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Minimizing the Detection Error in Cooperative Spectrum Sensing Using PSO

Prof. Keraliya Divyesh R[1], Dr. Ashalata Kulshrestha[2]

[1]Electronics and Communication, Government Engineering College, Rajkot
[2]Electronics and Communication, Kankeshwari Devi Institute of Technology, Jamnagar

Abstract — *Cognitive radio (CR) is a new paradigm in wireless communication system which is use for efficient utilization of radio frequency (RF) spectrum or RF channel for future wireless communication. Cooperative spectrum sensing is a key technology in cognitive radio networks (CRNs) to detect spectrum holes by combining sensing result of multiple cognitive radio users. This sensing information from CR users combines at the Fusion center (common receiver) by soft combination or conventional hard combination techniques. Sensing error minimization is an important aspect of cooperative spectrum sensing that needs attention. In this paper, the use of particle swarm optimization (PSO) under MINI-MAX criterion is proposed to optimize the weighting coefficients vector of energy level of spectrum sensing information so that the total probability of error is minimized. The particle swarm optimization (PSO) algorithm investigates the best weighting coefficient vector which minimizes total probability of error. The performance of the PSO based method is analysed and compared with conventional soft decision fusion schemes like EGC as well as hard decision fusion method like AND,OR, Majority etc. Simulation results show that the proposed scheme minimizes the detection error compared to conventional soft decision fusion schemes*

Keywords- *Cognitive Radio, Cooperative Spectrum Sensing, SNR Energy Detection, PSO*

I. INTRODUCTION

Inefficient usage of the radio spectrum, where a large portion of the licensed spectrum is underutilized, The Federal Communications Commission to consider opportunistic access to the licensed spectrum by SUs conditioned on no interference on the PUs or license holders [1]. In a cognitive radio network, to avoid the interference imposed on the licensed users, the SUs should be capable of identifying the presence or absence of the primary user (PU) signal. The PU signal is always subjected to deep fading effects due to propagation loss and secondary-user (SU) interference. To minimized the fading effects, we can use from the diversity gain that can be used by employing several SUs to cooperatively detect the spectrum.

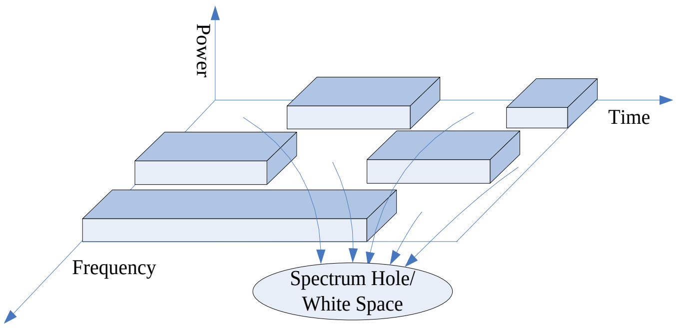

Figure 1. Utilization of Spectrum White Space (Holes)

In cooperative spectrum sensing system, SUs send their spectrum sensing information to fusion center (FC), which makes a global decision whether any PU is present or absent according to some rule. If SUs send all information received to FC without making any decision, it is called soft fusion [2]. On the other hand, if SUs send their decision information to FC (general one-bit decision), it is called hard fusion [3]. In [4], maximal ratio combining (MRC) and equal gain combining (EGC), based soft fusion method were used to calculate the optimal weighting vector. In this paper, we focus on a scenario of quantized cooperative spectrum sensing, in which a softened hard measurements from SU are send to fusion center where optimal weighting vector is evaluated. The particle swarm optimization (PSO) scheme for cooperative spectrum sensing is proposed to reduce probability of error for improvement of detection performance. The PSO based optimization process is implemented at the fusion center to optimize the weighting coefficients vector and to minimize global probability of error. Simulation results and analysis shows that the proposed schemes are efficient and stable as compare to conventional convention soft decision fusion i.e EGC and conventional hard decision fusion like AND, OR, MAJORITY etc.

The paper is organized as follows. We present the spectrum sensing in Section II. In Section III, we proposed the system model related to cooperative spectrum sensing and optimization problem, Section IV are for the PSO based weighting method for minimization of detection error. Simulation results in section V are given to compare our proposed technique with conventional scheme for minimization of detection error

II. SPECTRUM SENSING

Spectrum sensing is a key element in cognitive radio networks as it should be firstly performed before allowing CR users to access a vacant licensed channel. The goal of the spectrum sensing is to decide between the two hypotheses, H_0: no signal transmitted, and H_1: signal transmitted. In this regard, there are two probabilities that are most commonly associated with spectrum sensing: probability of false alarm P_f which is the probability that a presence of a signal is detected even if it does not exist and probability of detection P_d which is the probability for a correctly detected signal.

$$x(t) = \begin{cases} n(t) & H_0 \\ hs(t) + n(t) & H_1 \end{cases}$$

Where $x(t)$the signal is received by secondary user and $s(t)$ is primary user's transmitted signal, $n(t)$ is the additive white Gaussian noise (AWGN) and $h(t)$ is the amplitude gain of the channel. We also denote by γ the signal-to-noise ratio (SNR).

In AWGN channel environment the average probability of false alarm, the average probability of detection, and the average probability of missed detection are given, respectively, by [5]

$$P_d = P\{Y > \lambda | H_1\} = Q(\gamma, \lambda)$$

$$P_f = P\{Y > \lambda | H_0\} = \frac{\Gamma(TW, \lambda/2)}{\Gamma(TW)}$$

$$P_m = 1 - P_d$$

Where, λ is the energy detection threshold, γ is the instantaneous signal to noise ratio (SNR) of CR, TW is the time-bandwidth product of the energy detector, $\Gamma(.)$ is the gamma function, $\Gamma(.,..)$ is the incomplete gamma and $Q(.,..)$ is generalised Marcum Q-function defined as follow

$$Q_u(a,b) = \int_b^\alpha \frac{x^u}{a^{u-1}} e^{-\frac{x^2+a^2}{2}} I_{u-1}(ax)dx$$

The average probability of detection may be derived by averaging the conditional P_d in the AWGN case over the SNR fading distribution by following

$$P_d = \int Q_u(\gamma, \lambda) f_\gamma(x) dx$$

When the composite received signal consists of a large number of plane waves, for some types of scattering environments, the received signal has a Rayleigh distribution [5]. Under Rayleigh fading, γ would have an exponential distribution given by

$$f(\gamma) = \frac{\gamma}{\bar{\gamma}} \exp\left(\frac{\gamma}{\bar{\gamma}}\right), \gamma \geq 0$$

In this case, closed-form formula for probability of detection may be obtained (after some manipulation) by substituting $f(\gamma)$ in the above equation by

$$P_{dRay} = e^{-\frac{\lambda}{2}} \sum_{k=0}^{u-2} \frac{1}{k!}\left(\frac{\lambda}{2}\right)^k + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{u-1}\left(e^{\frac{\lambda}{2(1+\gamma)}} - e^{-\frac{\lambda}{2}} \sum_{k=0}^{u-2} \frac{1}{k!}\left(\frac{\lambda\bar{\gamma}}{2(1+\bar{\gamma})}\right)^k\right)$$

One of the main challenging issues of spectrum sensing is the hidden terminal problem for the case when the cognitive radio is shadowed or in deep fade. To mitigate this issue, multiple cognitive radios can be cooperative work for spectrum sensing so cooperative spectrum sensing can greatly improve the probability of detection in fading channels. In cooperative spectrum sensing common receiver calculates false alarm probability and detection probability with the help of average probability of each CR. The false alarm probability is given by [10],

$$Q_f = \sum_{k=n}^{N} \binom{N}{k} {P_f}^k (1 - p_f)^{N-k} = prob\{H_1/H_0\}$$

Also, Detection probability is given by;

$$Q_d = \sum_{k=n}^{N} \binom{N}{k} {P_d}^k (1 - p_d)^{N-k} = prob\{H_0/H_1\}$$

In hard combing based fusion scheme, each cognitive user decides on the presence or absence of the primary user and sends a one bit decision to the data fusion center. The main benefit of this method is that it needs limited bandwidth [6]. When binary decisions are reported to the common node, three rules of decision can be used, the "AND", "OR", Half Voting and "MAJORITY". While in soft combing based fusion scheme, CR users forward the entire sensing result to the fusion centre without performing any local decision and the decision is made by combining these results at the fusion centre by using appropriate combining rules such as equal gain combining (EGC) in which each sensing node gives equal weightage and at fusion center they are all combined equally, maximal ratio combining (MRC) in which weightage is given based on SNR of sensing data of secondary user and at the fusion center they all are combined with different weightage based on their SNR. Soft combination provides better performance than hard combination, but it requires a larger bandwidth for the control channel for reporting [7]. It also generates more overhead than the hard combination scheme [6]

$Q_{d,MAJORITY} = \sum_{K=N/2}^{N} \binom{N}{k} {P_d}^k (1-p_d)^{N-k}$

$Q_{d,OR} = 1-(1-P_d)^N$

$Q_{d,AND} = {P_d}^N$

Cooperative detection as well as false alarm performance with OR fusion rule and MAJORITY fusion rule can be evaluated by setting $\mathrm{k} = 1$ and $\mathrm{k} = \mathrm{N}/2$ in expression (9, 10) while AND rule corresponds to the case of $\mathrm{k} = \mathrm{N}$.

III. SYSTEM MODEL

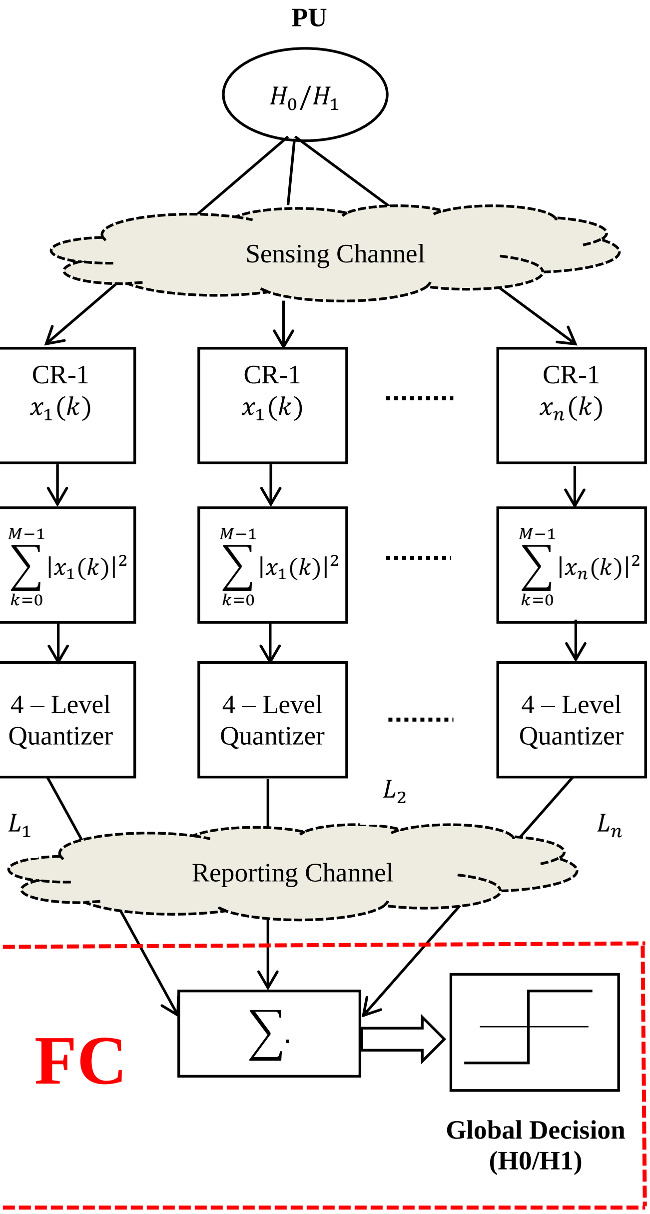

Figure 2. Principle of two-bit hard combination scheme

The system model for the proposed softened hard (quantize) cooperative spectrum sensing method is depicted in Figure 2. Each cooperating secondary user senses the spectrum locally and sends its 'quantized' local measurement as $\mathrm{L_n}$(index of the quantization level) to the fusion center at the cognitive base station. The fusion center makes a global decision according to $\mathrm{L_n}$ and weight of corresponding energy level quantization level.

In Soft combination based data fusion scheme, detection performance is obtained by allocating different weights to different CR users according to their SNR. In the conventional one-bit hard combination based data fusion scheme, there is only one threshold dividing the whole range of the observed energy into two regions. As a result, all of the CR users above this threshold are allocated the same weight regardless of the possible significant differences in their observed energies. *softened* two-bit hard combination based data fusion scheme achieve the better detection performance and less complexity with two-bit overhead by dividing the whole range of the observed energy into four regions, and allocate a different weights to this region.

Although the Soft combination based data fusion scheme has the best detection performance, soft combination schemes require lots of overhead for each CR user to transmit the sensing result periodically. In contrast, the conventional hard combination scheme requires only one bit of overhead for each CR user, but suffers performance degradation because of information loss caused by local hard decisions. Here we will use *softened* hard (Quantized) combination scheme with two-bit overhead for each CR user, which achieves a good detection performance and less complexity.

The probability of having observation in respective region under hypothesis H_0 and H_1 and AWGN channel are following.

$$P_{di} = \begin{cases} 1 - Q(\gamma, \lambda_i) & if\ i = 1 \\ Q(\gamma, \lambda_{i-1}) & if\ i = n \\ Q(\gamma, \lambda_{i-1}) - Q(\gamma, \lambda_1) & otherwise \end{cases}$$

In the proposed method, the global decision depends on the threshold values and the weight vector. Here the weights are assigned to the energy level not the reporting nodes. For this 2-bit *softened* hard combination based data fusion scheme, fusion center receives the quantized measurements and counts the number of users in each quantization level which is given by following.

$$\vec{N} = [n_1\ n_2\ n_3\ n_4]$$

$$\vec{W} = [w_1\ w_2\ w_3\ w_4]$$

The decision function is evaluated with the help of the weights and the number of users in the each energy level.

$$f(\vec{w}) = \begin{cases} 1 & if\ \vec{N}.\vec{W} > 0 \\ 0 & otherwise \end{cases}$$

Here the weighted summation is given by

$$N_c = \sum_{i=0}^{3} w_i . N_i$$

Where N_i = Number of observed energies falling in region i.

Then $N_c$is compare with the threshold, N_T If $N_c \geq N_T$, primary signal is declared present; Otherwise, it is declared absent

We consider the case of Rayleigh channel since it includes multipath effects. In *softened* hard combination based data fusion strategy the probabilities of cooperative detection under a Rayleigh channel are derived using [06] which is given by following.

$$P_d = \sum_{i=1}^{4} \sum_{j=1}^{4} P_r(N_1 = n_1, N_2 = n_2, N_3 = n_3, N_4 = n_4 | H_1)$$

$$P_d = \sum f(\vec{w}) \binom{N}{n_1} \binom{N - n_1}{n_2} \binom{N - n_1 - n_2}{n_3} \binom{N - n_1 - n_2 - n_3}{n_4} (1 - P_{d1})^{n_1} (P_{d1} - P_{d2})^{n_2} (P_{d2} - P_{d3})^{n_3} (P_{d4})^{n_4}$$

Similarly equation can be for probability of false alarm. Then, the overall probability of error is can be represented as

$$P_e = P_f + P_m$$
$$P_e = P_f + 1 - P_d$$
$$\mathrm{P_e} = \mathrm{P_f}(\vec{\mathrm{w}}) + 1 - \mathrm{P_d}(\vec{\mathrm{w}})$$

It is observable that the probability of error is highly dependent on $(\vec{w})$ vector. Therefore, the optimal solution is the weighting vector that minimize the total probability of error P_e. In our paper, above is used as objective functions that minimize the probability of error. However, to reduce the search space on which PSO algorithm works, the $\vec{w}$ used in this paper should satisfies the conditions $-5 \leq w_i \leq 5$

So, optimization problem $Minimize\ P_e\ subject\ to - 5 \leq w_i \leq 5$

3.1. PSO Based solution

A Particle swarm optimization is a population based and stochastic optimization approach designed primarily to mimic the social behavior of school of fish or flock of birds [8] [09] [10]. This social has been used in solving more complex optimization problems in the particle are grouped into swarm and each particle is a potential solution to the optimization problems. Each particle moves toward the best optimal solution in the neighborhood depending on the past experience and neighbors as well. The performance of each particle is determined by the fitness function. The key success to use of PSO in many optimization problems is due to the fact that it is very simple, high search capability[11][12]

Algorithm 1: Weight Optimization Algorithm using PSO

For $For\ each\ user$ **do**
  Repeat
    For $j = 1\ to\ swarm\ size$ **do**
      If $fitness(w_j) \geq fitness(w_{jpbest})$ **then**
        $w_{jpbest} = w_j$
        $fitness(w_{jpbest}) = fitness(w_j)$
      End
    End
    $w_{gbest} = \arg\ max(fitness);$
    For $j = 1\ to\ swarm\ size$ **do**
      Update velocity
      $v_j(n+1) = v_j(n) + C_1 r_1(n)[w_{jpbest}(n) - w_j(n)] + C_2 r_2(n)[w_{jgbest}(n) - w_j(n)]$
      Update position
      $x_j(n+1) = x_j(n) + v_j(n+1)$
    End
  Until $stop\ Condition\ is\ met$:
end

PSO is primarily governed by two fundamental equations representing the velocity and position of the particle at any particular time. After each iteration, the particle position and velocity is updated until the termination condition has been reached. The termination condition can be based on the number of iteration and achievable output required. Once the required number if iterations or predetermined outputs have been achieved, the searching process is terminated automatically. For a particle with n dimension can be represented by vector $X = (x_1, x_2 \dots \dots \dots \dots . x_n)$. The position of the particle at time t can be mathematically expressed as $P = (p_1, p_2 \dots \dots \dots \dots . p_n)$. which the corresponding velocity of the particle is represented as $V = (v_1, v_2 \dots \dots \dots \dots . v_n)$. In general, the velocity and position of the particle at *t +1* can be mathematically represented using following equation.

$$v(t+1) = v(t) + C_1 r_1 \big(P_l(t) - x(t)\big) + C_2 r_2 (P_g(t) - x(t)$$
$$x(t+1) = x(t) + v(t+1)$$

In the above equation C_1 and C_2 are referred as acceleration constants, r_1 and r_1 are uniformly distributed random values ranging in [0, 1]. $P_l(t)$ is best position found by the i particle in j dimension and $P_g(t)$ is best position found by the entire swarm. Algorithm for weight optimization using PSO are shown following. In this paper, the performance objective of CRN is to maximized the probability of detection. Thus, the fitness function to be optimized by PSO is the objective function in equation 16 and each particle represents a potential setting of the weight.

Each particle w_i is attracted to the position of the particle that encountered the best result globally;w_{jbest} ,and affected by its own best experience in exploring the field,w_{ipbest} ,The attraction is made by a certain velocity v(n) which is determined according to the quality of the particle's current result and the best particle in the swarm. The PSO algorithm is used to estimate the weight,w_i as shown in algorithm 1

IV. SIMULATION RESUL

A simulation has been done to assess the performance of proposed PSO algorithms based cooperative spectrum sensing. Table 1 demonstrate the probability of error in term of different value of threshold λ for PSO based as well as other conventional soft decision fusion technique i.e. EGC and convention hard design fusion technique i.e. AND, OR, MAJORITY rules etc., We have considered time-bandwidth product $TW = 5$, the channel is Rayleigh, the number of received signal samples $M = 2u$. In PSO, we have used the number of particles $S = 15$ and $iteration = 50$. We have assumed perfect reporting channels and there is no false reporting.

Table 1:Performance matrix of PSO based CSS P_e

Sr. No	Lambda	P_e	Sr. No	Lambda	P_e
1	0	0.46	8	14	0.34
2	2	0.45	9	16	0.41
3	4	0.41	10	18	0.42
4	6	0.43	11	20	0.44
5	7	0.38	12	22	0.54
6	10	0.36	13	24	0.56
7	12	0.39			

As it can be clearly observed, the PSO-based method generates the best weighting coefficients vector leading to minimized probability of error of cognitive radio system. On the other hand, conventional hard decision fusion (HDF) based spectrum sensing provides the worst error performance resulted from insufficient data fusion from secondary user (SU) in the network.

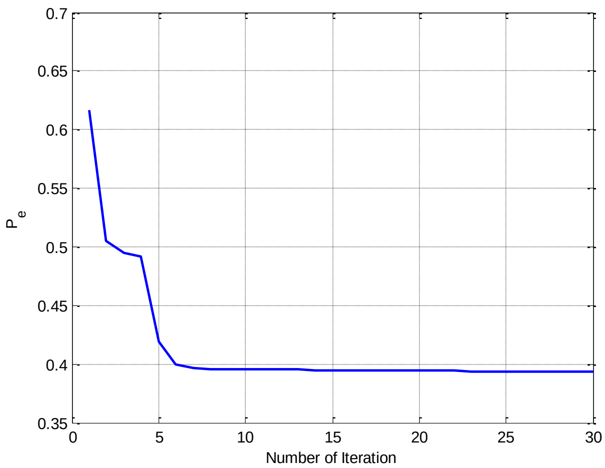

Figure 3. Performance of PSO-based method

The convergence of PSO based scheme for a given $\lambda = 6$ is shown in figure 3. It can be seen that the probability of error converges after around 30 iterations, which is so fast that it can ensure the computation complexity of the proposed method meets real time requirements of cognitive radio cooperative spectrum sensing. The standard deviation of the obtained probability of detection under 25 simulations can be negligible, which means that the PSO-based method is quite stable

REFERENCES

[1] S.Haykin, “Cognitive radio: Brain-empowered wireless communications,” IEEE J. Sel. Areas Commun., vol. 23, no. 2, pp. 201–220, Feb. 2005
[2] J. Ma, G. D. Zhao, and L. Ye, “Soft combination and detection for cooperative spectrum sensing in cognitive radio networks,” IEEE Transactions on Wireless Communications, vol. 7, no. 11, pp. 4502- 4507, 2008.
[3] D. C. Oh, H. C. Lee, and Y. H. Lee, “Linear hard decision combing for cooperative spectrum sensing in cognitive radio systems,” IEEE 72nd Vehicular Technology Conference, Ottawa, Canada, pp. 1-5, Sep. 2010
[4] B. Shen and K. S. Kwak, “Soft Combination Schemes for Cooperative Spectrum Sensing in Cognitive Radio Networks,” ETRI Journal, vo. 31, no. 3, 2009.
[5] Wei Zhang, Member, IEEE, Ranjan K. Mallik, Senior Member, IEEE, and Khaled Ben Letaief, Fellow, IEEE “Optimization of Cooperative Spectrum Sensing with Energy Detection in Cognitive Radio Networks”, IEEE transactions on wireless communications, vol. 8, no. 12, December 2009.

[6] J. Ma and Y. Li, “Soft combination and detection for cooperative spectrum sensing in cognitive radio networks,” in Proc. IEEE Global Telecomm. Conf., 2007, pp. 3139–3143
[7] Zhi Quan, Shuguang Cui, H. Vincent Poor, and Ali H. Sayed, “Collaborative wideband sensing for cognitive radios,” IEEE Signal Processing Magazine, Vol. 25, No. 6, pp. 63–70, 2008
[8] J. Kennedy, and R. C. Eberhart, “Particle swarm optimization”, Proc. IEEE International Conference on Neural Networks, Australia, 1995.
[9] J. Kennedy and R. C. Eberhart, Swarm Intelligence, Morgan Kauffman Publishers, California, 2001.
[10] M. Løvberg and T. Krink. “Extending Particle Swarm Optimisers with Self-Organized Criticality”. In Proceedings of the IEEE Congress on Evolutionary Computation, 2002
[11] C. Mendis, S. M. Guru, S. Halgamuge, and S. Fernando, "Optimized Sink node Path using Particle Swarm Optimization", 20th International Conference on Advanced Information Networking and Applications, IEEE computer society, 2006
[12] M. Adib Sarijari, Rozeha A. Rashid, N. Fisal, A. C. C. Lo, S. K. S. Yusof, N. H. Mahalin, “Spectrum Sensing Measurement Using GNU Radio and USRP Platform, 7th International Conference on Wireless & Mobile