering, Annamalai University in 2011. She is currently working as Associate professor in Electrical Engineering in Annamalai University. Her main

research work focuses on power Electronics and control system.