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A Survey on Cooperative Spectrum Sensing Techniques for Cognitive Radio Networks

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***Abstract*— The functionality of Cognitive Radio is to detect the presence and absence of licensed user (i.e.) Primary User, in the spectrum, so that the secondary user can use it. Many works has been contributed on spectrum sensing of cognitive radio with single user, which has less complexity but offers inferior detection performance compared to cognitive radio with multiple users. Further there arises hidden user problem in single user system which degrades the system performance. Therefore, it is advisable to use multiple cognitive radio users to sense the spectrum individually and combine their result at the fusion centre. This technique is known as co-operative spectrum sensing. Cooperative sensing is considered to be a boon to the problems that arise in spectrum sensing due to noise uncertainty, fading and shadowing. Further, co-operative sensing decreases the probabilities of miss detection and false alarm to a considerable extent. This paper presents various co-operative spectrum sensing techniques with exhaustive survey and comparison.**

***Index Terms*— CR - Cognitive Radio, FC - Fusion Center, PU - Primary User, SNR - Signal to Noise Ratio, SU - Secondary User**

I. INTRODUCTION

The rapid growth in wireless communication has led to huge demand of frequency spectrum. The fixed spectrum assignment has resulted in poor spectrum utilization, where some frequency bands are overcrowded and other frequency bands are underutilized [1]. In this regard, spectrum sensing has emerged as a new technology to avoid this problem. It enables the access of unoccupied frequency bands (i.e.) spectrum holes and thus increases the spectral efficiency. This becomes possible with the help of Cognitive Radio [3], [4], [5]. The Cognitive Radio paves way to allot the unused spectrum to the secondary unlicensed user without interrupting the primary user communication [2]. Radio Scene analysis is the most important unit in CR [4]. Now the main task is to identify these spectrum holes, so that the secondary user can use it.

There are several spectrum sensing methods widely used in communication applications, particularly energy detection, matched filter and cyclostationary feature detection [6], [10-12]. Energy detection is one of the simplest techniques in spectrum sensing [8-9]. In CR, measuring of energy involves various parameters like time, space, frequency and code. The main advantage of energy detection technique is that, it does not require any prior knowledge about the primary signal [14-18]. SNR wall is one drawback of energy detection technique, where detection fails at low SNR region. The author reported in [13-14] shows that how energy of signal is useful in detecting the spectrum over fading channels. Further the authors in [46-47] has presented about the design of energy detection technique with noise uncertainity. The probability of detection is an illustrating measure to be studied against primary (licensed) user signal to noise ratio.

There are few relay model cooperative spectrum sensing strategies, namely amplify and relay (AR) model and detect and relay (DR) model, which aims in increasing the detection performance [19], [30-32].

Rather than a single CR user involving the process of spectrum sensing, multiple CR users in a network can cooperate each other to improve the detection probability [36-39]. Multiple CR users sending their decisions to the fusion center for hard combination has been reported in [25]. The algorithms used in hard combination include OR rule [48-50], AND rule [52], majority rule [51] and optimized K out of N users [25].

In hard combination, fusion centre combines the decision from CR users, whereas soft combination scheme combines metric itself from CR users, has been reported in [20-21], [24], [26-27]. A method of Sequential Cooperative Spectrum Sensing scheme has been reported in [35] in which fusion center collects local sensing data efficiently from cognitive radio users based on the reputation of individual Cognitive user. In addition, cooperative spectrum sensing mitigates hidden user problem and decreases sensing time [29], [33-34], but challenges on security need to be taken care [7].

The works reported in [20-21], [27] comprise of linear combination of computed energies from each CR user. The author in [27] has optimized a non convex problem to obtain those weights. The work in [21] consists of obtaining optimized weight coefficients to maximize the detection probability. NP rule is used in deriving out the test metric for fusion centre in [20].

The main contribution of this paper is to propose a survey on cooperative spectrum sensing techniques which is an emerging and powerful solution for many problems in wireless communication [22-23]. In this regard, we would like to present and compare the detection performances for hard combining rules like OR, AND, M out of K rules. We would also like to compare the performances of soft combining rules like maximal ratio combining, equal gain combining and linear weighted combining of individual CR user results.

II. SYSTEM MODEL

We consider the CR network that consists of K CR users with one primary user. In each CR user k performs sensing individually and sends their result to common fusion center FC. The proposed system model is shown in fig. 1.

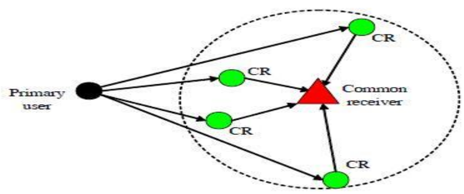

Fig. 1. System Model of Cooperative Spectrum Sensing

Local detection of each CR user is based on two hypotheses H_1 and H_0 respectively. The signal received at k_{th} CR user is given by

$$Y_k(t) = \begin{cases} w_k(n); & H_0 \\ h_k(n)\, s(n) + w_k(n); & H_1 \end{cases} \quad (1)$$

where n indicates signal sample number with N number of samples on total, $w_k(n)$ denotes white gaussian noise samples with zero specified variance N_0, and s(n) is the samples of primary user signal without loss of generality, s(n) is modeled as signal with unit energy. Finally, $h_k(n)$ in equation (1) is a Rayleigh fading channel, the same is assumed later as block fading, hence can be replaced by h_k.

Energy detection is the best detection method which does not require any prior idea on transmitted signal. Let us assume local detection of each CR user, k relies on the energy of the received signal. The signal energy is given by

$$E_k = \sum_{n=0}^{N} |Y_k(n)|^2 \quad (2)$$

Probability of false alarm, probability of detection and missed detection probability at each k_{th} user are given respectively, [13]

$$P_{f,k} = \text{Prob}\,(E_k > \lambda_k / H_0)$$
$$= \Gamma(u, \lambda_k/2) / \Gamma(u) \quad (3)$$
$$P_{d,k} = \text{Prob}\,(E_k > \lambda_k / H_1)$$
$$= Q_u(\sqrt{2\gamma k}, \sqrt{\lambda_k}) \quad (4)$$
$$\text{And} \quad P_{m,k} = 1 - P_{d,k} \quad (5)$$

In all the above equations, $\Gamma(a)$ is the complete gamma function, $\Gamma(a,x)$ is the incomplete gamma function given by $\Gamma(a,x) = \int_x^{\infty} t^{a-1} e^{-t}\, dt$, γ_k is the instantaneous SNR at each CR receiver, λ_k is the threshold for local energy detection, and $Q_u(a,x) = (1)/(a^{u-1}) \int_x^{\infty} t^u e^{-\frac{(t^2+a^2)}{2}} I_{u-1}(at)\, dt$ respectively.

The instantaneous signal to noise ratio γ_k is neither available at fusion center nor at cognitive radio receiver. But there exists technique to estimate signal to noise ratio as [41-43].

III. HARD COMBINING

The hard combining stands for combining the decisions themselves directly from each CR users. Let the decisions be d_k's and the same is given by

$$d_k = \begin{cases} 1; & \geq \lambda_k \\ 0; & < \lambda_k \end{cases} \quad (6)$$

The decisions d_k's are sent to common receiver which in turn fuses them. There are many fusion rules like 'OR', 'AND', and 'M out of K' rule, which are discussed below with closed form expressions.

A. OR Fusion Rule

The common receiver makes decision in favor of H1, if any one out of the K CR users had sent its decision as 1. Let D be the decision at common receiver, then

$$D = \sum_{k=1}^{K} d_k \quad (7)$$

Let us assume in all our analysis, that threshold λ_k at each user k is same as λ, local false alarm probabilities. The detection probabilities are same and let them be Pf and Pd respectively. Further, let $P_{d,or}$ and $P_{f,or}$ denote probability of detection and probability of false alarm at common receiver respectively for 'OR' logic rule, then the expressions for Q_d and Q_f can be given by

$$P_{d,OR} = \text{Prob}\,(D \geq 1/H_1)$$
$$= 1 - \text{prod}_{k=1}^{K} (1 - p_{d,k}) \quad (8)$$
$$P_{f,OR} = \text{prob}\,(D \geq 1/H_0)$$
$$= 1 - \text{prod}_{k=1}^{K} (1 - p_{f,k})\, P_f^l (1 - P_f)^{K-1} \quad (9)$$

B. AND fusion Rule

If all CR users had sent their decision as 1, then Common receiver decides in favor of H1. This rule is called 'AND' logic rule. Then D in equation (7) is becoming D = K.

With $P_{d,AND}$, $P_{f,AND}$ being detection and false alarm probabilities for AND rule respectively.

$$P_{d,AND} = \text{prob}\,(D = K/H_1)$$
$$= \Pi_{k=1}^{K} P_{d,k} \quad (10)$$
$$P_{f,AND} = \text{prob}\,(D = K/H_0)$$
$$= \Pi_{k=1}^{K} P_{f,k} \quad (11)$$

C. 'M out of K' fusion rule

When D in equation (7) is above some preset value M, where M < K, then fusion rule is said to be M out of K rule. It says that when majority of CR users are in favor of H1, common receiver will vote for that.

With $P_{d,MK}$, $P_{f,MK}$ being detection and false alarm probabilities for M out of K rule respectively,

$$P_{d,M\,K} = \text{prob}\,(D \geq K/H_1)$$
$$= \sum_{l=m}^{K} P_d^l\, (1 - P_d)^{K-1} \quad (12)$$
$$P_{f,M\,K} = \text{prob}\,(D \geq K/H_0)$$
$$= \sum_{l=m}^{K} P_f^l\, (1 - P_f)^{K-1} \quad (13)$$

The detection performance of all these hard combination logic rules are shown in figure . It can be inferred that 'OR' rule outperforms single user sensing performance, while 'AND' rule performance is inferior to that of single user whereas M out of K rule lies in between. Though the performance of 'OR' rule is good, it does not provide the quality of service for primary user, as it reduces the false alarm probability to a very less value, hence it makes interference with primary user transmission. On the other hand, 'AND' rule does not provide much opportunity for secondary transmission, since its detection probability is less. Therefore it is concluded that, by choosing optimal value of M in 'M out of K' rule, opportunity for secondary transmission is kept high without compromising primary user's quality of service.

D. Optimal M

In previous section we have discussed that there exists an optimal M value out of K users. A method is mentioned in [25] to find such an optimal M value. There are two error probabilities stated in [25] called missed detection probability and false alarm probability, both of which contribute to error probability. That is $P_e = P_m + P_f$, where $P_m = 1 - P_d$, and P_f, P_d are the false alarm and detection probabilities at the fusion center (For sake of convenience, $P_{d,OR}$,$P_{d,AND}$... are being treated simply as P_d). Optimum value of M will be the one to minimize error probability. Fig. 2 shows a plot between P_e and threshold λ_k for various M value. We observe from this figure that there comes a minimum of P_e at one particular value of M which we would like to express mathematically as follows, Let R be a function given by,

$$R = \sum_{k=1}^{K} \binom{K}{k} \left[P_f^k \left(1 - P_f\right)^{K-k} - \left(1 - P_f\right)^k P_m^{K-k}\right] \quad (14)$$

we also get, Pf + Pm = 1 + R, So we could write,

$$\frac{\partial R}{\partial k} \approx R\,(K+1) - R\,(k) = 0$$

$$= \binom{K}{k} \left[\, P_f^k \left(1 - P_m\right)^k P_m^{K-k} - P_f^k \left(1 - P_f\right)^{K-k} \right] = 0 \quad (15)$$

By solving we get the optimum value as $k = \frac{K}{1-\beta}$, where

$$\beta = \frac{\ln \frac{P_f}{1 - P_m}}{\ln \frac{P_m}{1 - P_f}}.$$

Hence $M = k = \frac{K}{1-\beta}$

Therefore, we come to following conclusion, that when P_f, and P_m are equal, then β = 1 and optimal M in this case is K/2. When P_f << P_m for larger K, we get 'OR' rule as the optimum rule. When P_m << P_f for larger K, 'AND' rule becomes the optimum rule. Fig. 3 displays the optimum M value with respect to threshold for various signal to noise ratio and the same verifies previous discussions [25].

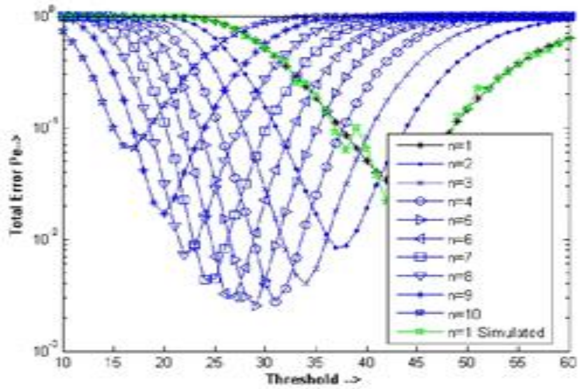

Fig. 2. Total Error Rate of Cooperative Spectrum Sensing for various k Values

IV. OPTIMAL HARD COMBINING

We illustrate a method presented in [45] here to optimize a hard combining rule. For illustration purpose, let us reconsider the system model in equation (1). Let s(n), in equation (1) is taken to be Gaussian random number with mean zero and variance σ^2 s, and $w_k(n)$ as white Gaussian noise samples with zero mean and variance σ^2 w. It is assumed that secondary users are separated by a distance which is known to the fusion center. The fusion center is located at a distance much far from primary user [45]. The proposed system model is shown in fig 4. Then the signal power received by secondary user according to path loss model is given by,

$$P_k = \frac{h_k^2 \sigma_s^2}{d_k^\alpha} \quad (16)$$

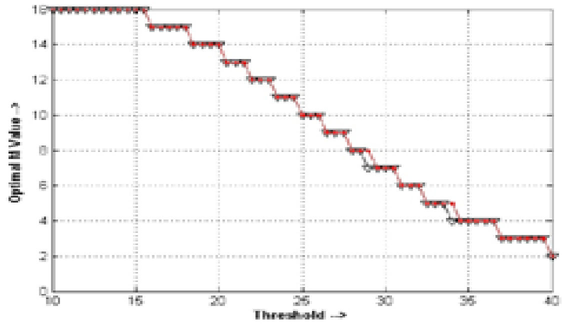

Fig.3.Optimal M Value of Cooperative Spectrum Sensing in AWGN channel when SNR = 10 dB

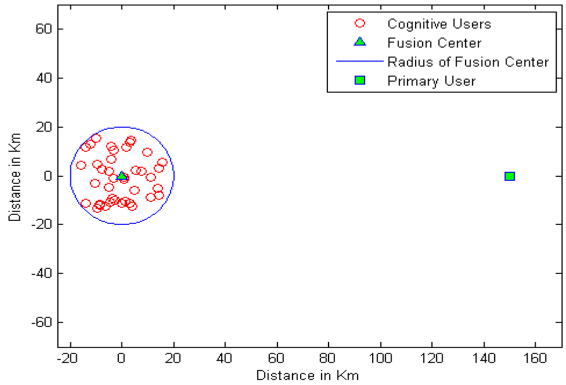

Fig. 4. Proposed System Model for Optimal Hard Combining

where α is the path loss exponent factor, β is a scalar and h_k is Rayleigh block fading channel as that in equation (1).Then d_k is the distance between k^{th} secondary user and primary user [45]. Then primary user signal to noise ratio at each cognitive receiver k is

$$\delta_k = 10 \log \frac{P_k}{\sigma_w^2} \quad (17)$$

Neyman Pearson detection problem is the one, where P_f is fixed and P_d is maximized [48]. It is known that maximum value of Pd ensures the protection of primary user from being interfered. Based on this, an idea has been proposed in [45] to set Pd to a higher value for protecting the primary user [45].

A. Constant Detection Rate

1) OR rule:

As discussed above, over all Pd at fusion center is kept at a targeted high value P_d which is called constant detection rate [45]. OR rule is made use for combining all decisions from cognitive users. $P_{d,k}$ in equation (5) is modified here as [45].

$$P_{d,k} = Q\left(\left(\frac{\lambda_k}{\sigma_w^2}\right) - \delta_k - 1\right)\sqrt{\frac{N}{2\delta_k + 1}} \quad (18)$$

similarly

$$P_{f,k} = Q\left(\left(\frac{\lambda_k}{\sigma_w^2}\right) - 1\right)\sqrt{N} \quad (19)$$

where Q(.) is the Q function, λ_k is the threshold at each user as before. Let $\overline{P_{d,k}}$ be a targeted detection rate in each cognitive user. Then from equation (8),taking only m best selected users out of total number of K users used for cooperation $P_{d,k}$ is,

$$\overline{P_{d,k}} = 1 - \sqrt[m]{1 - \overline{P_d}} \quad (20)$$

With this computed $\overline{P_{d,k}}$, from equation (20) and substituting in equation (19), we get false alarm probability of each user as

$$P_{f,k} = Q\left(\sqrt{2\delta_k + 1}\, Q^{-1}\left(1 - \sqrt[m]{1 - \overline{P_d}}\right) + \sqrt{N\delta_k}\right) \qquad (21)$$

Then, the total probability of false alarm based on OR combining is obtained from equation (19). By inspecting equation (21), we understand that for larger value of δ_k, $P_{f,k}$ decreases and hence P_f decreases, as this is the property of Q(.) function. These all m number of users contribute to minimize P_f. δ_m of these m users decides the optimization. These users are treated as best selected users. Figure 5 shows the plot of maximum $P_{f,k}$ among m users, as m increases from 1 to 100 in a network consisting of 100 users. We observe that curve decreases initially because of $Q^{-1}\left(1 - \sqrt[m]{1 - \overline{P_d}}\right)$ term in equation (19), but since δ_k decrease as k increases, $P_{f,k}$ goes up again. This shows that number of users selected must lie in a range 1 < m < K, and the same can be computed from equations (19, 20 ,21).

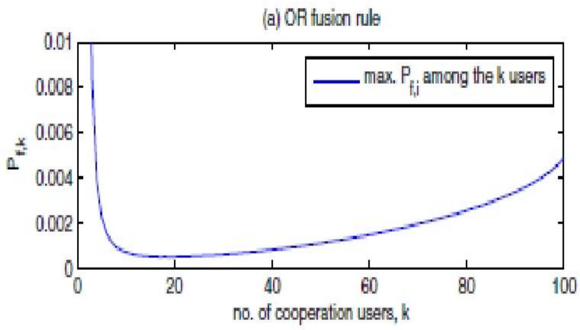

Fig. 5. Plot of maximum of $P_{f;k}$ among m users in case of constant detection rate OR rule

2) AND Rule:

Similar to the above discussion, in case of AND logic rule, for a given targeted probability of detection $\overline{P_d}$, $P_{d,k}$ in each user is,

$$P_{d,k} = \sqrt[m]{\overline{P_d}} \qquad (22)$$

for selected m best users. Then substituting equation (22) in equation (19), we get $P_{f,k}$ as

$$P_{f,k} = Q\left(\sqrt{2\delta_k + 1}\, Q^{-1}\left(\sqrt[m]{\overline{P_d}}\right) + \sqrt{N\delta_k}\right) \qquad (23)$$

from equation (23) it is known that, if δ_k's are larger, then $P_{d,k}$ is larger. Hence as like before, users with larger δ_k are chosen for cooperation. In fig 6 maximum of $P_{f,k(worst)}$ which is $P_{f,m}$ among all users is plotted with respect to number of users. The plot increases when number of users are added up in the cooperation. The same nature can be verified with the equation (23). Further the AND fusion scheme is exponentially decreasing and $P_{f,k}$ from equation (23) is exponentially increasing, it is difficult to find optimum for 1 < m < K. Even then equations (19, 23) are used for finding the number m.

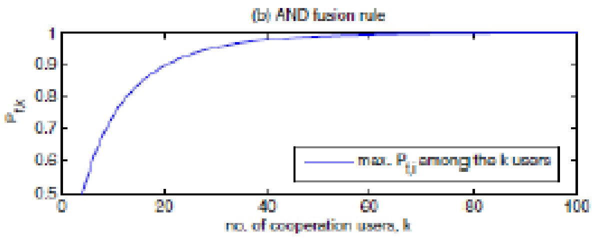

Fig.6. Plot of maximum of $P_{f,k}$ among m users in case of constant detection rate AND rule.

Simulation results for P_f in case of constant detection rate OR rule is shown in fig. 5. Similarly result for constant detection rate AND rule is shown in fig. 6. In this simulation, secondary users are distributed according to uniform random numbers within the distance of 30 km from fusion center, and primary user is said to be at 150 km away from fusion center as shown in fig. 4. The value of N is chosen to be 6000. The values of α, β are taken as such in [45]. Either d_k or δ_k are assumed to be known for fusion center. The results are shown in fig. 7 for number of cooperative users respectively as 50, 100, 150 and 200. In both the schemes AND and OR, P_f decreases initially and rises up again as k reaches K. These results are in concord with previous discussions.

V. SOFT COMBINING

We come back to the signal model expressed in equation (1). Without loss of generality, we assume here that s(n) being Gaussian random number with zero mean and unit variance. Let $w_k(n)$ be white Gaussian noise samples with zero mean and unit variance, $h_k(n)$ denote block Rayleigh fading channel and is equal to h_k for notation convenience. Let δ_k denote Signal to noise ratio which is equal to h_k. With these assumptions, the received signal is said to have Gaussian distribution as follows [21].

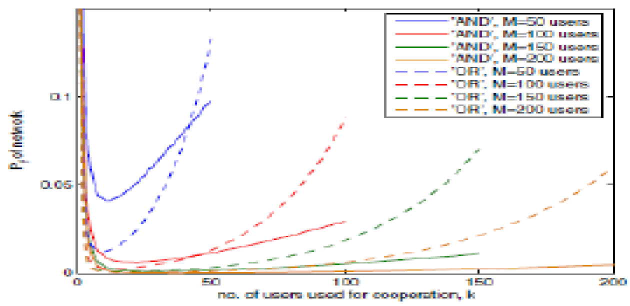

Fig.7. Plot between P_f of a network with respect to number of users as 50,100,150 and 200.

$$Y_k(n) \sim \begin{cases} N(0,1), & H_0 \\ N(0, 1 + h_k), & H_1 \end{cases} \qquad (24)$$

while $Y_k(n)$ follows the above distribution, the corresponding energy in equation (2) will follow chi square distribution as given below,

$$E_k = \begin{cases} b_k 0 & , \quad H_0 \\ (1 + \delta_k) b_k 1 & , \quad H_1 \end{cases} \qquad (25)$$

A. Optimal Soft Combination

In order to obtain the test statistic, we would like to maximize the detection probability by keeping false alarm probability to be small. This can be done through Neyman Pearson criterion, which is equal to likelihood ratio test (LRT).

Let $Y = (Y_1, Y_2, ... Y_N)$, then LRT is expressed as

$$LRT(Y) = \prod_{k=1}^{N} \frac{prob\ (Y_k/H_1)}{prob\ (Y_k/H_0)} \qquad (26)$$

can be obtained from equation (24) as,

$$prob\ (Y_K/H_0) = \frac{(1/2)^{\wedge\frac{N}{2}}}{\Gamma\frac{N}{2}}\ Y_k^{\frac{N}{2}-1}\ e^{\frac{1}{2}Y_k} \qquad (27)$$

similarly,

$$prob\ (Y_K/H_1) = \frac{1}{1+\delta_k}\ \frac{\left(\frac{1}{2}\right)^{\left(\frac{N}{2}\right)}}{1+\delta_k\Gamma\left(\frac{N}{2}\right)}\ \left(\frac{Y_k}{1+\delta_k}\right)^{\frac{N}{2}-1}\ e^{\frac{Y_k}{2(1+\delta_k)}}$$

(28)

Therefore, LRT is,

$$LRT(Y) = \left(\Pi_{k=1}^{K}\ \frac{1}{1+\delta_k}\right)^{\frac{N}{2}}\ e^{-0.5\sum_{k=1}^{K}\frac{\delta_k}{1+\delta_k}Y_k} \qquad (29)$$

from which, the test statistics is taken as,

$$T = \sum_{k=1}^{K} \frac{\delta_k}{1+\delta_k}\ Y_K \qquad (30)$$

and $T > \lambda$ during H_1, or $T < \lambda$ during H_0. λ is taken to be the new decision threshold and the same is obtained from equation (29) as $\lambda = 2\ln K + M \sum_{k=1}^{K} \ln(1+\delta_k)$

The quantity inside summation in equation (30) is treated as weight for linear combination. The same is being let as $w_k = \frac{\delta_k}{1+\delta_k}$. We like to classify this weighted combining as equal gain combining [21] where $w_k = 1$ for all k, and maximal ratio combining where in $w_k = \delta_k$ [21]. In fact, proposed weighted combining scheme becomes equal gain combining at high signal to noise ratio, and becomes maximal ratio combining at low signal to noise ratio. Using the method illustrated in [53], false alarm and detection probability are obtained using approximation of cumulative distributive function. By fixing false alarm probability to a small value, threshold can be obtained as mentioned before and in [53]. Further [44] reports on soft combining fusion scheme with mean cumulative sum algorithm.

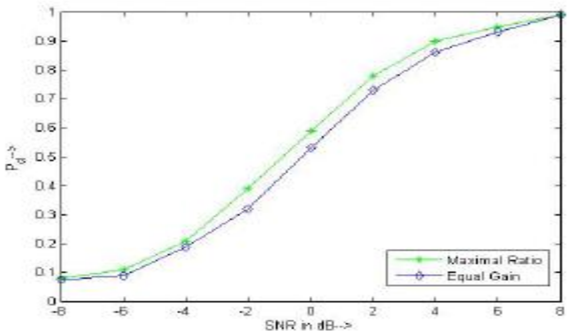

Fig. 8. Probability of detection plot for maximal ratio soft combining and equal gain soft combining with respect to SNR values.

For simulation purpose, K = 4 number of users are taken with N = 6 number of samples. The false alarm probability is set to 0.01. A plot in fig 8 shows detection performance for both maximal ratio and equal gain combining schemes respectively. It is obvious from the figure that maximal ratio combining outperforms equal gain combining.

VI. CONCLUSION

This paper presents a survey on cooperative spectrum sensing in a cognitive radio network. Though there are several sensing methods, cooperative spectrum sensing is considered as a solution to some of the common problems in spectrum sensing. The detection performance for various user co-operations like hard combining and soft combining is presented in this paper. In hard combining, the performance for 'AND' logic rule, 'OR' logic rule, and 'M out of K' rule are presented. We have also presented the result with optimum number of users to cooperate in a hard combinations like 'OR', 'AND', and 'M out of K' rules. Further, two kinds of soft combining methods viz. maximal ratio combining and equal gain combining were also discussed with detection performances. Security and privacy issues are considered to be some important challenges in CR users. Future works can be extended in these areas.

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