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Optimization of Cooperative Spectrum Sensing Using Genetic Algorithm (GA)

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Abstract — *Cognitive radio (CR) is a new paradigm wireless communication system which is use for efficient utilization of radio frequency (RF) spectrum or RF channel for future wireless communication. Spectrum sensing is the key component of cognitive radio technology. Cooperative spectrum sensing has proven its efficiency to detect spectrum holes in cognitive radio network (CRN) by combining sensing information of multiple cognitive radio users The sensing information from CR users combines at the Fusion center (common receiver) by soft combination or conventional hard combination techniques. Soft combination has excellent performance but, it requires a lot of overhead for feedback observation. In contrast, the conventional hard combination scheme requires only one bit of overhead, but it has worst performance because of loss of information caused by local hard decisions. Weighting the coefficients vector is the principal factor influencing the detection performance of the system in softened hard decision fusion based cooperative spectrum sensing. In this paper, the use of Genetic algorithm (GA) based on the Neyman-Pearson criterion as a significant method is proposed to optimize the weighting coefficients vector so that the probability of detection is improved. The proposed technique investigates the best weighting coefficients vector. The performance of the GA-based proposed method is examined and compared with soft combination technique as well as other conventional hard data combination scheme through computer simulations. Simulation result shows that detection performance of proposed GA based method is very close to equal gain combiner (EGC) which validate the strength of the proposed GA based method.*

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

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.

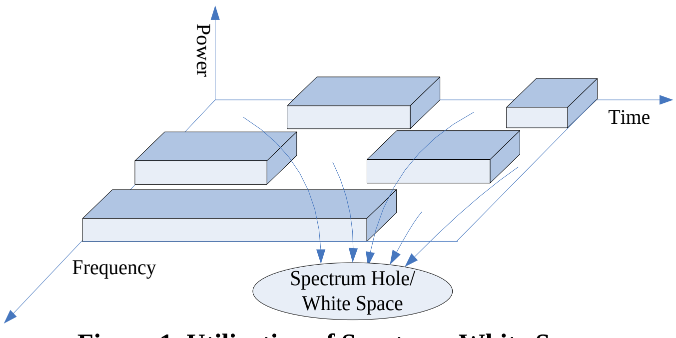

Figure 1. Utilization of Spectrum White Space

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 combination [2]. On the other hand, if SUs send their decision information to FC (general one-bit decision), it is called hard combination [3]. In a general way, the cooperative spectrum sensing with soft combination performs better than that with hard combination. However, the soft combination requires more traffic for SUs to feedback the sensing information. In contrast, the hard combination needs only one bit of overhead for each SU. It is obvious that the spectrum efficiency in hard. In this paper, we assume that each secondary user relies on energy detection for sensing. The way the local decision is reported to the fusion centre plays a main role in cooperative schemes in general and in spectrum sensing.

Quantized Cooperative spectrum sensing scheme have been proposed in various literatures. In [4], a spectrum sensing technique utilizing Welch's periodogram is proposed, along with the trade-off between the sensing information and cooperative users. In [5], the sensing procedure is based on Dempster-Shafer theory. Both uniform quantization and

Lloyd-max quantization techniques are considered. Also, in [6], Lloyd-max algorithm is used to minimize error for the optimal quantizer. In [7], Neyman-Pearson criterion is used. Log-likelihood is used in [6], [7] and, hence, increases the complexity for the system. In [8], the two-bit quantization scheme is proposed to maximize the probability of detection for a given false alarm. However, the optimal parameters need to be optimized.

The paper is organized as follows. We present in Section II cooperative spectrum sensing introduction In Section III, we describe the system model related to cooperative spectrum sensing and different data fusion scheme for cooperative spectrum sensing; several hard, soft and quantized schemes are proposed and discussed. In Section V we describe optimization of weight using Genetic algorithms(GA). Simulation results in section VI are given for our propsed *softened* hard data fusion scheme. We conclude this paper in Section VI.

II. COPERATIVE SPECTRUM SENSING

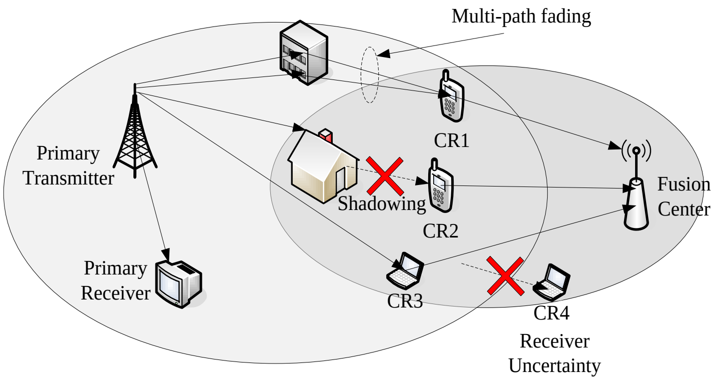

Figure 2.Cooperative spectrum sensing model of cognitive radio

Suppose there are N Secondary User (SU) and a FC in the Cognitive Radio RN, as shown in Fig 2. SUs sense their local spectrum information individually, and send their binary decisions to fusion centre, which make a final decision whether a PU is present or not. The goal of the spectrum sensing is to decide between the two hypotheses, *H*0: no signal transmitted, and *H*1: signal transmitted [9]. 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.

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

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 [10]

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

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

$$P_m = 1 - P_f$$

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 Threshold of CR user according to *Neyman-Pearson* criterion is given by

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

An alternative way of summarizing the detection performance of Neyman-Pearson based detector is to use the receiver operating characteristic (ROC) curve. Eliminating threshold from the above equation, gives the ROC curve of CR as:

$$P_d = Q(\gamma, \lambda^*)$$

The 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;

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

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 [10]. 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

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

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 [11]. When binary decisions are reported to the common node, three rules of decision can be used, the "AND", "OR", and "MAJORITY". Cognitive user send 1 means that the signal is present, and 0 means that the signal is absent. 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), maximal ratio combining (MRC) and selection combining (SC). Soft combination provides better performance than hard combination, but it requires a larger bandwidth for the control channel for reporting [12]. It also generates more overhead than the hard combination scheme [11].

III. SYSTEM MODEL

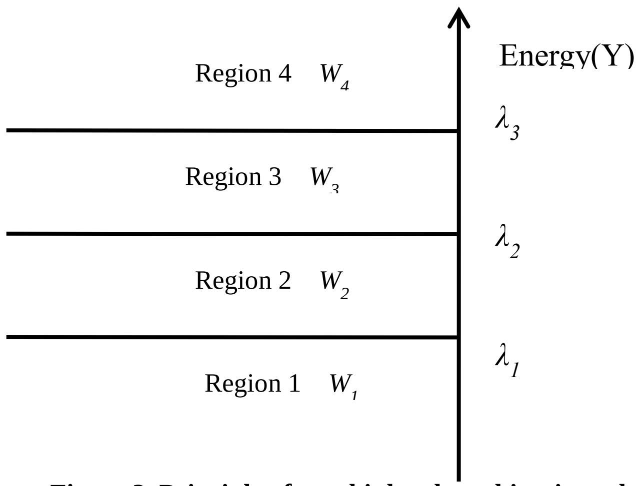

Figure 3. Principle of two-bit hard combination scheme

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 by dividing the whole range of the observed energy into more regions, and allocate a different weights to this region

Figure 3 shows the principle of the *softened* two-bit hard combination based data fusion scheme. Different from the conventional one-bit scheme with only one threshold, three thresholds in the two-bit scheme, λ1, λ1 and λ3, divide the whole range of the observed energy into 4 regions. Each cooperating secondary user senses the spectrum and sends its two bit information “quantized data ” to indicate which region its observed energy falls in to the fusion center at the cognitive base station. The fusion center makes a global decision according to its 2-bit value measurement.

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.

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

Here the weighted summation is given by

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

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

Then $N_c$is compare with the threshold, N_T If N_c≥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 [13] which is given by following.

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

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

The main goal of spectrum sensing is to decide between two hypotheses that the channel state is empty H_0 or it is actively used H_1.The most suitable optimality criterion for the decision is Neyman-Pearson optimality that maximizes the probability of detection. Proposed softened hard combination data fusion scheme and global decision logic need to optimize the weight vector $(\vec{w})$ by following

Optimization Problem: $Maximize\ P_d\ suject\ to\ P_f \leq \alpha$

3.1. Optimization with Genetic Algorithm (GA)

A Genetic algorithm [14] is adaptive heuristic search method premised on the evolutionary ideas of natural selection and genetics. The basic concept of Genetic Algorithm (GA) is designed to simulate processes in natural systems necessary for evolution, specifically those that follow the principles of survival of the fittest. It is generally used in situations where the search space is relatively large and cannot be traversed efficiently by classical search methods. This is mostly the case with problems whose solution requires evaluation and equilibration of many apparently unrelated variables. As such they represent an intelligent exploitation of a random search space within a defined search space to solve a problem.

Genetic algorithms as consider an abstract representation of variable of the Optimization Problems. A chromosome is composed of the weight vectors$\{w_1, w_2 \ldots w_n\}$. A population is made of different realizations of the chromosome, named generation, potential solutions to the Optimization Problems (OP). The population evolves as the algorithm selects the best chromosomes and discards the unfits. A fitness score by means of the maximization objective is calculated to determine which generations are suitable for surviving to the next generation. The chromosomes with the highest score are meant to be the closest to the maximum and are selected for surviving. Successive generations are created in three step

1) Selection: An intermediate population is created by performing the (natural) selection. The chromosomes with the best fitness scores are duplicated (in a predefined proportion) and the remaining are discarded.
2) Crossover: The intermediate population is recombined for the reproduction. A random crossover between couples of chromosomes is performed to create the offspring. There are different types of crossover criteria chosen.
3) Mutation: A percentage of the offspring randomly mutates to create new generation. Spreading the search at each generation avoids restraining in local maxima.

The last two steps are repeated when some elements do not respect the constraints of the optimization problem, The evaluation and generation steps are performed iteratively to increase the percentage of fit members. The stop criterion is the convergence of all the population to the same generation (i.e., to the same fitness value), which is supposed to be the fittest and thus the only optimal solution.

IV. SIMULATION RESUL

A simulation has been done to assess the performance of proposed Genetic algorithms based *softened* hard decision fusion based cooperative spectrum sensing. We consider a network with different number of CRs (N) and several channels such as AWGN, Rayleigh faded. We simulate the various decision fusion scheme i.e AND, OR, MAJORITY, EGC etc. and compare our *softened* hard decision fusion scheme based on Genetic algorithms (GA). The missed detection P_m and false alarm P_f probabilities are also evaluated with different soft data fusion schemes

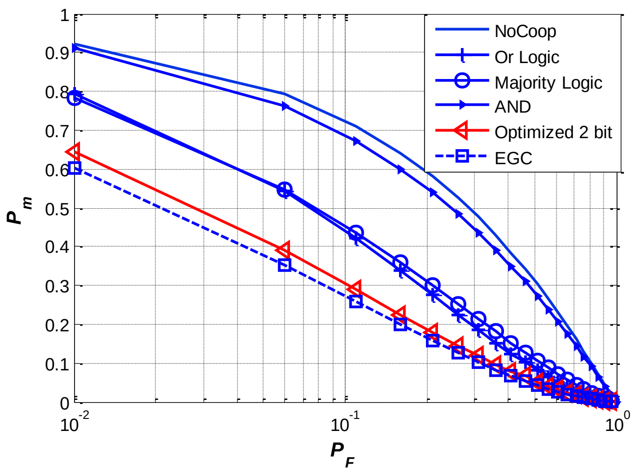

Figure. 4. A complementary ROC curve under AWGN channel

The optimal weights obtained GA algorithms in are used to plot the receiver operating characteristics (ROC) curve shown in Figure 4 which illustrates the probability of detection of GA-based scheme, as well as all other conventional methods for different given probabilities of false alarm. It is observable that the performance of GA based method is almost close to EGC which validates the robustness of our proposed technique.

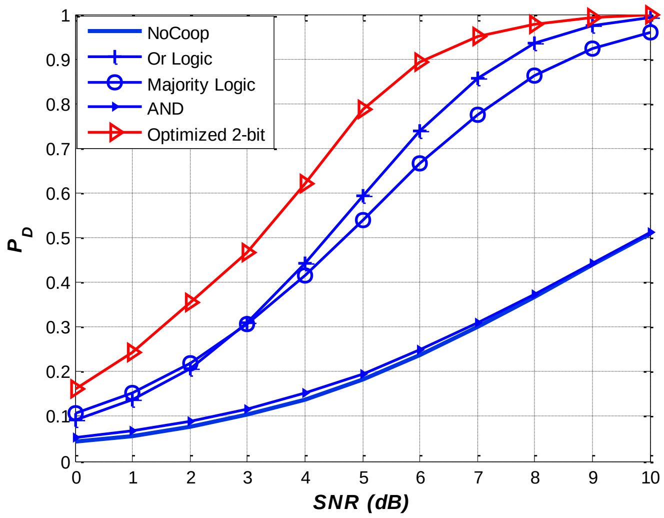

Figure 5. SNR versus P_d curves under Rayleigh channel

The effect of the different number of SNR in CRN is also investigated on GA-based scheme which is depicted in Figure 5. It is obvious that by increasing the SNR the performance is considerably improved. Thus, N and SNR increases, the separation between the hypotheses H_0 and H_1 increases and the performance of the ROC curve improves accordingly.

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