GENETIC ALGORITHM BASED OPTIMISED COLLABORATIVE SPECTRUM SENSING FOR COGNITIVE RADIO NETWORK

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ABSTRACT

Genetic Algorithm based weighted optimisation strategy for collaborative spectrum sensing is presented in this paper. It is shown that imperfect reporting channel and different mean SNR of secondary users have direct impact on the performance of collaborative spectrum sensing. Under channel fading, optimum collaborative spectrum sensing problem is formulated as a nonlinear optimisation problem and genetic algorithm is proposed as a solution approach. For a given probability of false alarm and given channel conditions, optimal weights are assigned to the secondary users to maximise global probability of detection at the fusion centre. The simulation result shows that the performance of proposed optimised collaborative spectrum sensing scheme yields higher collaborative gain.

1. INTRODUCTION

Tremendous growth of wireless services and applications in the last decade has led to the overcrowding of spectrum. Traditional approaches of spectrum access and allocation yield highly inflexible use of spectrum in which a large portion of spectrum have been assigned to the privileged users, often called Primary Users (PU), which have the exclusive rights to use assigned bands. However, recent measurements by Spectrum Policy Task Force (SPTF) indicate that many portions of the licensed spectrum are not used for significant periods of time [1]. The same claim has also been made in the UK by the Office of Communications (Ofcom) even though the entire spectrum is allocated [2]. This suggests that currently spectrum scarcity is mainly due to the inefficient fixed frequency assignments rather than the physical shortage of the spectrum.

Cognitive Radio (CR) is an emerging technology to solve spectrum under-utilisation problem in the next generation wireless communication systems by implementing opportunistic spectrum sharing [3]. Unlike traditional spectrum access approaches, CR allows the unauthorised users, called Secondary Users (SU), to use the licensed bands on a non-interfering basis with the PU. Therefore, CR has the potential to economically enhance the spectrum utilisation efficiency. Spectrum sensing is a key enabling functionality in the CR which makes opportunistic spectrum sharing possible. The main goal of spectrum sensing is to obtain awareness about the spectrum usage and the existence of PU in a certain geographical area. There are several different complex sensing techniques ranging from feature detection to energy level measurements, a brief overview is given in [3]. Energy detector based local spectrum sensing is used in this study because of its low complexity and computational power [4]. Although not many, there are some hardware platforms available for implementing spectrum sensing algorithms e.g. GNU radio [5], Universal Software Radio Peripheral (USRP) [6] and Shared Spectrum XG Radio [7].

Collaboration is proposed as a solution to the problems that arise due to the uncertainties in the channel such as fading and shadowing. It has been shown many times in the literature that spectrum sensing performance can be greatly improved with the collaborative or cooperative spectrum sensing in which a number of SU share their sensing information with each other, see [8-12] and references therein. Local observation (soft decision) or 1-bit local decision (hard decision) from the cognitive SU fused at the band manager node to make a global decision about the presence of the PU [13]. It has been argued that soft decision combining gives higher performance gains than hard decision combining [14].

Various techniques for the optimisation of collaborative spectrum sensing in terms of the fusion rule [12, 17], number of users [15] and thresholds [16] are available. However, most of the prior research work focused on the case when secondary users are far away from the primary user and hence the same mean SNR were assumed for all collaborating SU [8, 10, 12]. Moreover, previous research highlighted collaborative sensing techniques which combine data or decisions from the cognitive users with equal weights and with perfect reporting channels [8, 14]. Performance of collaborative spectrum sensing with noisy reporting channel was considered for the case of hard decision fusion in [18].

Collaborative spectrum sensing schemes with weighted user contributions have been recently proposed in [17] and [19]. In [17] average signal power at a secondary user was exploited to weight different collaborating cognitive nodes.

In [19] an optimal strategy for cooperative spectrum sensing was presented and optimal weights for each SU in an AWGN channel were derived analytically. However, the shortcoming of existing literature in weighted collaborative spectrum sensing (CSS) is that the perfect reporting channel has been assumed and doesn't considered effects of fading between PU and SU.

In this paper, Genetic Algorithm (GA) based weighted collaborative spectrum sensing strategy is presented to combat the channel effects and to enhance the spectrum sensing performance. The proposed optimum spectrum sensing mechanism is based on a model that is realistic and also takes into account both channels i.e. channel between primary user and the SU as well as the reporting channel. It is shown in this paper that the imperfect reporting channel has a direct impact on the performance of collaborative spectrum sensing. Secondary users transmit their local observations to the band manager and global decision made at the band manager is based on a weighted combination of the local test statistics from individual cognitive collaborative SU (CCSU). The weight of each secondary user at the band manager is indicative of its contribution to the global decision. For example, if a secondary user has a high SNR signal, better channel conditions and a good reporting channel then it is assigned a larger contributing weight.

The optimum collaborative spectrum sensing problem is formulated as a nonlinear optimisation problem in this paper. For a given probability of false alarm and given channel conditions, optimal weights are chosen in such a way to maximise global probability of detection at the fusion centre. With a realistic fading channel it is hard to derive an analytical expression for the optimum weights. This paper propose a GA based solution to calculate optimum weight for each secondary user that maximises the global probability of detection.

The paper is organised as follows. In section 2 we describe the system model considered in this paper. Section 3 introduces the spectrum sensing and collaborative spectrum sensing framework in cognitive radio network and details the problem formulation. In order to achieve optimum spectrum sensing performance, GA is used to calculate the weights for each collaborative user in section 4. Simulation results are presented in section 5 and finally section 6 concludes this paper.

2. SYSTEM MODEL

We consider a cognitive radio network, with M secondary users and a fusion centre, to sense a portion of the spectrum in order to detect PU, as shown in Fig. 1. Suppose the primary user is not far away from the M secondary users and each user has a different value of mean SNR depending on its distance from the PU. We assume that all the collaborating cognitive SU lie inside the decodability region of the PU. It is also assumed that SU have independent and identically distributed (i.i.d.) observations.

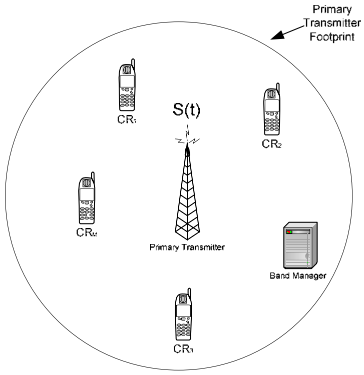

Figure 1: Spectrum sensing system model in a cognitive radio network

3. PROBLEM FORMULATION

3.1 LOCAL SPECTRUM SENSING

In this section, the local spectrum sensing problem is formulated as a binary hypothesis testing problem [4]:

$$x_i(k) = \begin{cases} \upsilon_i(k) & ;\mathcal{H}_o \\ h_i s(k) + \upsilon_i(k) & ;\mathcal{H}_1 \end{cases} \quad (1)$$

where $k = 1,2,3,...N$ and $i = 1,2,3,...M$ with M the number of SU while N is the total number of samples observed by a single secondary user. $s(k)$ is the primary transmitted signal at time instant k, $\upsilon_i(k)$ is the kth white additive gaussian noise sample and is defined as $\upsilon_i \sim \mathcal{N}(0,\sigma_i^2)$ and h_i is the channel gain between ith secondary user and the primary user and σ_i^2 is the noise variance. Without loss of generality, $s(k)$ and $\upsilon_i(k)$ are assumed to be independent of each other.

Each secondary user calculates a summary statistic u_i over a detection interval of N samples, i.e.,

$$u_i = \sum_{k=1}^{N} | x_i(k) |^2 \quad (2)$$

since u_i is the sum of squares of N Gaussian random variables and it is well known that the sum of squares of N Gaussian variables follows a chi-square distribution [20]. So u_i follows a chi-square distribution with N degrees of freedom under hypothesis $\mathcal{H}_0$ and a non-central chi-square distribution with N degrees of freedom and non-central parameter of γ_i, under hypothesis $\mathcal{H}_1$. Therefore, the statistics of u_i under the two hypothesis may be written as,

$$\frac{u_i}{\sigma_i^2} = \begin{cases} \chi_N^2 & ;\mathcal{H}_o \\ \chi_N^2(\gamma_i) & ;\mathcal{H}_1 \end{cases} \quad (3)$$

where $\overline{\gamma_i}$ is the mean SNR of ith secondary user. For a large number of samples N, the test statistics u_i is normally distributed and is given as [20],

$$u_i \sim \begin{cases} \mathcal{N}(N\sigma_i^2, 2N\sigma_i^4) & ;\mathcal{H}_o \\ \mathcal{N}((N+\overline{\gamma_i})\sigma_i^2, 2(N+2\overline{\gamma_i})\sigma_i^4) & ;\mathcal{H}_1 \end{cases} \quad (4)$$

If the decision threshold at ith secondary user is λ_i then the probability of false alarm and the probability of detection for ith user is given by,

$$P_f^i = Q\left(\frac{\lambda_i - N\sigma_i^2}{\sqrt{2N\sigma_i^2}}\right) \quad (5)$$

$$P_d^i = Q\left(\frac{\lambda_i - (N+\overline{\gamma_i})\sigma_i^2}{\sqrt{2(N+2\overline{\gamma_i})\sigma_i^2}}\right) \quad (6)$$

3.2 COLLABORATIVE SPECTRUM SENSING

The summary statistics at local secondary nodes $\{u\}$ as defined in (4) is then transmitted to the fusion centre through reporting channels. In this paper realistic reporting channels with variable channel gains $\{g\}$ are considered, as shown in Fig. 2.

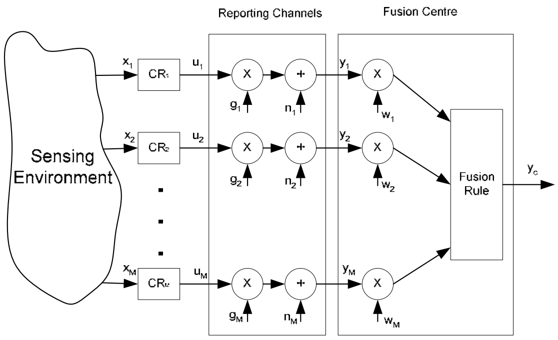

Figure 2: Schematic diagram of weighted collaboration at the fusion centre

Statistics of local observations after passing through the reporting channels of gain $\{g\}$ and noise $n_i \sim \mathcal{N}(0, \delta_i^2)$ is,

$$y_i \sim \begin{cases} \mathcal{N}(Ng_i\sigma_i^2, 2Ng_i^2\sigma_i^4 + \delta_i^2) & ;\mathcal{H}_o \\ \mathcal{N}((N+\overline{\gamma_i})g_i\sigma_i^2, 2(N+2\overline{\gamma_i})g_i^2\sigma_i^4 + \delta_i^2) & ;\mathcal{H}_1 \end{cases} \quad (7)$$

where δ_i^2 is the noise variance of reporting channels. A global test statistics is calculated at the fusion centre by assigning weights $\{w\}$ to the received observations $\{y\}$ by,

$$y_c = \sum_{i=1}^{M} w_i \cdot y_i = \mathbf{w}^T\mathbf{y} \quad (8)$$

where the weight vector $\mathbf{w}$ is defined as $\mathbf{w} = \{w_1, w_2, ..., w_M\}^T$ and the received decision vector at the fusion centre is defined as $\mathbf{y} = \{y_1, y_2, ..., y_M\}^T$. Weight vector $\mathbf{w}$ at the fusion centre satisfies $\| w \|_2^2 = 1$ where $\| . \|_2^2$ denotes the Euclidean norm. From (7) and (8) the distribution of y_c can be easily derived and is given as,

$$\begin{matrix} \mathcal{N}\left(\sum_{i=1}^{M} Ng_i\sigma_i^2 w_i, \sum_{i=1}^{M}(2Ng_i^2\sigma_i^4 w_i^2 + \delta_i^2 w_i^2))\right) & ;\mathcal{H}_o \\ \mathcal{N}\left(\sum_{i=1}^{M}((N+\overline{\gamma_i})g_i\sigma_i^2 w_i), \sum_{i=1}^{M}(2(N+2\overline{\gamma_i})g_i^2\sigma_i^4 w_i^2 + \delta^2 w_i^2))\right) & ;\mathcal{H}_1 \end{matrix} \quad (9)$$

If we assume $\mathbf{h} = \{h_1, h_2, ..., h_M\}^T$, $\mathbf{g} = \{g_1, g_2, ..., g_M\}^T$, $\boldsymbol{\gamma} = \{\gamma_1, \gamma_2, ..., \gamma_M\}^T$, $\boldsymbol{\sigma} = \{\sigma_1^2, \sigma_2^2, ..., \sigma_M^2\}^T$ and $\boldsymbol{\delta} = \{\delta_1^2, \delta_2^2, ..., \delta_M^2\}^T$, then statistics of y_c under H_0 and H_1 can be written as,

$$\begin{aligned} \mathrm{E}[y_c/\mathrm{H}_0] &= N\mathbf{g}^T \mathrm{diag}(\boldsymbol{\sigma})\mathbf{w} \\ \mathrm{Var}[y_c/\mathrm{H}_0] &= \mathbf{w}^T[2N\mathrm{diag}^2(\mathbf{g})\mathrm{diag}^2(\boldsymbol{\sigma}) + \mathrm{diag}(\boldsymbol{\delta})]\mathbf{w} \\ \mathrm{E}[y_c/\mathrm{H}_1] &= N\mathbf{g}^T \mathrm{diag}(\boldsymbol{\sigma})\mathbf{w} + \mathbf{g}^T \mathrm{diag}(\overline{\boldsymbol{\gamma}})\mathrm{diag}(\boldsymbol{\sigma})\mathbf{w} \\ \mathrm{Var}[y_c/\mathrm{H}_1] &= \mathbf{w}^T[2N\mathrm{diag}^2(\mathbf{g})\mathrm{diag}^2(\boldsymbol{\sigma}) + 4\mathbf{g}^T \cdots \\ &\quad \mathrm{diag}^2(\boldsymbol{\sigma})\mathrm{diag}(\overline{\boldsymbol{\gamma}}) + \mathrm{diag}(\boldsymbol{\delta})]\mathbf{w} \end{aligned}$$

(10)

where $\mathrm{diag}(.)$ is a diagonal matrix with elements of the given vector on its diagonal and $\mathrm{Var}(.)$ denotes the variance operator.

To make a decision on the presence of primary user, the global decision statistics y_c as defined in equation (8) is compared with a threshold λ_c. Global probability of false alarm and detection at the fusion centre is given as,

$$Q_f = Q\left(\frac{\lambda_c - \mathrm{E}[y_c/\mathrm{H}_0]}{\sqrt{\mathrm{Var}[y_c/\mathrm{H}_0]}}\right) \quad (11)$$

$$Q_d = Q\left(\frac{\lambda_c - \mathrm{E}[y_c/\mathrm{H}_1]}{\sqrt{\mathrm{Var}[y_c/\mathrm{H}_1]}}\right) \quad (12)$$

3.3 SPECTRUM SENSING UNDER FADING

When the channel between primary transmitter and secondary user is varying due to fading or shadowing, (6) and (12) gives the probability of detection conditioned on instantaneous SNR γ_i. On the other hand, local and global probability of false alarm as defined in (5) and (11) remains same, as it is independent of γ_i. Under both cases of local and collaborative spectrum sensing, average probability of detection may be derived by averaging instantaneous probabilities over the fading statistics.

$$P_d^i = \int_\gamma Q\left(\frac{\lambda_i - \mathrm{E}[u_i/\mathrm{H}_1]}{\sqrt{\mathrm{Var}[u_i/\mathrm{H}_1]}}\right) f_\gamma(x)dx \quad (13)$$

$$Q_d = \int_\gamma Q\left(\frac{\lambda_i - \mathrm{E}[y_c/\mathrm{H}_1]}{\sqrt{\mathrm{Var}[y_c/\mathrm{H}_1]}}\right) f_\gamma(x)dx \quad (14)$$

where distributions of u_i and y_c are defined in (4) and (9) respectively (by replacing $\overline{\gamma_i}$ with the independent variable x) and $f_\gamma(x)$ is the PDF of SNR under fading.

4. GA BASED OPTIMUM COLLABORATIVE SPECTRUM SENSING

In this paper, main goal is to maximise the global probability of detection (or alternatively minimise global probability of miss detection) for a given value of the global probability of false alarm. From (11) and (12),

$$Q_d = Q\left(\frac{\sqrt{\mathrm{Var}[y_c/\mathrm{H}_0]}Q^{-1}(Q_f)+\mathrm{E}[y_c/\mathrm{H}_0]-\mathrm{E}[y_c/\mathrm{H}_1]}{\sqrt{\mathrm{Var}[y_c/\mathrm{H}_1]}}\right)$$

where statistics of y_c under $\mathcal{H}_0$ and $\mathcal{H}_1$ is defined in equation (10). Maximising Q_d is equivalent to minimise $f(\mathbf{w})$ as $Q(x)$ is a decreasing function of x, where $f(\mathbf{w})$ is given by

$$f(\mathbf{w}) = \frac{\sqrt{\mathrm{Var}[y_c/\mathrm{H}_0]}Q^{-1}(Q_f)+\mathrm{E}[y_c/\mathrm{H}_0]-\mathrm{E}[y_c/\mathrm{H}_1]}{\sqrt{\mathrm{Var}[y_c/\mathrm{H}_1]}}$$

$$f(\mathbf{w}) = \frac{Q^{-1}(Q_f)\sqrt{\mathbf{w}^T\mathbf{A}\mathbf{w}}-\mathbf{w}^T[\mathrm{diag}(\mathbf{g})\mathrm{diag}(\boldsymbol{\sigma})]\boldsymbol{\gamma}}{\sqrt{\mathbf{w}^T\mathbf{B}\mathbf{w}}} \qquad (15)$$

where matrices $\mathbf{A}$ and $\mathbf{B}$ are defined as,

$$\mathbf{A} = 2N\mathrm{diag}^2(\mathbf{g})\mathrm{diag}^2(\boldsymbol{\sigma})+\mathrm{diag}(\boldsymbol{\delta})$$

$$\mathbf{B} = 2(NI_M+2\mathrm{diag}(\bar{\boldsymbol{\gamma}}))\mathrm{diag}^2(\mathbf{g})\mathrm{diag}^2(\boldsymbol{\sigma})+\mathrm{diag}(\boldsymbol{\delta})$$

Similarly, for fading channel, average probability of detection can be obtained by averaging Q_d over fading statistics as describe in section 3.3. Now optimisation problem can be formulated as,

$$\begin{array}{lll} \text{minimise} & & f(\mathbf{w}) \\ \text{st.} \quad \|\mathbf{w}\|_2^2 = 1 & \text{and} & w_i > 0 \ \forall i \in \{1,2,3,...,M\} \end{array}$$

A Genetic Algorithm (GA) is used as a solution approach to minimise $f(\mathbf{w})$ for a given value of Q_f. The GA has been proposed as a computational analogy of adaptive systems by Holland [22]. They are modelled based on the principles of natural evolution and selection. The algorithm starts by randomly generating an initial population (weights) and then computing and saving the fitness of each chromosome in the current population using (15), which serves as a fitness function for the GA. Next, using a selective algorithm, chromosomes are picked up probabilistically from a mating pool to produce offspring's via crossover and mutation operations. This process is repeated until a satisfied solution is obtained or the maximum generation number is reached. Details of the GA can be found in any standard text e.g. [21].

5. SIMULATION RESULTS

In this section, proposed GA based weighted collaborative spectrum sensing scheme is simulated and compared with existing weighting schemes i.e. Equal Gain Combining (EGC) and Proportional Combining (PC). EGC is the weighting scheme in which all the collaborating users have equal weights and in PC fusion centre assigns proportional weights to the cognitive users according to their mean SNR value. There are M collaborating SU located at different positions within decodability region of the PU as shown in Fig. 1. Numerical results are obtained from simulations over 1,000,00 noise realisations for the given set of noise variances. Noise variance of all collaborating users for the primary channel (i.e. channel between primary transmitter and secondary users) is assumed to be $\sigma_i^2 = 1$ and noise variance of the reporting channel is assumed to be $\delta_i^2 = 1$ dB. Value of N is assumed to be 10 in all simulations.

For the case of local spectrum sensing theoretical results are compared with simulation results in Fig. 4. This figure shows the ROC curves for local spectrum sensing in AWGN and Rayelgih fading channel for a single secondary user having $\bar{\gamma}_{dB} = 5$. It is clear from Fig. 4 that channel fading degrades the performance of spectrum sensing. For example in Rayleigh fading channel, in order to achieve $P_m < 10^{-1}$, maximum achieveable probability of false alarm is 0.4, which results poor spectrum utilisation and vice versa.

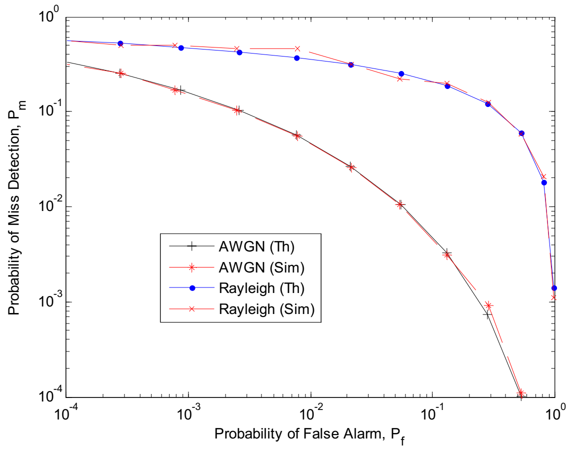

Figure 4: ROC curves in AWGN and Rayleigh faded channel for a single node with $\bar{\gamma} = 5$ dB, $N = 10$

Fig. 5 shows probability of miss detection Q_m against probability of false alarm Q_f with different number of collaborating users and their corresponding mean SNR values. Perfect reporting channel is assumed here and the channel between SU and PU is considered to be AWGN channel. Fig. 5 shows clearly that with an increase in the number of collaborating users sensing performance improves if all SU have same mean SNR. However, when the cognitive users have different mean SNR values than the sensing performance degrades with equal gain combining. Proportional weights assigned to different users according to their mean SNR values improves sensing performance as compared to equal gain combining approach. From Fig. 5, it is concluded that users SNR have a direct impact on the spectrum sensing performance.

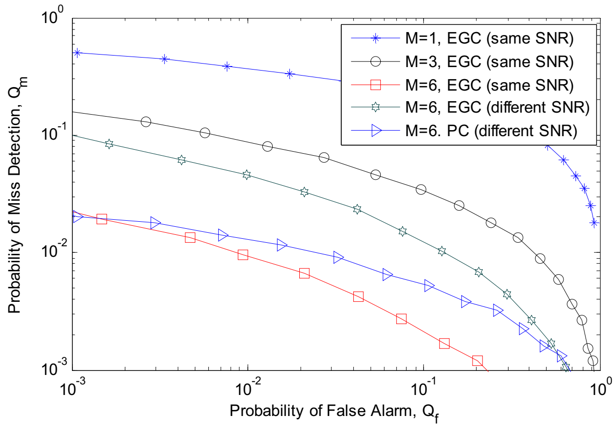

Figure 5: Q_m vs Q_f with perfect reporting channel

Fig. 6 plots the Q_m versus Q_f for the case when cognitive users have different mean SNR and the reporting channel is not perfect i.e. practical AWGN channels exist between cognitive users and the fusion centre with different channel gains. Value of channel gain is dependent on the location of the fusion centre and the CR and varying with time. It can be seen from Fig. 6 that reporting channel gains degrade the performance of spectrum sensing. Without channel gains, PC performs better than EGC, but, in the presence of reporting channel, PC doesn't perform much better than EGC. This is mainly because of the fact that in the presence of imperfect reporting channel, optimum weights of cognitive users are not only dependant on SNR values but also depend on reporting channel conditions. Under such conditions an analytical expression for the probability of detection is derived and optimum weights are calculated by using genetic algorithm. The result shows that the proposed GA based optimal weights, denoted as 'OPT', yield superior spectrum sensing performance in both cases i.e. with and without reporting channel gain.

In order to evaluate the performance of proposed optimised collaborative spectrum sensing framework, performance of GA based optimisation algorithm is tested assuming a fading channel. Three different cases were considered, case 1 refers to the case in which all the SU have good reporting channel, case 2 is the case in which all the collaborating cognitive users have a bad reporting channel while in case 3 two of the collaborating users have strong channel while others have a bad reporting channel. Good and bad reporting channel here means channels with high or low channel gains. As seen from Fig. 7 spectrum sensing performance is worst for case 1 and best for case 3, however, in all three cases, performance of the proposed optimised thresholds outperforms.

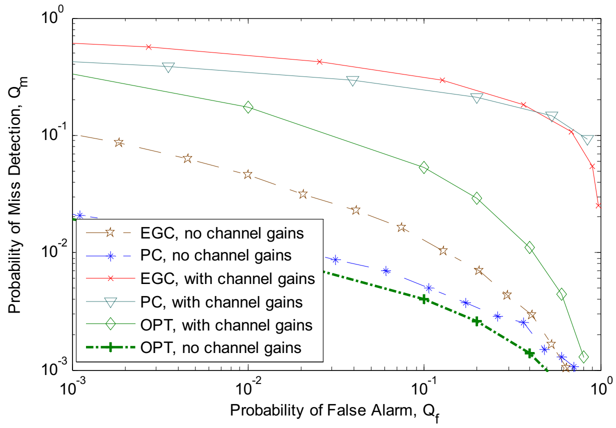

Figure 6: Q_m vs Q_f with M=6 in AWGN channel with imperfect reporting channel

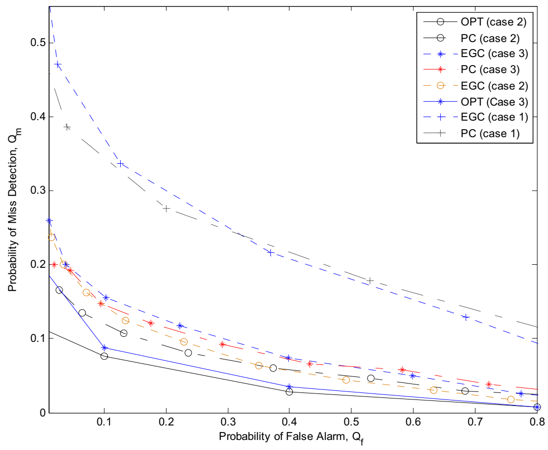

Figure 7: Q_m vs Q_f with M=6 in Rayleigh channel with imperfect reporting channel

6. CONCLUSIONS

In this paper we propose optimisation of weighted collaborative spectrum sensing in which different weights are assigned to collaborative users to improve collaborative spectrum sensing performance in terms of receiver operating characteristics curves. The optimum weight vector is obtained by minimising a function using Genetic Algorithm, which maximises the probability of detection for a given probability of false alarm and given channel conditions. In this paper, realistic noisy reporting channels are considered with variable channel gains. It has been shown in this paper that observation fusion with optimum weights always outperform other weighting schemes considered in the literature. Proposed GA based optimisation scheme requires knowledge about local mean SNR of all secondary users as well as reporting channel conditions. In practical situations with a large number of cognitive users, the bandwidth utilisation can be high. Our future research will investigate mechanisms to optimise bandwidth utilisation for the collaborative framework presented in this paper.

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