Optimization of Detection Error Rate in Cooperative Sensing using ACO algorithm

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Abstract:* Cognitive radio (CR) is the next generation communication technology that combined the use of radio technology and networking technology. One of the key elements of cognitive radio is Cooperative spectrum sensing which sensing results from a different node are combined either through hard decision fusion (HDF) scheme or through soft decision fusion(SDF) scheme at fusion center (FC). SDF has excellent performance, but a lot of overhead is required while HDF requires only one bit of overhead, but has the worst performance. There is a trade-off between overhead and accuracy in this conventional scheme. In this paper, ant colony optimization (ACO) based hybrid cooperative sensing framework is proposed which optimizes the weighting coefficient vector of sensing result from a different node. The novelty of this paper is to use the ACO algorithm as significant tools that evaluate the optimal values of sensing weight for cooperative sensing so that it minimizes the overall cooperative sensing error under min-max criteria. The performance of the proposed ACO based framework is thoroughly analyzed and compared with conventional HDF approaches i.e. AND, OR, majority as well as conventional SDF based approaches like equal gain combing (EGC), MRC, etc., through simulation. The experimental result shows the proposed framework outperforms with the conventional HDF scheme and it has a low overhead requirement compared to the conventional SDF scheme. Finally, analytical evaluation and validation for the performance of ACO algorithm in this framework is also examined and it gives the excellent convergence performance with lower computation time and less complexity which meet the real-time requirement of cooperative spectrum sensing

***Keywords*: Ant Colony Optimization, Cognitive Radio, Equal Gain Combining, Fusion Center, Primary User, Soft Decision Fusion Rule, Hard Decision Fusion Rules.**

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I. INTRODUCTION

According to federal communications board (FCC) report about 80% of the spectrum is idle most of the time because the existing frequency allotment policies cannot fulfill the actual time requirement such that the operators are allowing opportunistic access to licensed spectrum limited by no integer. The inefficiency of the radio spectrum used when a large part of the licensed spectrum is not used in today's wireless communication system. The modern age of wireless communications is intelligent radio. It is a smart radio. The appearance or absence of a Main User (PU) signal should be determined by secondary users (SU) for network of cognitive radio to reduce interference placed on licensed users. Due to propagation loss SU interference, the PU signal is often subject to deep decay. In order to mitigate the effects of fading effects, we should use the benefit of variety to co-detect spectrum in the cognitive radio for wireless communication by employing multiple SUs.These SUs pass their observation to fusion center (FC), which responsible for final decision, in this cooperative spectrum detection system. If SUs send complete sensors obtained to FC without deciding, the soft mix is called. If SUs send in the form of a binary bit their decision, if the main signal is present or absent from FC, then this is called a hard combination [1]. The main user signal is present or absent. The soft combination has a higher accuracy but it is complex while hard combination has lower complexity but it not complex. In a general way, there is a trade-off between complexity and accuracy.

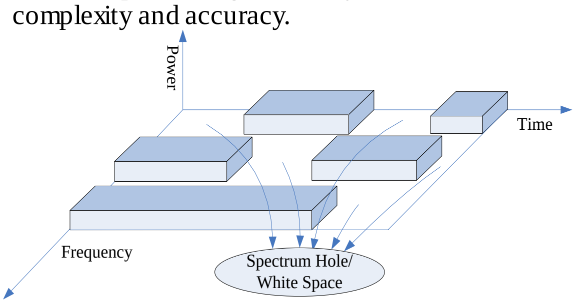

Fig. 1. Idle spectrum Utilization

In cooperative spectrum sensing (CSS), the way the local decision sends to the FC provides a major role. Global decision is based on sensing data sent to FC by SU, in this cooperative spectrum detection system. If SUs send complete sensors obtained to FC without deciding, the soft mix is called [2]. If SUs send in the form of a binary bit their decision, if the main signal is present or absent from FC, then this is called a hard combination. The soft combination has a higher accuracy but it is complex while hard combination has lower complexity but it not complex. In this paper, we focus on quantized cooperative sensing of spectrum situation where weighing vector optimum is measured, where the softened hard measurements from SU are sent to the FC. To improve detection efficiency, ant colony optimization (ACO) scheme is proposed for CSS. Results of simulations and analysis indicate that the proposed systems in comparison with traditional soft decision fusion (SDF), i.e. the equal gain combing (EGC) and modern fusion hard decision, such as AND, OR, MAJORITY, etc., are successful and stable. The scheme is also strong in convergence, which verifies that the ACO has a lower calculation complexity.

II. Spectrum Sensing

One of the challenging functions of cognitive radio is Spectrum sensing, as it is first required before CR consumers have access to a permitted vacant link. The spectrum analysis helps to distinguish between the two possibilities, the H0: no transmitted signal and the H1: transmitted signal. In this case, the likelihood of false P_f warning this is a possibility of signal existence being identified even though it doesn't occur and the probability of detection P_d is a possibility that a correctly sensed signal does appear. There is also the probability of a fake message.

$$x(t) = \begin{cases} n(t) & H_0 \\ hs(t) + n(t) & H_1 \end{cases} \quad (1)$$

When the secondary user receives x(t), and s(t) is the primary user signal, the additional white noise of the white Gaussian (AWGN) is the n(t), and the channel is enhanced by amplitude. The signal-to-noise ratio (SNR) is often demonstrated by γ

$$P_d = P\{Y > \lambda | H_1\} = Q(\gamma, \lambda) \quad (2)$$

$$P_f = P\{Y > \lambda | H_0\} = \frac{\Gamma(TW, \lambda/2)}{\Gamma(TW)} \quad (3)$$

$$P_m = 1 - P_d \quad (4)$$

In equation 4, $\Gamma(.,..)$ is the incomplete gamma, λ is the threshold of energy detection, the time-bandwidth ration is TW of the detector, $Q(.,..)$ is generalized Marcum Q-function which is also used in the spectrum sensing estimation of the cognitive user and γ is the signal to noise ratio (SNR). According to Neyman-Pearson criteria the threshold of i^{th} secondary user is evaluated by the equation

$$\lambda^* = 2\Gamma^{-1}(P_f, TW) \quad (5)$$

Replace the above-mentioned threshold for a detection equation likelihood, gives the recipient operating properties (ROC) for the following false alert.

$$P_d = P\{Y > \lambda | H_1\} = Q(\gamma, \lambda^*) \quad (6)$$

When there are many airplane waves in the composite signal received, there is a Rayleigh distribution for some types of scattered environments [3]. With Rayleigh's degradation, gamma will have an exponential variance distribution,

$$f(\gamma) = \frac{\gamma}{\bar{\gamma}} exp\left(\frac{\gamma}{\bar{\gamma}}\right), \gamma \geq 0 \quad (7)$$

For this case, probability of detection formula can be obtained (after some mathematical calculation) in a closed form by replacing $f(\gamma)$ in the equation (7) by

$$P_{dRay} = e^{-\frac{\lambda}{2}} \sum_{k=0}^{u-2} \frac{1}{k!} \left(\frac{\lambda}{2}\right)^k + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{u-1} \ldots\ldots\ldots \left(e^{\frac{\lambda}{2(1+\bar{\gamma})}} - e^{-\frac{\lambda}{2}} \sum_{k=0}^{u-2} \frac{1}{k!} \left(\frac{\lambda\bar{\gamma}}{2(1+\bar{\gamma})}\right)^k\right) \quad (8)$$

One of the key problems in spectrum sensing is the secret terminal issue of the case when the cerebral antenna is shaded or in the extreme fade. Multiple cognitive radios may collaborate to alleviate this issue by spectrum sensing, thereby improving the possibility of identification in fading networks [4]. For cooperative sensing of spectrum, a specific receiver calculates the likelihood of false warning and the likelihood of identification using the average probability of increasing CR. The probability of false alarm is following [5][6].

$$Q_f = \sum_{k=n}^{N} \binom{N}{k} P_f{}^k (1 - p_f)^{N-k} = prob\left\{\frac{H_1}{H_0}\right\} \quad (9)$$

Also, Detection probability is given by;

$$Q_d = \sum_{k=n}^{N} \binom{N}{k} P_d{}^k (1 - p_d)^{N-k} = prob\left\{\frac{H_0}{H_1}\right\} \quad (10)$$

Each cognitive user senses the channel in a hard-combing fusion system Devises whether or not the primary consumer is present and sends to the data fusion centre a one-bit decision. This method requires a limited bandwidth [7] which is the main advantage. If conditional choices are submitted to a specific node, the "MAJORITY", "OR" and "AND" principles should be used. When CR users use the soft combination-based fusion system to send the entire sensing result to FC without having to make local decisions, and the decision is calculated by collecting this result in the fusion center, using appropriate combination rules such as the EGC, MRC, etc. In EGC scheme, equal weightage is given to each sensing node while in MRC weightage is given based on this SNR. More overhead is also occurring than the hard combination system [8] [9].

$$Q_{d,MAJORITY} = \sum_{K=N/2}^{N} \binom{N}{k} {P_d}^k (1-p_d)^{N-k} \quad (11)$$

$$Q_{d,OR} = 1 - (1 - P_d)^N \quad (12)$$

$$Q_{d,AND} = {P_d}^N \quad (13)$$

III. SYSTEM MODELLBO ALGORITHMS

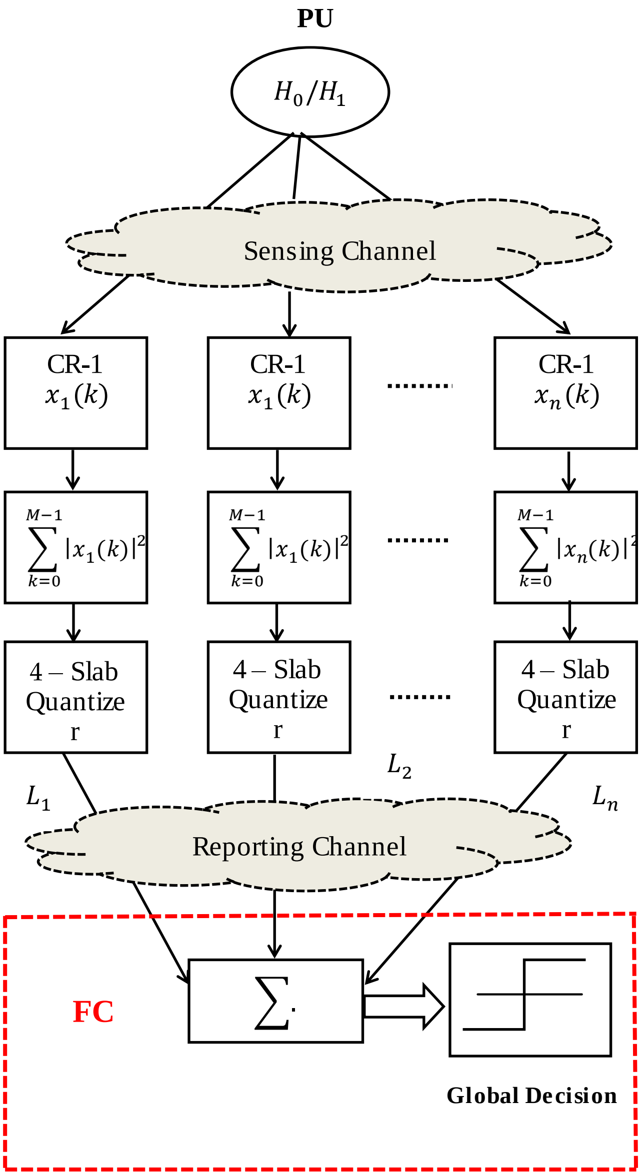

Fig.2 The architecture of the proposed system

Figure 2 displays the device model of the proposed structure for the cooperative spectrum detection process. In that architecture, each co-operating secondary node, first of all, senses the channel locally and sends their observation in the form of a quantized local level to the fusion center as L_n(index of the quantization slab). The FC takes a global decision in compliance with L_n and the weight given to their observed energy level.

Detection by assigning different weights in the soft data fusion system to Various CR consumers by their SNR is not performed well because sometimes malicious node can change SNR value and it leads to an improper decision. In the conventional HDF method, there is just one threshold that divides the whole spectrum of energy measured through two levels. As such, all secondary nodes in this stage (CR), regardless of the considerable energy differences, have the same weight. In softened hard two-bit hard combination data fusion method or our proposed ACO based algorithm achieved improved detection efficiency and less difficulty with the overhead of two bits by grouping the whole measured energy range into four stages and assigning the plate unique weights.

Whilst the soft data fusion method offers the greatest identification performance, soft mix schemes need loads of overhead to relay the findings periodically through each CR customer. For each CR Node the current hard blend method only needs a bit of overhead but is influenced by a lack of local decision-making expertise. Looking at these two examples, we can conclude that there is an overhead-accuracy balance

According to its 2-bit meaning metric and weight for the increasing unit, the FC takes a global judgment. When we split the measured energy into two slabs, rough decision logic like AND, MAJORITY and OR logic, can be extended to the general decision logic of the fusion center [10]. In this case, however, for the further quantization, each cognitive user can either send only 0 and 1 for L no of levels. Every cooperative user sends two-bit data as an index for his or her measured resources, we use four quantization level is used for the above example.

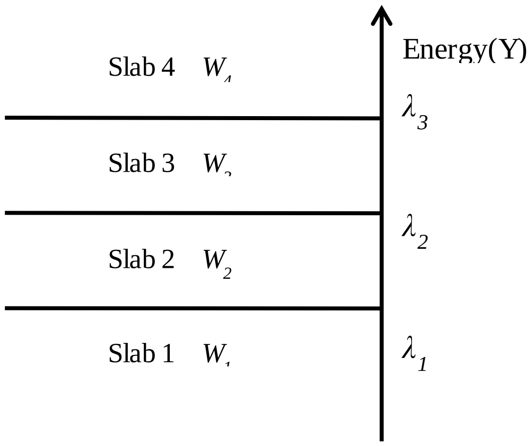

Fig.3 Principal of proposed two-bit scheme

Here, we can use a quantified hybrid scheme with a two-bit overhead for each CR end, which ensures excellent detection efficiency and overhead is very less. Figure2 illustrates the concept of a proposed scheme data fusion system. There are 4 two-bit thresholds, which split the whole continuum of measured energy into 4 slabs depending on the sensing outcome contrasted with the conventional one-bit method with a single threshold only. Via a cooperative secondary consumer locally senses the spectrum and sends information on the calculated energy level using two-bit "quantified details"

The likelihood that the H_0 and H_1 and AWGN channels are found in their respective plate is the following [11]

$$P_{di} = \begin{cases} 1 - P_d(\lambda_k) & if\ k = 1 \\ P_d(\lambda_{k-1}) & if\ k = n \\ P_d(\lambda_{k-1}) - P_d(\lambda_k) & otherwise \end{cases} \quad (14)$$

In the suggested solution, the global determination relies on the threshold values and the weight function. The weights here are not the reporting nodes assigned to the energy platform. The fusion center collects measurements and counts the number of users for each measuring device specified below to achieve the soft-hard combination-based data fusion method.

$$\vec{N} = [n_1 n_2\ n_3\ n_4] and \vec{W} = [w_1 w_2\ w_3\ w_4]$$

The calculation of decision function is evaluated based on the weights and number of users of the energy level.

$$f(\overrightarrow{w}) = \begin{cases} 1 & if \vec{N}.\vec{W} > 0 \\ 0 & otherwise \end{cases} \quad (15)$$

Here is provided the weighted description

$$N_c = \sum_{i=0}^{3} w_i . N_i \quad (16)$$

Where N_i= observed energies number falling in i.

In the equation (16), compare N_c with threshold N_T If $N_c \geq N_T$, PU is present otherwise it decided to absent. The probabilities for collaborative detection using a Rayleigh channel are extracted employing the endorsed hard (quantified) combination fusion strategy [12] as provided below.

$$P_d = \sum_{i=1}^{4} \sum_{j=1}^{4} P_r(N_1 = n_1 \ldots . N_4 = n_4 | H_1) \quad (17)$$

$$P_d = \sum f(\overrightarrow{w}) \binom{N}{n_1} \binom{N - n_1}{n_2} \binom{N - n_1 - n_2}{n_3} \ldots \ldots \ldots \ldots$$
$$.. (1 - P_{d1})^{n_1} (P_{d1} - P_{d2})^{n_2} (P_{d2} - P_{d3})^{n_3} (P_{d4})^{n_4} \quad (18)$$

The likelihood of false alarm can be also be equated. The general probability of error can be represented as [13]–[16]

$$P_e = P_f(\overrightarrow{w}) + 1 - P_d(\overrightarrow{w}) \quad (19)$$

$$P_e \propto f(\overrightarrow{w}) \quad (20)$$

The probability of error is strongly contingent $(\overrightarrow{w})$ on the function is observed. The optimal approach is then to measure the matrix, which minimizes the overall probability of error Pe. The equation (18) in our text is used to limit the probability of error as objective functions.

So, Problem of optimization

$$Minimize P_e\ limit\ to -5 \leq\ w_i \leq 5$$

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IV. ACO ALGORITHM BASED SOLUTION

Ant Colony Optimization is influenced based on the actions of actual animals in nature, and their actions are plain [17]. However, by teamwork, the ants may determine the minimal route between their nest and food. Actually, during the cycle of forage, the ant can drop on the pathway a chemical material called a pheromone; it will inject pheromone on the track and evaporate with time [18]. The pheromone and its strength can occur in this course from other ants of the same colony. Higher the amount the pheromone concentrate, the greater the likelihood of path being chosen, and vice versa, the ants rely always-on information to search the path. Both ants choose the shortest route after a time of quest. The distribution of ants across various times is seen as shown in figure 4.

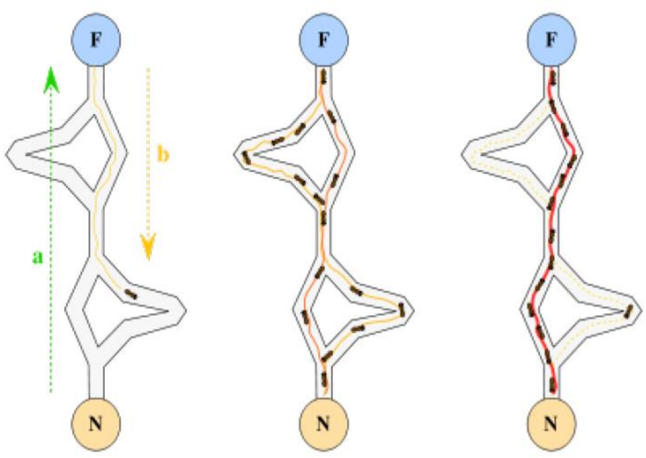

Fig. 4 ACO concept[33]

In figure 4, the following can be observed. The ants number in the path a and b is roughly the same in the initial period of the food searching behaviour of ant for optimization. Over time, the pheromone is higher in a shorter path than the original route in the middle figure, which is enticing for more ants. Ultimately, virtually all the ants chose the best track as seen in the figure.

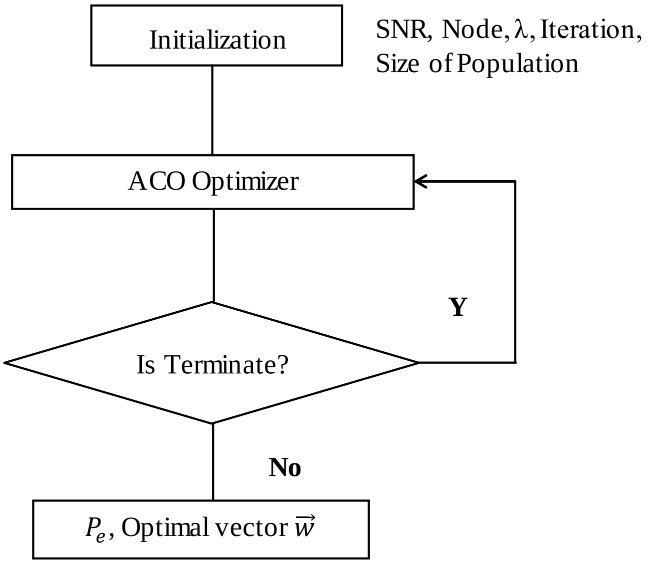

Fig.5 ACO Flow Chart

ACO algorithm was first proposed by Marco Dorigo [19] which is initially used to solve the Travelling Salesman issue in a decade of 90. In this case, ACO can be represented as the G = (V, E, T) graph, in which V refers to the node collection and an increasing node represents the area. E is the range of tip, and T is the pheromone amount.

The details flow chart of ACO algorithms are shown in the above figure 5 in which algorithms start with initialization of parameter like SNR, Number of nodes, threshold(λ), Number of Iterations and Size of Population. This initial value is given to the ACO optimizer which used to find the optimal value of the weighting coefficient vector for minimization of the probability of sensing error. This algorithm works until some criteria are not satisfied or the number of iterations is over. At the end of the entire iteration process, the optimal value of the weight vector is obtained for the minimization of total sensing error which is shown in the mentioned figure. Two aspects of the basic ACO model are individual ant routing and pheromone update [34]. First, when the ants are searching for the path, two variables can be listed. The first variable is the measure of support η (t), also called heuristic information, which is a problem specific. Such calculation will store costs or the utility of a decision. The second one is the pheromone function, τ_{ij} (t) and it is defined by following

$$\tau_{ij}(t+1) = (1-\ p)\tau_{ij}(t) + \Delta\tau_{ij} \tag{21}$$

Where
τ_{ij} is the pheromone amount for given edge i,j
p is the pheromone evaporation rate
$\Delta\tau_{ij}$ is the deposited amount of pheromone

The mathematical formulation for the different conditions of ants are derived through the actual movement of ant from their nest to food location.

Ant passes with probability P_{ij} (t) from node I to node j.

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{allowedK}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}} \tag{22}$$

Where
τ_{ij} is the pheromone amount for given edge i,j
α is the control parameter for the influence of τ_{ij}
η_{ij} is the edge desirability of i,j
β is the control parameter for the influence of τ_{ij}

The equation (22) allows metaheuristic technology and further technologies to be built from vehicle routing problems to wireless networking and spectrum sensing.

ACO 's principal benefits are the intrinsic parallelism and robust implementation that allows it to be used for dynamics [20]. Thanks to ACO's advantages it has become necessary to incorporate ACO in the sensing of spectrum activities, because of the need to find innovative methods of describing and simulating the actions of users of cognitive nodes. For routing data packets and web-based applications, other ACO technologies are also available. Wang et al. have presented a multi-cast path algorithm to reduce traffic on hypercube networks in multi-channel communications. Lin et al. present a Navigation Trend Detection System focused on ACO that uses a help method based on actual pages transformations [21]. To increase the probability of benefit, White et al. utilizes ACO to increasingly identify the strongest correlation between web content and online ads. A vector space model with the notion of the preferred web user is used for this purpose. ACO-based algorithm for forecasting site usage trends that involves mining web content as well as mining of web use is present in Loyola et al.

Algorithm: ACO Algorithm for Weight Optimization

I/O: SNR, User(N), Iteration, Particle Size, TW, Channel
Set the initial value of the solution $x_i(i = 1,2, \dots SN)$
and Pheromone value(τ)
$Interation = 1;$
While $Iteration <= Target\ Value$ **do**
    $x_{interation} = \emptyset$
    $x_{best} = NULL$
    For $j = 1 \dots\dots n$ **do**
        Solution x_j = Construct Solution(τ)
        If x_j is valid solution **then**
            x = Local search result(x)
            If $f(x) < f(x_{best})$ $or\ = NULL$ **then**
            $x_{best} = x_i$
            $x_{interation} = x_{iteration} U \{x_j\}$
        End if
    End for
    Apply the updated value (τ, $x_{interation}, x_{best}$)
End while
O/P: Optimal weight vector $\vec{w},\ P_e$

Fig.6. Pseudocode for ACO Algorithm

V. SIMULATION RESULT AND DISCUSSION

Effectiveness of the proposed cooperative sensing system based on the ACO is assessed by computer simulation to check the effectiveness of the proposed framework. In this simulation we have taken the total number of cooperative user/nodes is 10, time-bandwidth product TW=2, SNR=2dB, received signal samples number $M = 2$, a channel is Rayleigh. We have also assumed that there is not a false reporting node and not any imperfect channel. In ACO algorithm, we have taken the simulation for 30 iterations, α =2.0 β = 2.0, ρ = 0.8, τ =1 and other simulation parameter is taken as the default value of ACO algorithms.

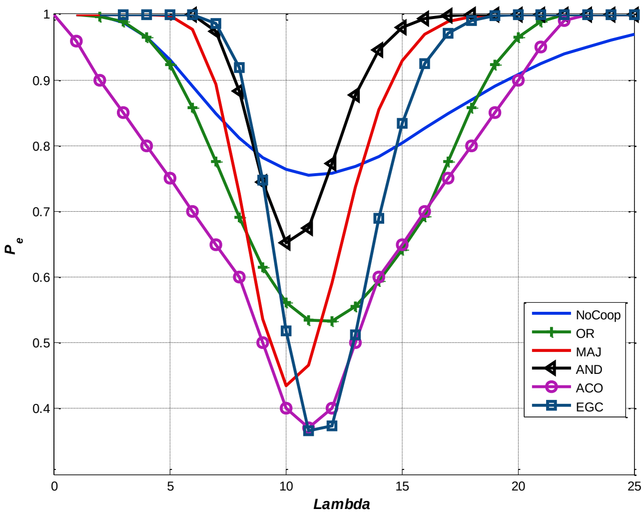

Fig.7 Result of Lambda versus cooperative sensing error P_e

Figure 7 shows the graph of λ versus cooperative sensing error P_e for different decision fusion schemes. In the simulation result, the performance of ACO based cooperative spectrum sensing improved by increasing the threshold value and it reaches at the best value for the optimum value of the threshold. From figure 7, it is observed that the ACO based proposed framework finds the optimal vector weighting coefficients to minimise sensor error likelihood as compared to other conventional decision fusion schema at the fusion center. From the result, it is also shown that there is the worst performance in terms of sensing error for conventional HDF i.e. AND, OR, MAJ, etc., due to very less amount information collected from the SU at the FC. On the other hand, The achievement is outperformed in the suggested system with the conventional SDF scheme like EGC with low overhead.

P_d detection probability is also a very important parameter which is useful for evaluating and comparing the efficiency of the proposed ACO based system with other methods. P_d is inversely proportional to the probability of the P_m miss detection. The trade-off between P_d and P_f is, therefore. The complementary operating characteristic receiver (C-ROC) is used for the output evaluation between P_d and P_f shown in figure 8.

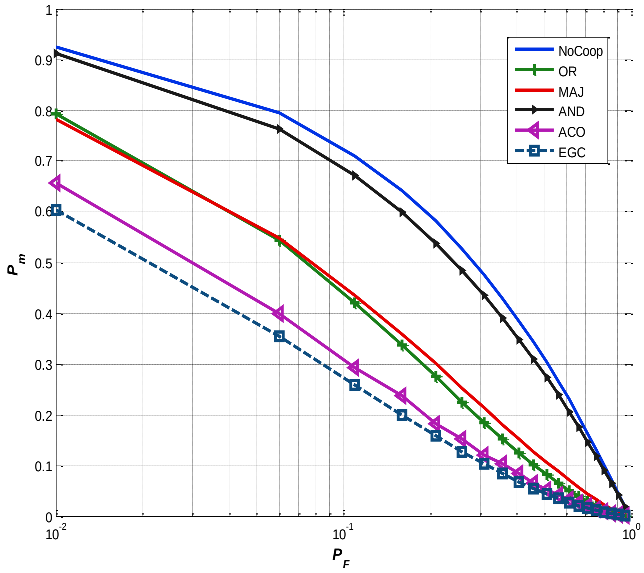

Fig.8 C-ROC curve for the proposed framework

Figure 8 shows the impact of SNR on the efficiency of the proposed ACO system. In this simulation we have taken the total number of cooperative user/node is 10, time-bandwidth product TW=2, SNR= 2dB, received signal samples number $M = 2$,. We have also assumed that there is not a false reporting node and not any imperfect channel. In ACO algorithm we have taken the simulation for 30 iterations, α =2.0 β = 2.0, ρ = 0.8, τ =1 and other simulation parameter is taken as a default value of ACO algorithms. From this graph, it is shown that the implementation of the plan ACO based method increases as SNR increases and the performance of OR logic and proposed framework is the same when the SNR value is 10dB.

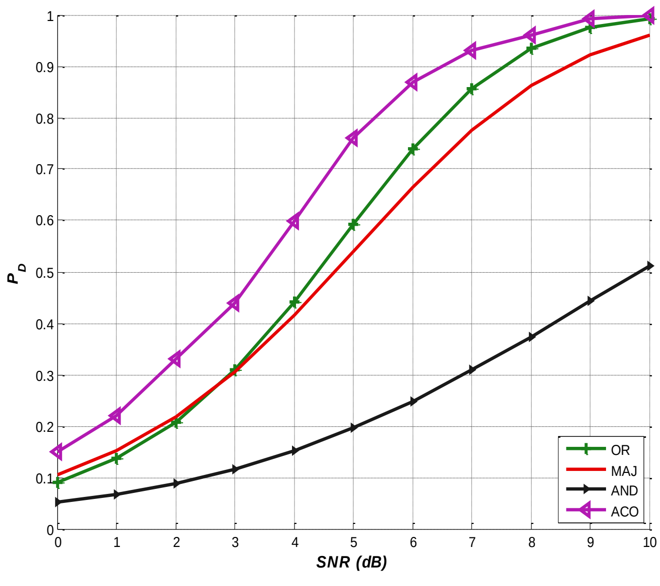

Fig.9 Graph of SNR versus probability of detection

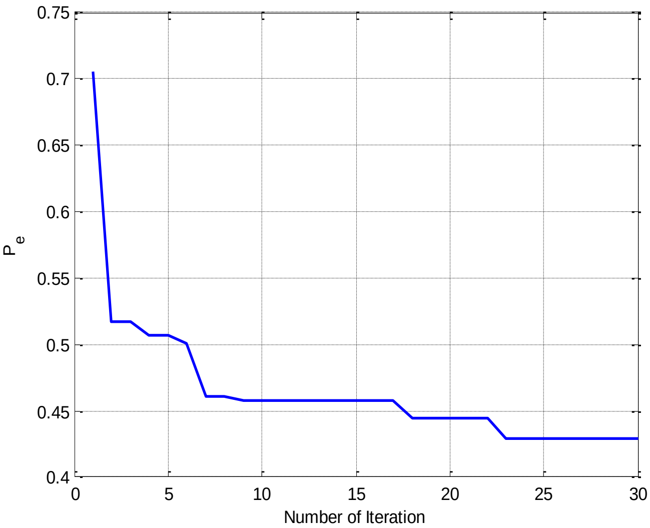

Fig.10 ACO based method Performance

The convergence performance of Ant Colony ACO based cooperative sensing framework for a given $\lambda = 6$ is shown in figure 10. It is shown in the simulation result that the proposed ACO based solution makes stable after 25 cycles, which it indicates that it very fast to becomes stable and also have less complexity with low overhead which the essential requirement of the real-time application of cooperative spectrum sensing

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VI. CONCLUSION AND FUTURE WORK

In this research paper, ACO based cooperative sensing framework is proposed to optimize the weighting coefficient vector of local sensing results which have a 2-bit hybrid decision fusion scheme at the fusion center. The results of the simulation conclude that the proposed system with a low overhead is stable and efficient. It gives the excellent performance with conventional HDF and SDF based cooperative spectrum sensing method. It gives almost 10% to 20% improvement in sensing error compared to this conventional scheme with the same environment with low overhead. ACO based framework gives better convergence output with lower computation time and less complexity in the wireless environment which meet the real-time requirement of spectrum sensing

REFERENCES

[1] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative Spectrum Sensing in Cognitive Radio Networks: A Survey," *Phys. Commun.*, vol. 4, no. 1, pp. 40–62, Mar. 2011.

[2] R. L. Haupt and S. E. Haupt, *Practical genetic algorithms*. John Wiley & Sons, 2004.

[3] P. K. Varshney, *Distributed detection and data fusion*. Springer Science & Business Media, 2012.

[4] J. Ma, G. Zhao, and Y. Li, "Soft Combination and Detection for Cooperative Spectrum Sensing in Cognitive Radio Networks," *IEEE Trans. Wirel. Commun.*, vol. 7, no. 11, pp. 4502–4507, Nov. 2008.

[5] Z. Quan, S. Cui, and A. H. Sayed, "Optimal Linear Cooperation for Spectrum Sensing in Cognitive Radio Networks," *IEEE J. Sel. Top. Signal Process.*, vol. 2, no. 1, pp. 28–40, Feb. 2008.

[6] M. Ranjeeth, "Cooperative spectrum sensing with square law combining diversity reception," in *2015 3rd International Conference on Signal Processing, Communication and Networking (ICSCN)*, 2015, pp. 1–6.

[7] B. Wang, K. J. R. Liu, and T. C. Clancy, "Evolutionary cooperative spectrum sensing game: how to collaborate?," *IEEE Trans. Commun.*, vol. 58, no. 3, pp. 890–900, Mar. 2010.

[8] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt Generation/Dynamic Spectrum Access/Cognitive Radio Wireless Networks: A Survey," *Comput. Netw.*, vol. 50, no. 13, pp. 2127–2159, Sep. 2006.

[9] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proc. IEEE*, vol. 55, no. 4, pp. 523–531, Apr. 1967.

[10] D.-C. Oh and Y.-H. Lee, "Cooperative spectrum sensing with imperfect feedback channel in the cognitive radio systems," *Int. J. Commun. Syst.*, vol. 23, no. 6–7, pp. 763–779, 2010.

[11] S. J. Zahabi, A. A. Tadaion, and S. Aissa, "Neyman-Pearson Cooperative Spectrum Sensing for Cognitive Radio Networks with Fine Quantization at Local Sensors," *IEEE Trans. Commun.*, vol. 60, no. 6, pp. 1511–1522, Jun. 2012.

[12] H. Sakran, M. Shokair, E. S. El-Rabaie, and A. A. El-Azm, "Three bits softened decision scheme in cooperative spectrum sensing among cognitive radio networks," in *2011 28th National Radio Science Conference (NRSC)*, 2011, pp. 1–9.

[13] C. W. Helstrom, "Improved multilevel quantization for detection of narrowband signals," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 24, no. 2, pp. 142–147, Mar. 1988.

[14] W. A. Hashlamoun and P. K. Varshney, "Near-optimum quantization for signal detection," *IEEE Trans. Commun.*, vol. 44, no. 3, pp. 294–297, Mar. 1996.

[15] M. Mustonen, M. Matinmikko, and A. Mammela, "Cooperative spectrum sensing using quantized soft decision combining," in *2009 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, 2009, pp. 1–5.

[16] H. A. Shah and I. Koo, "CSS..Optimal Quantization and Efficient Cooperative Spectrum Sensing in Congnitive Radio Networks," *2015 Int. Conf. Emerg. Technol.*, pp. 1–6, 2015.

[17] X. Deng, W. Yu, and L. Zhang, "A new ant colony optimization with global exploring capability and rapid convergence," in *Proceedings of the 10th World Congress on Intelligent Control and Automation*, 2012, pp. 579–583.

[18] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," *IEEE Trans. Syst. Man, Cybern. Part B*, vol. 26, no. 1, pp. 29–41, 1996.

[19] L. Li, S. Ju, and Y. Zhang, "Improved Ant Colony Optimization for the Traveling Salesman Problem," in *2008 International Conference on Intelligent Computation Technology and Automation (ICICTA)*, 2008, vol. 1, pp. 76–80.

[20] H. M. Rais, Z. A. Othman, and A. R. Hamdan, "Improved Dynamic Ant Colony System (DACS) on symmetric Traveling Salesman Problem (TSP)," in *2007 International Conference on Intelligent and Advanced Systems*, 2007, pp. 43–48.

[21] A. YILDIZ, M. POLAT, and M. T. �zdemir, "Design Optimization of Inverted Switched Reluctance Motor using Ant Colony Optimization Algorithm," in *2018 International Conference on Artificial Intelligence and Data Processing (IDAP)*, 2018, pp. 1–6.

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