Minimizing Sensing Decision Error in Cognitive Radio Networks using Evolutionary Algorithms

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Abstract

Cognitive radio (CR) is envisioned as a promising paradigm of exploiting intelligence for enhancing efficiency of underutilized spectrum bands. In CR, the main concern is to reliably sense the presence of primary users (PUs) to attain protection against harmful interference caused by potential spectrum access of secondary users (SUs). In this paper, evolutionary algorithms, namely, particle swarm optimization (PSO) and genetic algorithm (GA) are proposed to minimize the total sensing decision error at the common soft data fusion (SDF) centre of a structurally-centralized cognitive radio network (CRN). Using these techniques, evolutionary operations are invoked to optimize the weighting coefficients applied on the sensing measurement components received from multiple cooperative SUs. The proposed methods are compared with each other as well as with other conventional deterministic algorithms such as maximal ratio combining (MRC) and equal gain combining (EGC). Computer simulations confirm the superiority of the PSO-based scheme over the GA-based and other conventional MRC and EGC schemes in terms of detection performance. In addition, the PSO-based scheme also shows promising convergence performance as compared to the GA-based scheme. This makes PSO an adequate solution to meet real-time requirements.

Keywords: CR , cooperative spectrum sensing, SDF, PSO, GA

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1. Introduction

Electromagnetic spectrum is a scarce resource for wireless communication. With the advancement of technology, demands for new spectrum bands have increased significantly and have consequently led to spectrum scarcity. Using the static spectrum allocation scheme, Federal Communications Commission (FCC) allocates spectrum bands to users exclusively. FCC research proves that the main reason for the scarcity of spectrum is the underutilization of frequency spectrum by the licensed users either temporally or spatially [1]. To overcome this problem, dynamic spectrum allocation has been widely proposed as means to improve spectrum efficiency [1][2]. Cognitive Radio (CR) is a new paradigm that can be seen as a considerable step towards realizing dynamic spectrum allocation. CR users are defined as secondary users (SUs) that can sense the spectrum bands of licensed or primary users (PUs) and access these bands temporarily if the PUs are declared absent. Using this access strategy, the spectrum resources can be assured that they can be always in use and thus, spectrum efficiency is enhanced. This secondary access of PU bands can be suggested for any upcoming emerging wireless technologies and therefore the spectrum scarcity can be greatly resolved.
Among the main CR functions, CR systems have to keep monitoring the spectrum periodically; detect the occupancy of the spectrum and opportunistically use spectrum holes with least possible interference with PUs. However because of the shadowing effect and hidden terminal problem, the SU may not detect the activity of the PU within the short interval of sensing period. And thus the detection performance might be hugely degraded [3]. In [4][5][6], authors proposed cooperative spectrum sensing to overcome this problem and minimize the interference. Among all spectrum sensing techniques, energy detection is recognized by its low implementation cost and compatibility with legacy primary systems. The simplicity of energy detectors is due to the fact that they only need to measure the power of the received signal to identify the presence of PU signals with unknown frequency locations, waveform structures and power strengths. Fusion Center (FC) makes a final decision on the presence of PU based on different schemes. These schemes are classified as hard decision fusion (HDF) [4][7][8], soft decision fusion (SDF) [9][10][11]. In [12], it has been shown that the detection performance of the SDF-based techniques is better than that of HDF techniques. In [12], maximal ratio combining- (MRC-) and equal gain combining- (EGC-), based SDF-based linear cooperative spectrum sensing method were used to find the optimal weighting vector. In this paper, SDF based particle swarm optimization (PSO) and genetic algorithm (GA) in cooperative spectrum sensing has been used to evaluate the optimal weighting vector. Proposed schemes are implemented at the fusion center of a linear SDF scheme to reduce global probability of error and compared with other conventional methods. Simulation results and analysis confirm that the proposed schemes are efficient and stable and outperform conventional MRC- and EGC- based SDF schemes. In addition, it has been shown that PSO-based method provides better error and convergence performance than GA-based SDF scheme.

2. System Model

In cognitive radio networks (CRNs), the detection performance could be degraded when the sensing decisions are forwarded to a fusion center through fading channels. In this paper, SDF-based cooperative spectrum sensing is used to minimize probability of sensing error. **Fig.**

1 shows a deployment of CRN [13]. As it can be seen in **Fig. 1**, *M* SUs are acting as relays and they amplify-and-forward (AF) their individual statistical measurements of PU availability to a common FC. The use of a weighting vector in the linear soft fusion helps to eliminate the need for finding optimal thresholds for individual SU. **Fig. 1** presents two links, namely primary user-secondary user (PU-SU) link and secondary user-fusion center (SU-FC) link.

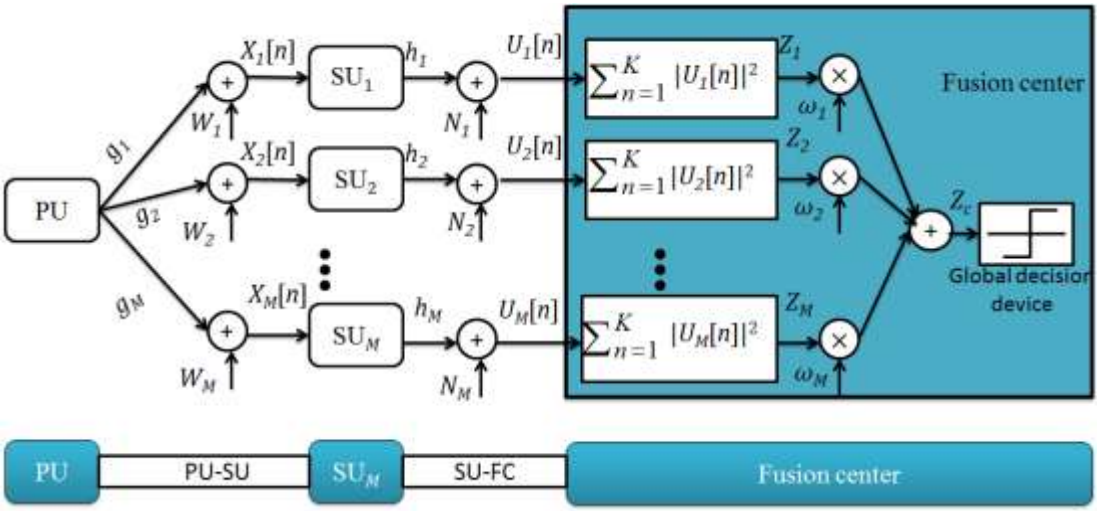

Fig. 1. Block diagram of the CRN

Each SU individually performs spectrum sensing individually to detect whether the PU is present or absent. The formulation of binary hypothesis test is:

$$\begin{aligned} \text{Absence} \rightarrow H_0: X_i[n] &= W_i[n] \\ \text{Presence} \rightarrow H_1: X_i[n] &= g_i S[n] + W_i[n] \end{aligned} \tag{1}$$

where the received sampled signal is denoted by $X_i[n]$ at i^{th} SU receiver and $i = 1,2,\dots,M$, $n = 1,2,\dots,K$, K is the total number of samples of the received signal defined by K=$2BT_s$ wherein B and T_s are, respectively, the bandwidth of the signal and sensing time, g_i is the channel gain between PU and i^{th} SU, $S[n]$ is the PU transmitted signal which is presumed to be independent and identically distributed (i.i.d.) Gaussian random process with zero mean and variance σ_S^2, and $W_i[n]$ is assumed as AWGN with zero mean and variance $\sigma_{W_i}^2$. FC calculates the final test statistic Z before representing decision making block by $Z = \sum_{i=1}^{M} \omega_i Z_i$ where Z_i is the energy collected by FC from the i^{th} SU signal and calculated by $Z_i = \sum_{n=1}^{K} |U_i[n]|^2$ where $U_i[n] = \sqrt{P_{R,i}} h_i X_i[n] + N_i[n]$ is the analogous signal which is received at FC wherein $P_{R,i}$ is the transmit power of i^{th} SU and h_i is the channel gain between i^{th} SU and FC.

By denoting $\{Z_{0,i}\} = \{ Z_i|H_0\}$ and $\{ Z_{1,i}\} = \{Z_i|H_1\}$, the two sets of test statistics can be written as $\overrightarrow{Z_0} = \left[Z_{0,1}, Z_{0,2}, Z_{0,3} \dots Z_{0,M}\right]^T$, $\overrightarrow{Z_1} = \left[Z_{1,1}, Z_{1,2}, Z_{1,3} \dots Z_{1,M}\right]^T$, each test statistic is approximated by central limit theorem (CLT) for a large number of samples, which is normally distributed with mean and variance given by [9]:

$$(Z_i|H_0) \sim \mathcal{N}(\mu_{0,j}, 2K\sigma_{0,i}^4) \tag{2}$$

$$(Z_i|H_1) \sim \mathcal{N}(\mu_{1,j}, 2K\sigma_{1,i}^4) \tag{3}$$

where $\mu_{0,j} = K\sigma_{0,i}^2$ and $\mu_{1,j} = K\sigma_{1,i}^2$. $\sigma_{0,i}^2 = P_{R,i}|h_i|^2\sigma_{W_i}^2 + \delta_i^2$ and $\sigma_{1,i}^2 = P_{R,i}|g_i|^2|h_i|^2\sigma_s^2 + \sigma_{0,i}^2$ are variances of $U_i[n]$ under hypotheses H_0 and H_1, respectively. Assuming that $\vec{\boldsymbol{\theta}} = [\theta_1, \theta_2, \dots, \theta_M]^T$ and $\theta_i = KP_{R,i}|g_i|^2|h_i|^2\sigma_s^2$, in calculation we have: $\mu_{1,i} = \mu_{0,i} + \theta_i$ or $\overrightarrow{\mu_1} = \overrightarrow{\mu_0} + \vec{\boldsymbol{\theta}}$ where $\overrightarrow{\mu_0} = \left[\mu_{0,1}, \dots . \mu_{0,M}\right]^T$ and $\overrightarrow{\mu_1} = \left[\mu_{1,1}, \dots . \mu_{1,M}\right]^T$.

Next, all the individual test statistics $\{Z_i\}$ are used to linearly formulate the resultant test statistic of the j^{th} cluster, Z_j, which can be expressed as $Z_j = \sum_{i=1}^{M} \omega_i Z_i = \vec{\boldsymbol{\omega}}^T \vec{Z}$ when $j = 1,2, \dots, N$.

It is assumed that the reporting channel (SU-FC) noise $N_i[n]$ is AWGN with zero mean and variance δ_i^2 and finally, ω_i is the weighting coefficient of the i^{th} path. Since all random variables $\{Z_i\}$ are normally distributed, their linear combination which represents the j^{th} cluster test statistic Z_j has also normal distribution with parameters as follows:

$$(Z|H_0) \sim \mathcal{N}(\vec{\boldsymbol{\omega}}^T\overrightarrow{\mu_0}, \vec{\boldsymbol{\omega}}^T\Phi_{\mathrm{H}_0}\vec{\boldsymbol{\omega}}) \tag{4}$$

$$(Z|H_1) \sim \mathcal{N}(\vec{\boldsymbol{\omega}}^T\overrightarrow{\mu_1}, \vec{\boldsymbol{\omega}}^T\Phi_{\mathrm{H}_1}\vec{\boldsymbol{\omega}}) \tag{5}$$

where $\vec{\boldsymbol{\omega}} = [\omega_1, \omega_2, \dots, \omega_M]^T$ denotes the weighting coefficients vector which is to be optimized and the superscript T represents the transpose of the vector. The covariance matrices under H_0 and H_1 are $\Phi_{H_0} = diag\left(2K\sigma_{0,i}^4\right)$ and $\Phi_{H_1} = diag\left(2K\left(P_{R,i}|g_i|^2|h_i|^2\sigma_s^2 + \sigma_{0,i}^2\right)^2\right)$, respectively where $diag(.)$ is square diagonal matrix whose diagonal elements are the elements of a given vector. Assuming the energy threshold at FC is β, then, $Z \gtrless_{H_0}^{H_1} \beta$ demonstrates the likelihood ratio. Therefore, the final probability of detection P_d and probability of false alarm P_f can be expressed as

$$P_f = P\left(Z_j > \beta_j \mid H_0\right) = Q\left(\frac{\beta_j - E(Z_j|H_0)}{\sqrt{\mathrm{var}(Z_j|H_0)}}\right) = Q\left(\frac{\beta_j - \vec{\boldsymbol{\omega}}^T\overrightarrow{\mu_0}}{\sqrt{\vec{\boldsymbol{\omega}}^T\Phi_{\mathrm{H}_0}\vec{\boldsymbol{\omega}}}}\right) \tag{6}$$

$$P_d = P\left(Z_j > \beta_j \mid H_1\right) = Q\left(\frac{\beta_j - E(Z_j|H_1)}{\sqrt{\mathrm{var}(Z_j|H_1)}}\right) = Q\left(\frac{\beta_j - \vec{\boldsymbol{\omega}}^T\overrightarrow{\mu_1}}{\sqrt{\vec{\boldsymbol{\omega}}^T\Phi_{\mathrm{H}_1}\vec{\boldsymbol{\omega}}}}\right) \tag{7}$$

Probability of detection P_d in terms of a given probability of false alarm P_f, and P_f in terms of a given P_d, are concluded as fallow:

$$P_{d,j}(\vec{\boldsymbol{\omega}}) = Q\left(\frac{Q^{-1}(\overline{P_{f,j}})\sqrt{\vec{\boldsymbol{\omega}}^T\Phi_{\mathrm{H}_0}\vec{\boldsymbol{\omega}}} - \vec{\boldsymbol{\omega}}^T\vec{\boldsymbol{\theta}}}{\sqrt{\vec{\boldsymbol{\omega}}^T\Phi_{\mathrm{H}_1}\vec{\boldsymbol{\omega}}}}\right) \tag{8}$$

$$P_{f,j}(\vec{\boldsymbol{\omega}}) = Q\left(\frac{Q^{-1}(\overline{P_{d,j}})\sqrt{\vec{\boldsymbol{\omega}}^T\Phi_{\mathrm{H}_1}\vec{\boldsymbol{\omega}}} + \vec{\boldsymbol{\omega}}^T\vec{\boldsymbol{\theta}}}{\sqrt{\vec{\boldsymbol{\omega}}^T\Phi_{\mathrm{H}_0}\vec{\boldsymbol{\omega}}}}\right) \tag{9}$$

where $Q(x) = \int_x^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$.

For simplicity, it is assumed that the probability of false alarm $P_{f,j}$ is the same with probability of miss match $P_{m,j}$. It means $P_{f,j}$=$P_{m,j}$ or $P_{f,j}$= 1-$P_{d,j}$. Hence, by equating the expressions in

equations (8) and (9), we would obtain:

$$Q\left(\frac{\beta_j-\vec{\omega}^T\,\overrightarrow{\mu_1}}{\sqrt{\vec{\omega}^T\Phi_{H_1}\vec{\omega}}}\right)=1-\;Q\left(\frac{\beta_j-\vec{\omega}^T\,\overrightarrow{\mu_0}}{\sqrt{\vec{\omega}^T\Phi_{H_0}\vec{\omega}}}\right) \tag{10}$$

$$Q\left(\frac{\beta_j-\vec{\omega}^T\,\overrightarrow{\mu_1}}{\sqrt{\vec{\omega}^T\Phi_{H_1}\vec{\omega}}}\right)=\;Q\left(\frac{\vec{\omega}^T\,\overrightarrow{\mu_0}-\beta_j}{\sqrt{\vec{\omega}^T\Phi_{H_0}\vec{\omega}}}\right) \tag{11}$$

After some simplifications, the optimal threshold β_j can be obtained that will minimize the total probability of error, P_e and can be expressed as:

$$\beta_j=\left(\frac{\sqrt{\boldsymbol{\omega}^T\Phi_{H_1}\boldsymbol{\omega}}\;\mu_0^T\,\vec{\omega}+\sqrt{\boldsymbol{\omega}^T\Phi_{H_1}\boldsymbol{\omega}}\mu_1^T\,\boldsymbol{\omega}}{\sqrt{\boldsymbol{\omega}^T\Phi_{H_0}\boldsymbol{\omega}}+\sqrt{\boldsymbol{\omega}^T\Phi_{H_1}\boldsymbol{\omega}}}\right) \tag{12}$$

Finally, the replaced value of β_j (which should be a scalar value) will then be substituted back into equations (6) and (7). Summing them up, the total probability of error, P_e has been obtained and is simply represented by:

$$P_e=\;P_f+\;P_m=Q\left(\frac{\beta_j-\vec{\omega}^T\,\overrightarrow{\mu_0}}{\sqrt{\vec{\omega}^T\Phi_{H_0}\vec{\omega}}}\right)+\;Q\left(\frac{\vec{\omega}^T\,\overrightarrow{\mu_1}-\beta_j}{\sqrt{\vec{\omega}^T\Phi_{H_1}\vec{\omega}}}\right) \tag{13}$$

It is observable that the probability of error is greatly dependent on $\vec{\boldsymbol{\omega}}$. Therefore, the optimal solution is the weighting vector that minimizes the total probability of error P_e so that the interference to PU is reduced. In our paper, equation (13) is used as an objective function, However, to reduce the search space on which the PSO works, the $\vec{\boldsymbol{\omega}}$ used in this work should satisfies the conditions $0<\omega_i<1$ and $\sqrt{\sum_{i=1}^{M}\omega_i^2}=1$.

3. SDF Based Weighting Methods For Cooperative Spectrum Sensing

3.1 Conventional Schemes

Equal gain combining (EGC) scheme is one of the simplest SDF-based weighting schemes and it is same as the one used in systems with multiple receive antennas. It does not require any channel estimator but it still performs much more accurate than the conventional HDF techniques. Weights of each path are individually assigned at fusion center and are reversely related to the number of SUs. In [12], authors discussed EGC scheme where weighting coefficient vector is-

$$\omega_i={}^1\!/_{\sqrt{M}} \tag{14}$$

Another SDF scheme is the maximal-ratio combining (MRC) where a distinct weighting coefficient is allocated for each SU's signal at the fusion center; the final sensing decision is made by combining all contributions from SUs. The allocated weighting vector is correlated to the quality of the received PU signal at the global fusion center. Thus, if the received

signal-to-noise ratio (SNR) of a particular SU at the fusion center is high, a larger weighting coefficient is assigned. On the other hand, a small weighting coefficients is assigned when their corresponding SNR values are low to reduce the negative contribution on the final sensing decision due to shadowing or deep fades over the SU-FC links. By satisfying $\| \boldsymbol{\omega} \| = 1$, the weighting coefficient for the i^{th} SU is determined as follows [12]

$$\sum_{i=1}^{M} \gamma_i = \gamma_T \Longrightarrow \sum_{i=1}^{M} \frac{\gamma_i}{\gamma_T} = 1 = \sum_{i=1}^{M} \omega_i^2 \Longrightarrow \omega_i^2 = \frac{\gamma_i}{\gamma_T}$$

$$\omega_i = \sqrt{\frac{\gamma_i}{\gamma_T}} \tag{15}$$

where γ_i is the estimated signal-to-noise ratio at the fusion center for the i^{th} SU. To observe the performance of the MRC, weighting coefficient obtained from equation (15) is applied in equation (13) which is performed in next section.

3.2 Evolutionary Algorithm-Based SDF-Based Linear Cooperative Spectrum Sensing

In this part, the GA and PSO evolutionary algorithms used to minimize the total sensing error by optimizing the weighting coefficients vector.

3.2.1 Proposed GA Based Cooperative Spectrum Sensing

GA is classified as a stochastic evolutionary search algorithm that mimics natural evolution. It has been used to solve difficult non-deterministic problems and machine learning as well as for many other engineering applications. GA is a population-based method in which each individual in the population evolves to create new individuals that form new populations. This evolutionary process continues until no improvement on the fitness score and then the optimal individual is obtained from the last obtained population.

In this paper GA-based method has been proposed, an initial population of *pops* possible solutions is generated randomly and each individual is normalized to satisfy the constraints. The goal is to find the optimal set of weighting vector values to maximize detection performance. When it reaches the predefined maximum number of generations, GA is terminated and the weighted vector values that minimize the probability of error is considered as the best solution. Let assume that there are $\boldsymbol{M}$ SUs and Z_1, $Z_2 \ldots Z_M$ are the soft decisions of SU_1, $SU_2 \ldots SU_M$ on the presence of PUs, and $\overrightarrow{\boldsymbol{\omega}_j}$ is the weighting vector of the j^{th}individual that consists of $\omega_1, \omega_2, \omega_3, \ldots \omega_M$, the fitness value for the j^{th} individual is defined as

$$f_j = p_e\left(\overrightarrow{\boldsymbol{\omega}_j}\right) \text{ where } \left\|\overrightarrow{\boldsymbol{\omega}_j}\right\|=1 \tag{16}$$

p_e stands for probability of error. The main operations of the proposed GA are selection, crossover, and mutation. For selection, the idea is to choose the best chromosomes for reproduction through crossover and mutation. The smaller the fitness (probability of error) value the better the solution obtained. In this paper "Roulette Wheel Selection" method has been used. The probability of selecting the j^{th} individual or chromosome, p_j , can be written as

$$p_j = \frac{f_j}{\sum_{j=1}^{pops} f_j} \tag{17}$$

The chromosomes with minimum probability of error value will be directly transferred to the next generation through elitism operation. After the selection process is done, the next step is crossover. The crossover starts with pairing to produce new offspring. A uniform random number generator has been used to select the row numbers of chromosomes as mother (*ma*) or father (*pa*). Here a random population of choromosomes is shown in matrix A, where *pops* is total number of chromosomes, *M* is number of secondary users.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1M} \\ a_{21} & a_{22} & \ldots & a_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ a_{pops\,1} & a_{pops\,2} & \cdots & a_{pops\,M} \end{bmatrix} \tag{18}$$

It begins by randomly choosing a variable in the first pair of parents to be the crossover point. In the illustration crossover point is $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ is a random value on the interval [0, 1]. As for the GA crossover operation, two parents are chosen and the new offsprings are formed from combinations of these parents. In our proposed algorithm, hybridization of an extrapolation method with a crossover method is imvoked to enhance the quality of obtainable solutions [13]. Commonly, one of the main reasons of a population converging to local optima is when large number of individuals sharing the same genetic material. In this work, the random offspring generation is realized by the usage of roulette wheel crossover technique so that there is a very narrow possibility to get similar genotype [13], and consequently, this will prevent premature convergence of genetic algorithm to local minimum. The GA crossover operation is graphically expalined in **Fig. 2.**

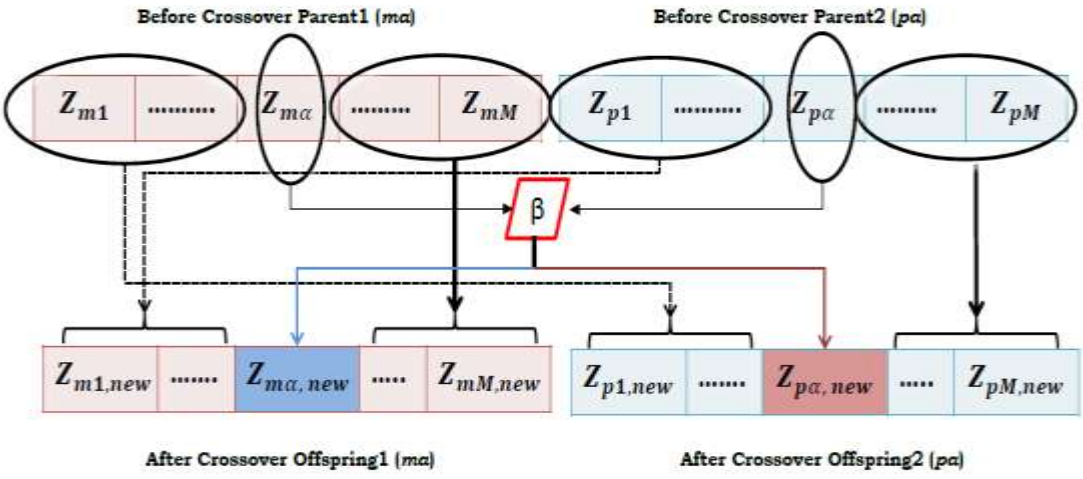

Fig. 2. GA crossover operation

For Parent1 (*ma*) → offspring1 (*ma*):

$$\{Z_{p1}, \dots, Z_{p(\alpha-1)}\} \rightarrow \{Z_{m1,new}, \dots, Z_{m(\alpha-1),new}\}$$
$$\{Z_{m(\alpha+1)}, \dots, Z_{mM}\} \rightarrow \{Z_{m(\alpha+1),new}, \dots, Z_{mM,new}\}$$
$$Z_{m\alpha,new} = Z_{m\alpha} - \beta[Z_{m\alpha} - Z_{p\alpha}]$$

For Parent2 (*pa*) → offspring2 (*pa*):

$$\{Z_{m1}, \dots, Z_{m(\alpha-1)}\} \rightarrow \{Z_{p1,new}, \dots, Z_{p(\alpha-1),new}\}$$
$$\{Z_{p(\alpha+1)}, \dots, Z_{pM}\} \rightarrow \{Z_{p(\alpha+1),new}, \dots, Z_{pM,new}\}$$
$$Z_{p\alpha,new} = Z_{p\alpha} + \beta[Z_{m\alpha} - Z_{p\alpha}]$$

The next step after crossover is the mutation operation. The total number of variables that can be mutated equals to the mutation rate times the population size. The row and column numbers of variables are nominated randomly and then these nominated variables are replaced by new random ones. For instance, if the mutation rate is 60% and the population size = 5 chromosomes as showns in matrix ***A***, then, the total number of variable that has to be mutated is 0.6 * 5 = 3 variables. Assume that the following pairs have been selected randomly from ***A***: *mrow* = [4 3 5] and *mcol* = [2 5 1], where *mrow* is the row index and *mcol* is the column index of the population. Then, the varibales to be mutated can be highlighted as shown in matrix ***A*** below.

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \quad (19)$$

Assume that the 4th chromosome in ***A*** is defined as $[a_{41}\ a_{42}\ a_{43}\ a_{44}\ a_{45}]$= [0.0551 0.8465 0.9891 0.2478 0.0541]. Then, the mutation process of, for example, the variable A(4, 2) → a_{42} is illustrated in **Fig. 3**. During the mutation operation, the previous value of $a_{42} = 0.8465$ is replaced by another random value and the new coefficient becomes $a_{42} = 0.3041$. The mutation parameter helps to enhance the exploration of a predefined search space.

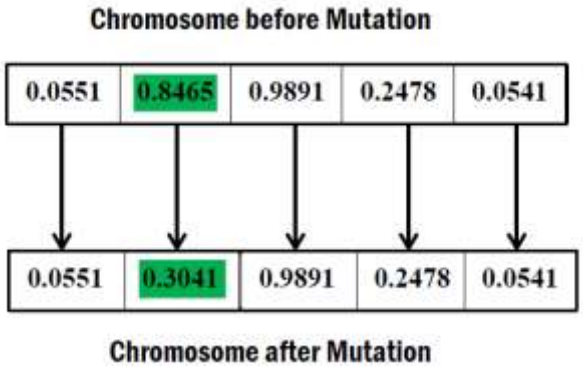

Fig. 3. GA mutation representation

The proposed GA based optimization algorithm for SDF-based cooperative spectrum sensing can be outlined as follows:

Step 1: Set $t = 0$ and randomly generate a population of *pops* chromosomes each of which is *M* digits long, where *M* is the number of secondary users in the network.

Step 2: Decode each chromosome in the random population into its corresponding weighting coefficients vector where the weighting coefficient vector $\vec{\boldsymbol{\omega}} = [\omega_1, \omega_2, \dots, \omega_M]^T$; $\omega_1 \geq 0$ satisfying the condition; which is used to minimize the detection error.

Step 3: Normalize the weighting coefficient vector dividing $\vec{\boldsymbol{\omega}} = [\omega_1, \omega_2, \dots, \omega_M]^T$ by its 2-norm such that $\overrightarrow{\boldsymbol{\omega}_i} = \overrightarrow{\boldsymbol{\omega}_i} \Big/ \left[\sum_{i=1}^{M} (\omega_i)^2\right]^{1/2}$ so that the constraint $\|\overrightarrow{\boldsymbol{\omega}_i}\| = 1$ is satisfied.

Step 4: Compute the fitness value of every normalized decoded weighting vector, $\overrightarrow{\boldsymbol{\omega}_i}$ rank their corresponding chromosomes according to their fitness value and identify the best chromosomes$\lfloor pops * elite \rfloor$, where $elite \in [0,1)$ and $\lfloor . \rfloor$ denotes floor operation.

Step 5: Update $t = t + 1$and reproduce $\lceil pops * (1 - elite) \rceil$ new chromosomes (candidate solutions) using genetic algorithm operations: selection, crossover and mutation where $\lceil . \rceil$ denotes ceiling operation.

Step 6: Construct a new set of population pops by concatenating the newly $\lceil pops * (1 - elite) \rceil$ reproduced chromosomes with the best $\lfloor pops * elite \rfloor$ found in $P(t-1)$.

Step 7: Decode and normalize the chromosomes of the new population pops as in Step 2 and Step 3 respectively.

Step 8: Evaluate the fitness value of each chromosome as in Step 4.

Step 9: If it is equal to predefined number of generation(iterations) *ngener*, stop. Otherwise go to Step 5

3.2.2 Proposed PSO Based Cooperative Spectrum Sensing

PSO algorithm, introduced by Kennedy and Eberhart in 1995 [14], is abstracted from social behavior of swarm of fishes and birds. The behavior of these social organizations is emulated by PSO algorithm .Each particle in PSO algorithm functions based on its own knowledge as well as group knowledge and has two main features: position and velocity. The particles follow an important and simple rule: to take after the success of individuals and their own successes. In this algorithm, each particle in the design space iteratively tries to find the best position, such as objective function optimum value. The information about the best position is exchanged among the particles during iterations. This information enables individual particles to update their positions and velocities to obtain the best position. As such, after adequate number of iterations, the algorithm converges to the optimal solution of the objective function.

In this work, we have used an inertia weight in the velocity update equation of the algorithm. Logically, at the beginning of the run a large inertia weight allows the PSO to locate the approximate region in which the minimizer (global minima) is situated. Empirical experiments have been performed with an inertia weight set to decrease linearly from 0.9 to 0.4 during the course of a simulation [15]. This setting allows the PSO to explore a large area

at the start of the simulation run (when the inertia weight is large) and to refine the search later by using a smaller inertia weight (better exploitation). The higher the inertia weight the greater the probability that the algorithm will explore a region outside the basin of attraction of the current local minimum whereas lower inertia weight helps the algorithm to search with small variations of promising regions so that global optimal solutions can be captured [16]. In this paper, the problem is to minimize the objective function $P_e(\vec{\boldsymbol{\omega}})$ where $\vec{\boldsymbol{\omega}} = [\omega_1, \omega_2, \dots, \omega_M]$ and M is the number of variables of $P_e(\vec{\boldsymbol{\omega}})$ with $\boldsymbol{\omega}^l \leq \boldsymbol{\omega} \leq \boldsymbol{\omega}^u$ where $\boldsymbol{\omega}^l = 0$ and $\boldsymbol{\omega}^u = 1$ are lower and upper limits on $\boldsymbol{\omega}$. The steps involved in the PSO algorithm are as follows:

Step 1: Initialization of the PSO algorithm by randomly generating N particle positions each of which is of M-length representing $\vec{\boldsymbol{\omega}}_s = [\omega_1, \omega_2, \dots, \omega_M]^T$ and are uniformly distributed in the range of $\boldsymbol{\omega}^l$ to $\boldsymbol{\omega}^u$ whereas the N particle velocity vectors which are initially set to zero; that is $\vec{\boldsymbol{v}}_s^{(j)} = [0, 0, \dots, 0]^T : (s = 1, \dots, N)$. To simplify the notation, particle position and velocity at iteration j are demonstrated by $\vec{\boldsymbol{\omega}}_s^{(j)}$ and $\vec{\boldsymbol{v}}_s^{(j)}$, respectively. The uniform distribution helps to prevent premature convergence of swarm particles to local minimum.

Step 2: In this step, the value of the objective function for each of the particle positions generated in step 1 is calculated as $P_e\left(\vec{\boldsymbol{\omega}}_1^{(0)}\right), P_e\left(\vec{\boldsymbol{\omega}}_2^{(0)}\right), \dots, P_e\left(\vec{\boldsymbol{\omega}}_N^{(0)}\right)$.

Step 3: The values of the objective functions obtained in step 2 are compared in this step and their smallest value is selected. Next, the particle position corresponding to minimum function value is defined as $\boldsymbol{P}_{best,0}$ and iteration number is set to $j = 1$.

Step 4: The velocity of the s^{th} particle at the j^{th} iteration is updated based on the following equation:

$$\vec{\boldsymbol{v}}_s^{(j)} = w\vec{\boldsymbol{v}}_s^{(j-1)} + c_1 r_1 \left[\boldsymbol{P}_{best,j} - \vec{\boldsymbol{\omega}}_s^{(j-1)}\right] + c_2 r_2 \left[\boldsymbol{G}_{best} - \vec{\boldsymbol{\omega}}_s^{(j-1)}\right] \tag{20}$$

where individual and social learning acceleration coefficients are, respectively, denoted by c_1 and c_2, r_1 and $r_2 \sim U(0\,, 1)$ are random numbers with uniform distributions in the range of 0 to 1 which introduce stochastic components to the algorithm and w is the inertia weight whose value is reduced from 0.9 to 0.4 during the process to obtain compromised performance between exploration and exploitation [16]. At the j^{th} iteration, the best experienced particle position which minimizes the objective function is denoted by $\boldsymbol{P}_{best,j}$. The best experienced particle position among all iteration is called global best position and is expressed by $\boldsymbol{G}_{best}$.

Step 5: At the j^{th} iteration, the new position of the s^{th} particle is updated as follows:

$$\vec{\boldsymbol{\omega}}_s^{(j)} = \vec{\boldsymbol{\omega}}_s^{(j-1)} + \vec{\boldsymbol{v}}_s^{(j)} \tag{21}$$

Again, the value of the objective function for each of the particle positions generated in this step is calculated as $P_e\left(\vec{\boldsymbol{\omega}}_1^{(j)}\right), P_e\left(\vec{\boldsymbol{\omega}}_2^{(j)}\right), \dots, P_e\left(\vec{\boldsymbol{\omega}}_N^{(j)}\right)$.

Step 6: The values of the objective functions obtained in step 5 are compared and the particle position corresponding to minimum value of the objective function is defined as $\boldsymbol{P}_{best,j}$. The value of the $\boldsymbol{G}_{best}$ will be replaced by the value of the $\boldsymbol{P}_{best,j}$ if $P_e\left(\boldsymbol{P}_{best,j}\right) \leq P_e(\boldsymbol{G}_{best})$.

Step 7: The convergence of the algorithm is checked in this step and if the algorithm is converged to a stable value, the procedure is terminated. Otherwise, the iteration number is set

to $j = j + 1$ and the process in repeated from step 4.

In this paper, the objective function is the probability of error of primary users in CR networks. The algorithm aims to find the optimized weighting coefficient vector that minimizes the total probability of decision error in [13] as explained in section 2.

4. Experimental Results and Analysis

In this section, simulation results and analyses are provided for proposed evolutionary algorithms based cooperative spectrum sensing as well as conventional MRC- and EGC-based SDF schemes. *M* and B are the number of users and bandwidth and equal to 25 and 6 MHz, respectively. T_s is 25 μsec , $P_{R,i} = 33$ dBm, ${\sigma_s}^2 = 35$ dBm . Also, we randomly generate the noise $\{20 \leq \sigma_{W_i}^2 \leq 30$ dBm, $20 \leq {\delta_i}^2 \leq 30$ dBm $\}$ and the channel gain $\{10 \leq g_i \leq 20$ dBm , $10 \leq h_i \leq 20$ dBm $\}$ which eventually affect the performance of the system. The operating parameters of the GA and PSO algorithms are given in **Table 1**.

It is well-known that the optimal set of GA and PSO parameters is different for each different problem. Thus, the values of GA and PSO parameters given in Table 1 are obtained based on set-and-test approach where the convergence speed and quality of obtainable solutions are taken into account when finding these set of optimal GA and PSO setting. For GA and PSO algorithm total number of generation *gener* =300, and given probability of false alarm P_f is calculated dynamically according to threshold value. The whole iteration was averaged for 100 times. The values of c_1 and c_2 relatively affects the position of the particles on the swarm and usually assumed to be 2 so that $c_1 r_1$ and $c_2 r_2$ guarantee that the particles would fly over the target about half the time [17]. The algorithm is affected by number of iterations and swarm size, though there is a trade-off between them.

Table 1. Optimal set of GA parameters

Parameter Name	***GA Parameter Value Used***	***PSO Parameter value used***
Population size/No. of Particles	50	25
Mutation rate	0.3	-
Crossover rate	0.95	-
Percentage chrom. For reproduction	0.90	-
No. of Secondary user	25	-
Leaning Coefficients	-	$c_1 = c_2 = 2$

However, in experiential research it has been shown that the number of iterations to reach a good solution is also problem-dependent. To confirm the efficiency of the algorithm, low SNR condition (SNR < -10 dB) at FC level is provided. The values of the $\{g_i\}$ and $\{h_i\}$ are assumed to be constant over the same sensing period so that it acts as slow fading channel [18]. **Fig. 4** demonstrates the probability of error of the decision maker in cognitive radio network in terms of different values of SNR for PSO- and GA-based methods as well as other traditional SDF techniques. As it can be clearly observed, the best weighting coefficients vector is generated by PSO-based method, resulting in minimized probability of error of the system. On the other hand, EGC-based spectrum sensing provides the worst error performance resulted

from inefficient fusion of the SU measurements in the network. Since the sensing decision error characterizes the aggregated miss-detection and false alarm errors, lesser probability of sensing decision error means that the evolutionary algorithms, PSO and GA, can provide better protection to PUs and higher efficiency of spectrum access by SUs.

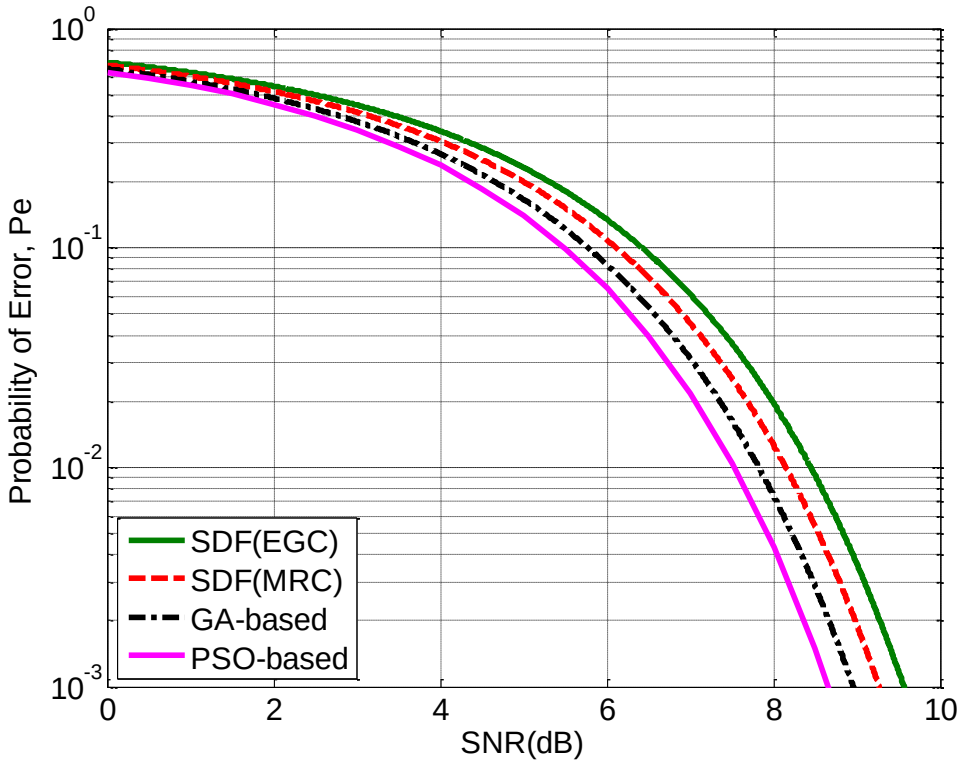

Fig. 4. Comparison of probability of error versus SNR for different schemes

Fig. 5 compares the convergence performance of the PSO- and GA-based schemes. Here, the probability of error over 100 iterations is evaluated for both methods. As it is seen, to achieve a probability of error equal to 0.5×10^{-4}, the PSO algorithm requires about 40 iterations while same error rate can be obtained after 150 iterations for GA. In addition, after the test duration of 300 iterations, the PSO algorithm is converged to probability of error of about 0.2×10^{-4} while GA achieves 0.45×10^{-4} with the same number of iterations.

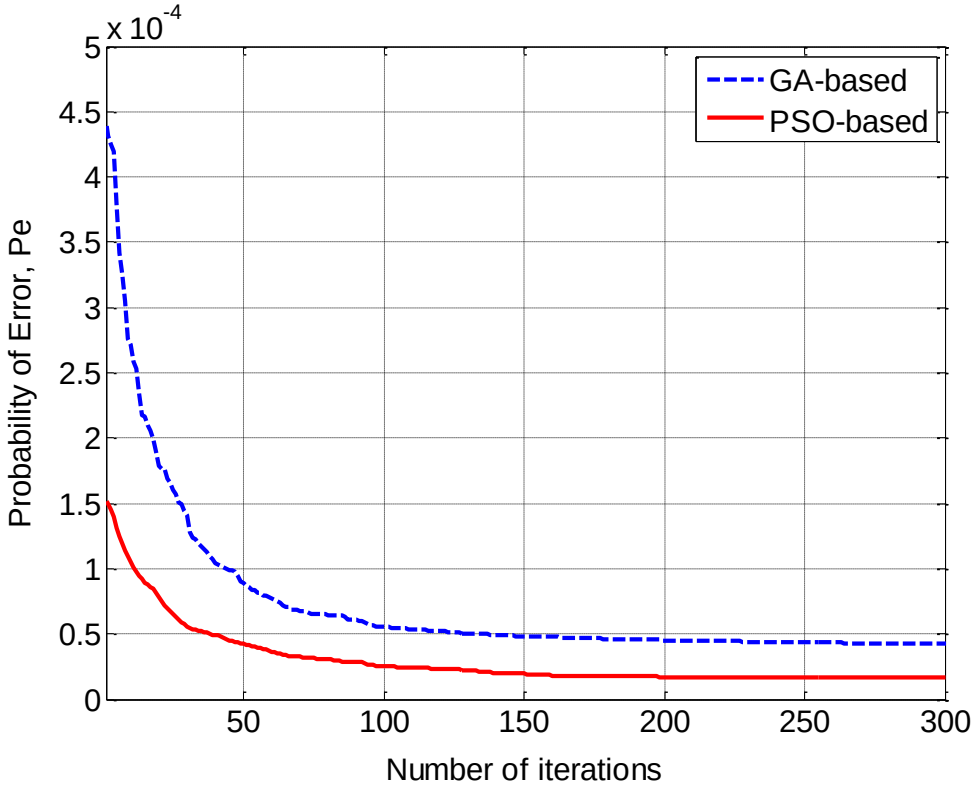

Fig. 5. Comparison of probability of error over 300 iterations for PSO and GA

5. Conclusion

In this paper, PSO and GA evolutionary algorithms have been proposed to optimize the weighting coefficient vectors which have been used to fuse final decision signals at the global fusion center of a CRN. The proposed evolutionary algorithms have been compared with other conventional techniques such as EGC and MRC. Simulation results show that the proposed PSO- and GA-based methods perform better detection performance than the conventional ones. It was also observed that the PSO-based method outperforms the GA-based method as it provides the least possible decision for a given channel condition. This minimal decision error is a crucial factor as it allows opportunistic access of PU bands by SU or CR users without causing harmful interference to both clients. In addition, the convergence speed of the PSO and GA algorithms has been found fast enough to meet real-time requirements of CRN.

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