ADAPTIVE COOPERATIVE SPECTRUM SENSING USING GROUP INTELLIGENCE

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ABSTRACT

Opportunistic Spectrum Access in Cognitive Radios (CRs) calls for efficient and accurate spectrum sensing mechanism that provides the CR network with current spectral occupancy information. For a CR using energy detection for spectrum sensing, exact knowledge of Signal to Noise Ratio (SNR) at the receiver is crucial for determination of the decision threshold. This threshold in turn determines the probability of error (Probability of missed detection and probability of false alarm). In this paper, an innovative technique is proposed wherein spectral occupancy decisions from different CRs are combined and used as a training signal to adapt the local decision threshold. Each CR trains itself such that its decision is in alignment with other CRs in the network. Same can be looked at from group intelligence perspective where, multiple users, each with incomplete information, can learn from the group's wisdom to reach a supposedly correct conclusion. Simulations under Rayleigh fading show probability of error at par with other co-operative spectrum sensing techniques albeit at lower complexity levels. We also probe into the accuracy of those decisions with standard techniques from a Cognitive Network perspective to prove the wisdom in group knowledge.

KEYWORDS

Group Intelligence, Cognitive Adhoc Networks, Opportunistic Spectrum Access, Co-operative Spectrum Sensing.

1. INTRODUCTION

Cognitive Radio has been considered a promising technology that would address the conflicting situation of scarcity of the electromagnetic radio spectrum and under-utilization of spectrum in many places [1]. Opportunistic spectrum access is one of the solutions proposed to address this situation. A Cognitive Radio (CR) is a technology that enables wireless devices to be aware of their surroundings and enable them to access these unutilized spectrum bands (referred to as spectrum holes) opportunistically, without affecting the licensed or the Primary User (PU). Given its potential, the CR systems have been described as "disruptive but unobtrusive technology" [1]. To be able to use a spectrum hole successfully, the unlicensed CR, also referred to as the Secondary User (SU) must satisfy the following requirements.

1. It must be able to detect the presence of a spectrum hole with high accuracy and reliability.
2. It must be able to vacate the spectrum once the PU arrives within allowed time period.

An SU can satisfy these requirements using a spectrum sensing technique that is fast and accurate. Spectrum sensing is considered a key technology that needs to be matured before CRs become reality. As a result, much work has been done in the area focusing on accuracy of spectrum sensing mechanism as well as the sensing speed [2].

Commonly used spectrum sensing techniques include energy detection, matched filter, cyclostationarity based feature extraction *etc*. In this work, focus is on the energy detection based spectrum sensing technique because of its ease of implementation and speed of operation. An energy detection device provides a binary decision, indicating spectral band occupancy by a

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PU. The decision is based on a threshold which depends on the current SNR. This threshold can be adjusted to balance between the probability of false alarms and probability of detection [8]. In time varying channel conditions, where signal strength changes frequently, the threshold should be updated continually to accommodate the changing SNR. Optimal threshold in such conditions can be determined dynamically, using learning techniques as seen in [3]. These techniques require a training sequence consisting of spectrum status of the PU for learning, which is an overhead to the bandwidth. Mobility of the transmitter and receiver implies changing channel conditions which make the results achieved from training worthless after a small duration. Other adaptive techniques such as floating threshold, floating/fixed threshold, double floating thresholds have been proposed in [4-6], where the methods are based on SNR measurements. Such methods are prone to noise power estimation uncertainty which is discussed further in subsection 2.2.

In this paper, a new threshold learning technique for a Cognitive Adhoc Network (CAN) is proposed. The scenario is as shown in Figure 1. The training signal for this adaptive system is derived from the spectral occupancy information received from other users in the network over the common control channel. Each CR adjusts its threshold such a way that its decision is in alignment with other CRs in the network. The technique is differentiated from the adaptive data fusion techniques [14] in the sense that it is the decision process that is adapted, not the process of the combining the available results (Fusion techniques). Same can be looked at from group intelligence point of view; where multiple users, each with unreliable information can train themselves to reach the correct conclusion using information from others.

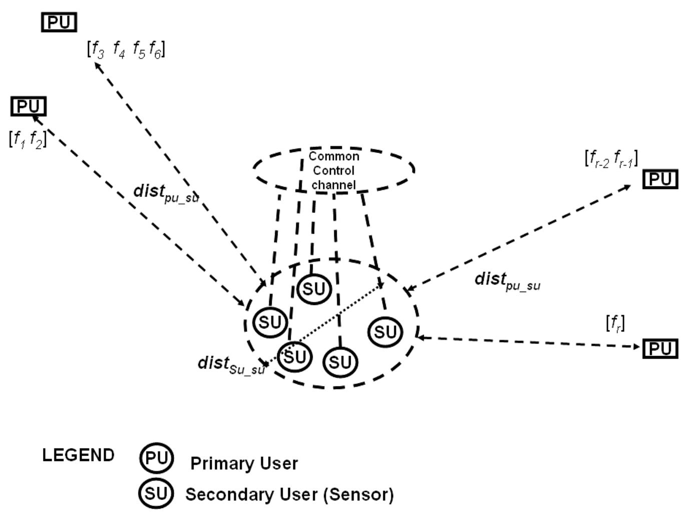

Figure 1. A Scenario for CAN

Remainder of the paper is organized as follows. Section 2 describes the system model under the considered scenario. Section 3 describes the proposed adaptive threshold method. Simulation model with results are described in section 4. Finally the conclusions and future work are presented.

2. SYSTEM MODEL

In this section, the local spectral sensing technique and the data fusion techniques as applied to the scenario under consideration are discussed in detail. The optimal threshold and the proposed adaptation of local threshold are also discussed here.

2.1. Local Spectrum Sensing: Energy Detection

Energy detection has been the technique of choice for spectrum sensing due to its low complexity, ease of implementation and faster decision making capability. For purpose of this work, the focus is solely on the binary decision (PU present or absent) provided by the energy detector, rather than the technique itself. Figure 2 shows the block diagram of an energy detector [8]. Output of the band-pass filter (with bandwidth W) is followed by a squaring device and integrator to measure the received signal energy over the observation interval of T seconds. Output is normalized by the noise spectral density N_0 to obtain Y, which is compared with a decision threshold λ to make the spectral occupancy decision. Same can be formulated as a binary hypothesis testing problem [10, 11], where H_0 corresponds to the case where PU is absent and H_1 corresponds to PU being present.

$$Y \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \tag{1}$$

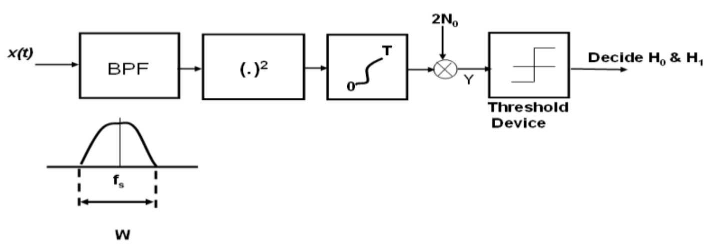

Figure 2. Energy Detector

The normalized output Y has central and non-central chi-square distributions under H_0 and H_1 respectively, each with *2m* degrees of freedom as shown below.
Where *m* is an integer denoting the time-bandwidth product 'WT' and γ is the SNR. The distribution of random variable Y under the two hypotheses is as shown below.

$$f_{Y|H_0}(y) = \frac{y^{m-1}e^{-y/2}}{\Gamma(m)2^m}$$
$$f_{Y|H_1}(y) = \frac{y^{m-1}e^{-(y+2m\gamma)/2}}{\Gamma(m)2^m}\,{}_0F_1(m, \frac{m\gamma y}{2}) \tag{2}$$

Γ(.) is the gamma function and ${}_0F_1(.,.)$ is the confluent hyper geometric limit function [8]. The conditional distributions under hypothesis H_0 and H_1 are as shown in Figure 3.

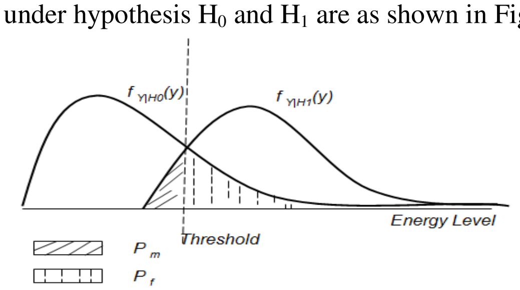

Figure 3. Distributions of Y under hypothesis H_0 and H_1

The success of a spectral sensing technique can be evaluated in terms of its ability to detect the presence of PU with minimal false alarms. It can be expressed in terms of probability of detection (P_d) and probability of false alarm (P_f). P_f is the measure of lost opportunity by the SU where the spectral band is falsely declared as occupied, while P_d is the measure of ability of the

SU to use the white spaces without interfering with the PU. Higher P_d is essential for the SU to be able to use the licensed band without causing hindrance to the PU. The need to maximize P_d conflicts with the requirement for a lower P_f. Design criterion should be chosen such that P_f is minimized while guaranteeing P_d to remain above a certain threshold. For the detector shown in Figure 2, the expressions for P_d and P_f have been derived in literature [8] as shown below.

$$P_d = P\{Y > \lambda \mid H_1\} = Q_m(\sqrt{2m\gamma}, \sqrt{\lambda}\ )$$
$$P_f = P\{Y > \lambda \mid H_0\} = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)} \triangleq G_m(\lambda\lambda \qquad (3)$$
$$\Gamma(a,b) = \int t^{a-1} e^{-t} dt \qquad (4)$$

$\Gamma(a,b)$ is the incomplete gamma function and $Q_m(.;.)$ is the generalized Marcum function. Reader is referred to [8,9] for more details. Value of this decision threshold will determine whether the receiver is too sensitive (high P_d, high P_f) or too aggressive (low P_d, low P_f).

2.2. Determination of Optimal Threshold for known SNR and 'm'

To determine the value of λ that would minimize the decision error for the situation concerned, a combined error function is formed based on P_f and $P_{m.}$ ($P_m = 1 - P_d$)

$$\varepsilon = \alpha P(Y < \lambda \mid H_1) + (1-\alpha)P(Y > \lambda \mid H_0)$$
$$\varepsilon = \alpha P_m + (1-\alpha)P_f = \alpha(1-P_d) + (1-\alpha)P_f \qquad (5)$$
$$0 \le \alpha \le 1$$

α is the weighting factor to be adjusted based on the situation. For example, if sensitivity is crucial, λ is chosen such that P_m is minimized at the expense of high P_f. This can be achieved by choosing α close to 1 and vice versa. Since the error term (ε) consists of probabilities and a non-negative variable α, the error term is guaranteed to be non-negative. Value of λ that will minimize the error can be found by determining the first derivative.

$$\frac{d\varepsilon}{d\lambda} = \alpha \frac{dP_m}{d\lambda} + (1-\alpha)\frac{dP_f}{d\lambda} \qquad (6)$$
$$\frac{dP_f}{d\lambda} = \frac{d}{d\lambda}\left[\frac{1}{\Gamma m}.\Gamma(m, \lambda/2)\right]$$

$$\frac{d}{dx}\Gamma(s,x) = -x^{s-1}.e^{-x}$$
$$\frac{dP_f}{d\lambda} = \frac{1}{\Gamma m}\left[-\left(\frac{\lambda}{2}\right)^{m-1} e^{-\lambda/2}\right].\frac{1}{2} \qquad (7)$$

Next, substituting expression for $P_m = 1\text{-}P_d$, we get

$$\frac{dP_m}{d\lambda} = \frac{1}{2\sqrt{\lambda}}\left[\frac{\sqrt{\lambda}^{m}}{\sqrt{2m\gamma}^{m-1}}\right] e^{-\left(\frac{2m\gamma+\lambda}{2}\right)} .I_{m-1}\left(\sqrt{2m\gamma\lambda}\right) \qquad (8)$$

Substituting (7) and (8) in equation (5) and equating it to zero we get,

$$\frac{d\varepsilon}{d\lambda}=\alpha\frac{1}{2\sqrt{\lambda}}\left[\frac{\sqrt{\lambda}^{m}}{\sqrt{(2m\gamma)^{m-1}}}.e^{-\left(\frac{2m\gamma+\lambda}{2}\right)}.I_{m-1}\left(\sqrt{2m\gamma\lambda}\right)\right]+(1-\alpha)\frac{1}{2\Gamma(m)}\left[-\left(\frac{\lambda}{2}\right)^{m-1}e^{\frac{-\lambda}{2}}\right]=0$$

$$\alpha\frac{1}{2\sqrt{\lambda}}\left[\frac{\sqrt{\lambda}^{m}}{\sqrt{(2m\gamma)^{m-1}}}.e^{-\left(\frac{2m\gamma+\lambda}{2}\right)}.I_{m-1}\left(\sqrt{2m\gamma\lambda}\right)\right]=(1-\alpha)\frac{1}{2\Gamma(m)}\left[\left(\frac{\lambda}{2}\right)^{m-1}e^{\frac{-\lambda}{2}}\right] \tag{9}$$

$$2\lambda^{(m-1)/2}=\left(\frac{\alpha}{\alpha-1}\right)\frac{\Gamma(m)}{(2m\gamma)^{(m-1)/2}}e^{-m\gamma}\left[.I_{m-1}\left(\sqrt{2m\gamma\lambda}\right)\right].2^{m}$$

$$\frac{\lambda^{(m-1)/2}}{.I_{m-1}\left(\sqrt{2m\gamma\lambda}\right)}=\left(\frac{\alpha}{\alpha-1}\right)\frac{\Gamma(m)}{(2m\gamma)^{(m-1)/2}}e^{-m\gamma}.2^{m-1} \tag{10}$$

Optimum value of the threshold λ for given α, SNR (γ) and m can be obtained by solving equation (10). The first derivative of the error function as shown by equation (9) can be seen in Figure 4, for α = 1/4, 1/2 and 3/4. Relationship between threshold for different SNRs and degrees of freedom has been well investigated in [10-11]. Inclusion of the weighing parameter α, gives additional flexibility of choosing the threshold based on the situational requirements.

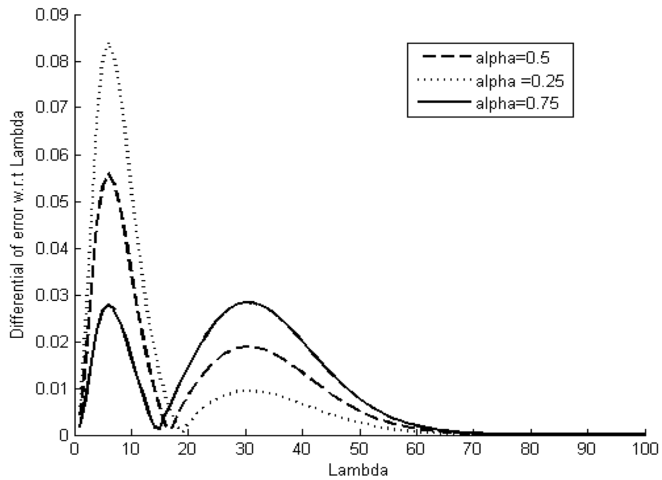

Figure 4. Differential of Error versus Lambda for m=4 and SNR=5dB

The performance of a spectrum sensing scheme is limited by the SNR estimation at the CR. Error in the SNR estimation will result in incorrect threshold estimation and effectively higher probability of error. Figure 5 (reproduced from [16]) shows the performance of the energy detector under noise uncertainty, for large values of m. It can be seen that with no noise uncertainty, the energy detector can perform well at negative SNR values. However, the performance degrades sharply, with errors in noise estimation. In practice, an energy detection device must estimate the operating SNR and use them to determine the decision threshold. Due to time varying channel conditions and inherent uncertainty associated with the estimation process, the estimated SNR and the threshold chosen is sub-optimum, resulting in large decision errors. The performance can be improved by updating the threshold using information about the local noise and signal power [8,11]. Such adaptation can compensate for local changes in SNR and improve on the performance of the energy detector. However, in "hidden node" situations, the SU is likely to make incorrect decision with only local measurements at its disposal.

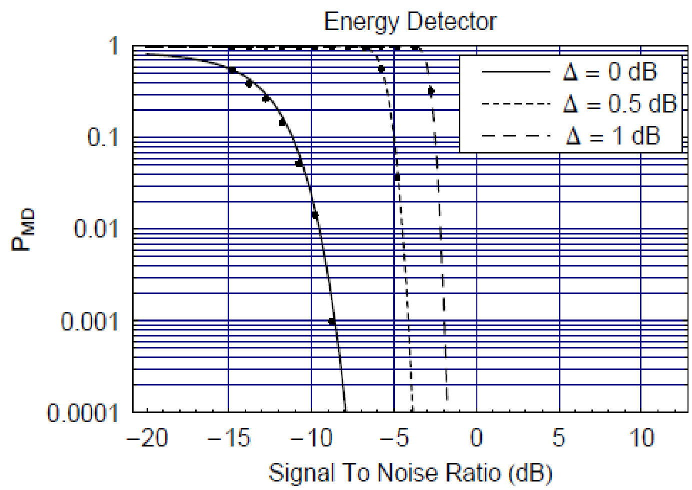

Figure 5. P_m Versus SNR: Static Threshold (replicated from Reference [16])

2.3. Distributed Sensing and Data Fusion

Hidden node conditions can be better handled using spatial diversity or the so-called cooperative or distributed spectrum sensing [8, 13]. In the CAN scenario under consideration, SUs in the network broadcast their spectral decisions over the common control channel (Figure 1). Each SU then can use these decisions, along with its own estimation to make a more accurate decision about the spectral occupancy. Spatial diversity between different SUs is expected to provide considerable performance improvements in the presence of hidden nodes and channel fading.

The combined decision about the occupancy of the spectrum band can be made using simple logical techniques such as AND, OR or Majority Logic. These techniques treat all decisions equally, without taking into account the fact that some SUs may be in lower fading zone, and hence more reliable than others. As a result, the performance improvement is minimal. Considerable improvement can be obtained if each SU transmits its reliability information (P_d and P_f) along with spectral occupancy information (+1 for occupied and -1 for not being occupied).

This information would be used to combine the data using log-likelihood (LR) data fusion rule [13,15]. With N active SUs in the network, log-likelihood ratio test is

$$\left[\sum_{S^+}\log_e\frac{P_{di}}{P_{fi}}+\sum_{S^-}\log_e\frac{(1-P_{fi})}{(1-P_{di})}+\log\frac{P_1}{P_0}\right]\underset{H_0}{\overset{H_1}{\gtrless}}0 \tag{11}$$

The local decision of the i^th^ SU is denoted by d_i and S^+ indicates subset with occupancy result d_i=1 and S^- with result d_i=-1. P_1 and P_0 are the prior probability of the presence & absence of PU signals [13]. Decision from each SU is weighed based on its reliability, i.e. P_d and P_f. This technique is considered the optimum technique for data fusion provided correct estimates of the local probabilities are available. As a result, distributed spectrum sensing with adaptive weighing of the local decisions before fusion has been the general approach so far for performance improvements [13,14]. However, it has a major drawback of the necessity of computing P_d and P_f, which is an overhead and can lead to its own uncertainties.

2.4. Adaptive Threshold based on Group Intelligence

In our work, concepts from both the ideas *i.e.* optimal/adaptive threshold along with data fusion discussed above are utilized in an innovative manner. With energy detection as the chosen approach for spectral detection, the performance is limited by local SNR conditions and accuracy of local noise power estimate. Goal is to improve the accuracy of spectral occupancy results by training the SU. This training is done using the global decision derived from other SUs in the network. This approach is preferable in following ways:

1. Separate training signal indicating the presence or absence of PU is not required. Training can be done continually, not limited to the training signal.
2. Training signal derived from spatially diverse SUs is expected to be robust and less sensitive to local channel fading.

Looking at the situation from Group Intelligence point of view, each SU "learns" to be more like rest of the SUs in its group. Together the SUs are expected to reach a unanimous decision, which should be correct in most situations. Group intelligence emerges from the collaboration and competition among many individuals, enhancing the social pool of existing knowledge [12]. The concept of Group Intelligence obtains prominence in the context of Multi Agent scenarios wherein the global decision made is an essence of the all the individual local decisions. In the CAN scenario, the group intelligence in terms of the accuracy of the spectral information learned by the group of SUs. In other words lesser the number of decision errors, wiser is the network. Success of Group Intelligence or wisdom in crowds relies on four basic characteristics. An analogy has been drawn with a CAN perspective and is presented in Table 1. (Reference [12])

Table 1. Criteria for a Group to Be Wise & CAN Analogy

Criteria	**Description**	**CAN Features**
Diversity of opinion	Each person should have private information even if it is just an eccentric interpretation of the known facts.	SUs are spatially distributed, each having its own view point and showing space diversity
Independence	People's opinions aren't determined by the opinions of those around them.	Each SU's measurements of the spectrum are independent of the other SUs.
Decentralization	People are able to specialize and draw on local knowledge.	It is an adhoc group having no centralized entity.
Aggregation	Some mechanism exists for turning private judgments into a collective decision.	The data fusion methodology is the mechanism which makes the group decision regarding the spectrum.

2.4.1. System Model

The proposed adaptive threshold system is as shown in Figure 6. The input, output and the desired signals for the adaptive system are as described below:

Input: Y_t, output of the energy detector at time instance t.
Desired Output: Decision d_t made using available decisions from other SUs in the group. The decision may be obtained using majority logic and is a hard decision, limited to +1 or -1 at instance t. 1 indicating presence of PU and vice versa.

Output: Output of the adaptive system is the local soft decision z_t obtained using current threshold λ_t , where λ_t is the current estimate of threshold. z_t is limited to a closed interval [0,1]. The decision device is a scaled sigmoid function. Larger the difference between the received signal power and the threshold, closer is the output (z_t) to +1 or 0.

The error is defined as the difference between the output of the decision device and the global decision. The threshold λ_t is updated such that the error is minimized in the mean square sense. The update takes place every time instance 't', where t is the sampling period of the energy detection device.

Update Algorithm:

$$\lambda_{t+1} = \lambda_t - \mu \frac{\partial E\left(e_t^2\right)}{\partial \lambda_t}$$

$$e_t = d_t - z_t$$

$$z_t = f\left(Y_t - \lambda_t\right) = \frac{1}{1+e^{-(Y_t - \lambda_t)}}$$

$$E(e_t^2) \approx e_t^2$$

$$\frac{\partial e_t^2}{\partial \lambda_t} = 2e_t \frac{\partial e_t}{\partial \lambda_t} = 2e_t \frac{\partial\left(d_t - z_t\right)}{\partial \lambda_t} = -2e_t \frac{\partial z_t}{\partial \lambda_t}$$

$$\frac{\partial z_t}{\partial \lambda_t} = \frac{\partial f(Y_t - \lambda_t)}{\partial \lambda_t} = -f(Y_t - \lambda_t)\left[1 - f(Y_t - \lambda_t)\right]$$

$$\frac{\partial z_t}{\partial \lambda_t} = \frac{\partial f(Y_t - \lambda_t)}{\partial \lambda_t} = -f(Y_t - \lambda_t)\left[1 - f(Y_t - \lambda_t)\right]$$

$$\frac{\partial z_t}{\partial \lambda_t} = -z_t\left(1 - z_t\right)$$

$$\frac{\partial e_t^2}{\partial \lambda_t} = -2e_t \frac{\partial z_t}{\partial \lambda_t} = 2e_t z_t (1 - z_t)$$

Update equation

$$\lambda_{t+1} = \lambda_t - \mu \frac{\partial e_t^2}{\partial \lambda_t} = \lambda_t - 2\mu\mu_t z_t (1 - z_t) \qquad (12)$$

At each time instance t, the updated threshold λ_{t+1} is used to make the hard decision about the spectral occupancy. It can be seen from the update equation that, the threshold remains relatively unchanged in two situations:

- When the error $e_t \sim 0$, indicating that the local decision is in agreement with the global decision.
- When output of the decision device is close to 1 or 0. This indicates saturation of the sigmoid function or large distance between the input and the threshold.

Thus, the update is slow when local decision is in agreement with global decision (the training signal) and when local SNR is high, implying higher confidence in local decisions.

However, in case of "hidden node" situations, the local signal strength may be very poor, resulting in a strong "no" decision (z_t ~ 0). In this case, local decision is deemed not reliable, and instead the global decision is used.

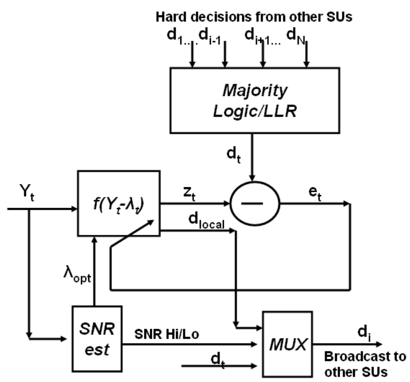

Figure 6. System model at ith SU

The event diagram of the sensing process is depicted in Figure 7. Each SU senses the spectrum continually, generates a hard decision on the presence/absence of the PU and broadcasts this information to the entire network. The SUs sense the spectrum and transmit the hard decision at least once in a T_s second frame and at the end of which data fusion is performed to obtain the desired signal (global decision) d_t. The spectrum sensing and broadcasting by each SU is asynchronous in nature. Each SU uses the available information from other SUs to generate global decision or the training signal. Since the SUs sense asynchronously, the training signal may vary for each SU.

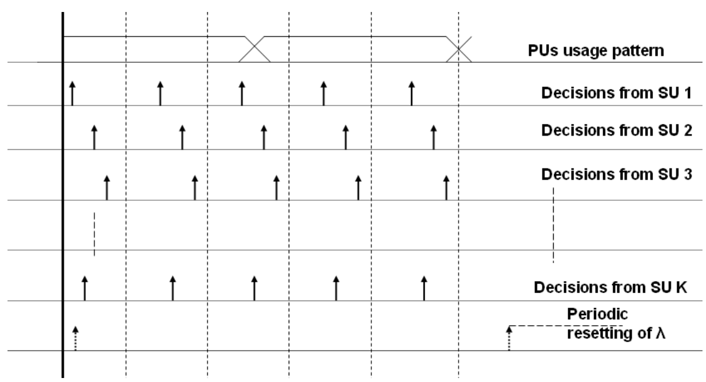

Figure 7. Event Diagram at an SU

The decision threshold at each SU is re-calibrated periodically based on the estimated local SNR at that instant. This re-calibration is done using optimal threshold as derived in Equation (10). This periodic resetting process prevents accumulation of errors in the feedback system.

3. SIMULATION ENVIRONMENT AND RESULTS

The simulated Cognitive Radio Network scenario consists of 'N' SUs and one PU. The PU goes on and off randomly. Each SU senses the spectrum periodically, generates a hard decision on the presence or absence of the PU and broadcasts this information to the entire network every T_s seconds. The SUs operate in Rayleigh fading channel and in presence of Additive White

Gaussian Noise (AWGN). The results from individual SUs with local threshold are compared with the global decision which is obtained using fused decisions from the remaining (N-1) SUs. The fusion logic may be based on simple Majority Logic (ML) or Log Likelihood Ratio Test (LLRT) [15].

At every SU, the threshold is updated as per equation (12). The updated threshold is used to make the local decision about spectral occupancy. This local decision is compared with ground-truth to determine the probability of error. It can be seen that the adaptive technique achieves lower probability of missed detection than using a static threshold, especially in presence of SNR uncertainty at the receiver.

Other set of results are obtained by using the optimum LLRT based data fusion technique. For LLRT based data fusion, each node must broadcast its hard decision along with reliability information (P_d and P_f). This information is used to make a decision about the channel occupancy, which serves as the training signal from the adaptive process. Since LLRT based data fusion technique is superior to majority logic, the training signal is more reliable, and as a result, the adaptive technique performs better. In both cases, the adaptive technique achieves lower probability of missed detection than using a static threshold. Figure 8 represents the pseudo code of the simulation scenario.

```
Initialize m, Number_SUs,N_Simulations, N_SNR_Changes, SNR_Distribution_mean,dg
// m no. of degrees of freedom
// Number_SUs is the set of sizes of the Adhoc Network
// N_Simulations is the no. of Monte Carlo Simulations
// N_SNR_Changes is the number of times SNR changes
// dg is the group decision using majority logic

for i=1 : length (Number_SUs)
    Set Primary User Usage Pattern
    for j=1:N_Simulations
        for k= 1: length (Number of data samples)
            check SNR estimate update count
            if true estimate SNR and Optimal Lambda
            Y= sum of square of m input data samples
            dec= Sigmoid (Y- Optimal Lambda) // dec is an SU's SoftDecision
            mu=500 set empirically
            error= dg-dec
            Lambda= Lambda-mu*error*dec(1-dec)
            FinalDec = ((Y – Lambda)>0)*1
        end // data samples
        error (cnt) = mean (abs (Usage Pattern-FinalDec)
        cnt=cnt+1;
    end // no. of Monte carlo Simulations
    Net Error= mean(error)
end // for different group sized
```

Figure 8: Pseudo code for Simulation

Figure 9 shows simulation results using 10 (N) SUs. The mean operating SNR for the group of SUs is 5 dB with a variance of 5 dB. The SNR estimate error at the SUs is 5 dB. In the first case, it assumed that each SU broadcasts its hard decision (PU present or absent). The training signal for each SU is obtained by fusing these decisions using majority logic decision. In the second case, knowledge of (P_d, P_f) for each SU is assumed and training signal is obtained using

LLRT. It can be seen that the proposed adaptive technique outperforms the corresponding distributed decision technique. The gain is substantial as the local SNR increases, and the method always performs as well as the corresponding distributed decision method.

Figure 10 shows the simulation results under same conditions as before, except here the error in SNR estimation is smaller; 1 dB. It can be see that the method is relatively insensitive to SNR estimation error and continues to perform better than the distributed sensing methods. Figures 11 and 12 show similar results when, the mean SNR of the group is low (0 dB). P_f is assumed to be 0.1 for all simulations.

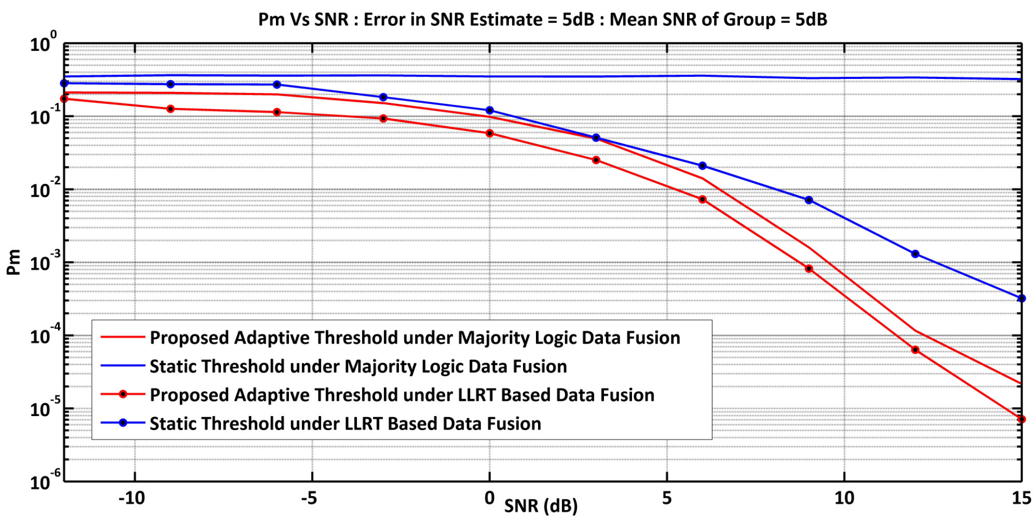

Figure 9. P_m Vs SNR with SNR Estimate Error=5dB, Mean SNR of Group= 5dB.

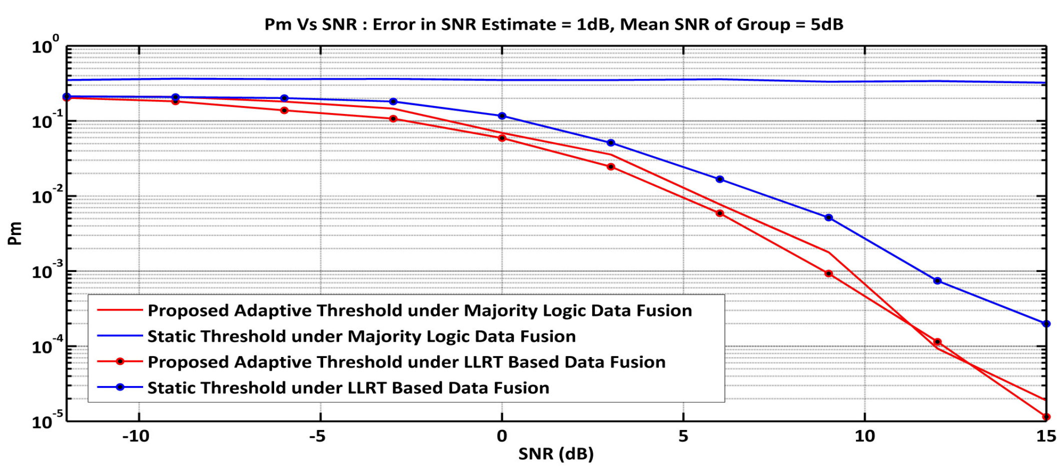

Figure 10. P_m Vs SNR with SNR Estimate Error=1dB, Mean SNR of Group= 5dB

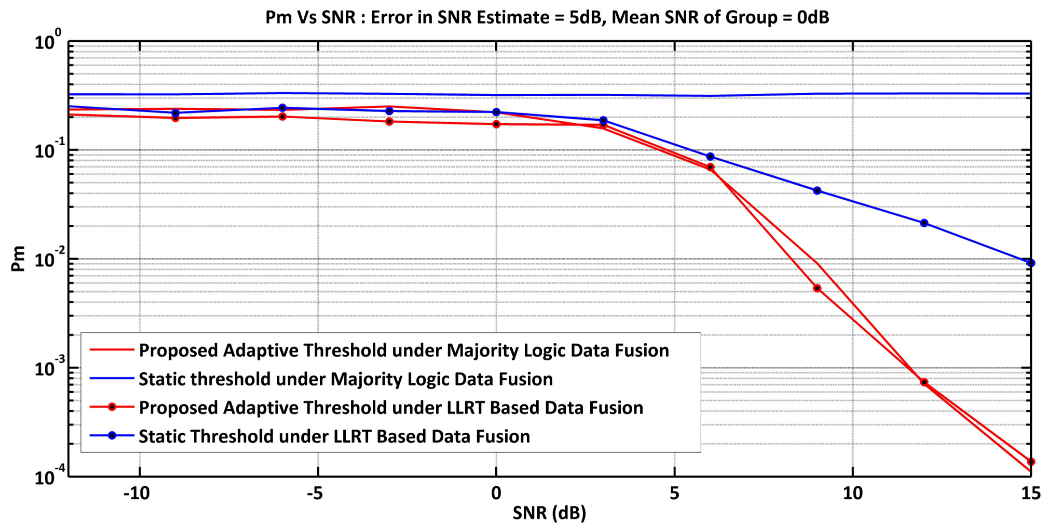

Figure 11. P_m Vs SNR with SNR Estimate Error = 5dB, Mean SNR of Group = 0dB

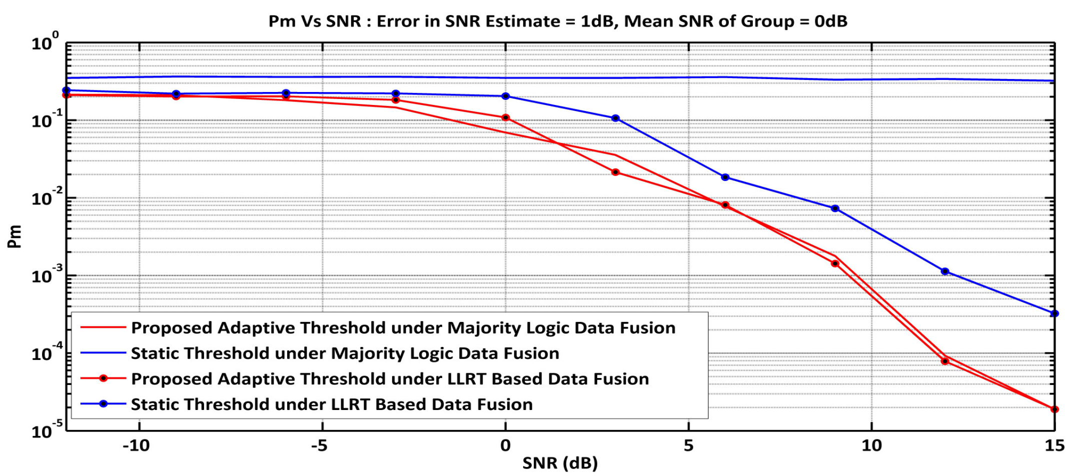

Figure 12. P_m Vs SNR with SNR Estimate Error=1dB, Mean SNR of Group= 0dB

The performance is depicted in terms of P_m versus SNR, which is a methodology to quantify the performance of a given spectrum sensing mechanism [17]. The lowest SNR for a particular targeted reliability is the metric to compare sensing mechanisms.

A decision margin is essentially the distance of the raw data from the decision boundary. For example, in a majority logic technique using 20 SUs, the decision boundary is 10. If more than 10 SUs indicate that spectrum is occupied (d=1), the majority decision is d=1. There would be more confidence in the decision if say 19 SUs indicated d=1 rather than 11. So the decision margin for a group of N SUs is defined as decision_margin = (SUs in majority-N/2)/N/2 If 11 SUs were in majority, the decision margin would be very low ~0.1. With 19 SUs in majority, the decision margin would be 0.9. Thus the decision margin is an indicator of the confidence we have in our final decision and can also be interpreted as reliability of the result. Figure 13 represents this scenario.

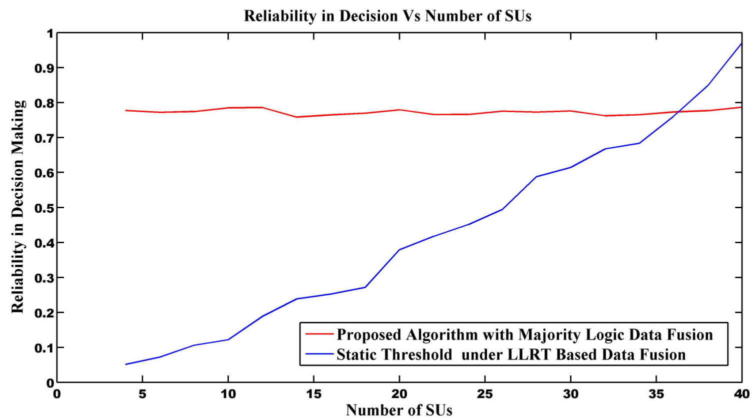

Figure 13. Reliability Versus No. of SUs

Possible explanation from this phenomenon could be that irrespective of the group size, adapting the threshold based on group decision forces the group to be equally good or equally bad together. This is essentially the gist of group intelligence and the cognitive radio network achieves it using this group intelligence based adaptation.

Extending the established results, it is imperative to observe the performance of the proposed algorithm when the group becomes wiser with better SNR conditions. Figures 14 and 15 depict this scenario by comparing the P_m with increasing Group SNR. The mean SNR of the group has been increased with a constant variance and the error in SNR estimate is retained the same for the comparisons. The figures prove the point that the proposed algorithm does better than static threshold with majority logic data fusion methods when the group intelligence is low (under low Group SNR) and equally well when the group gets wiser(under higher group SNR). The results also establish the fact that an empowered self (when SNR of Self SU is higher), as depicted in Figure 15, does much better in a group decision making scenario unlike the majority logic data fusion technique.

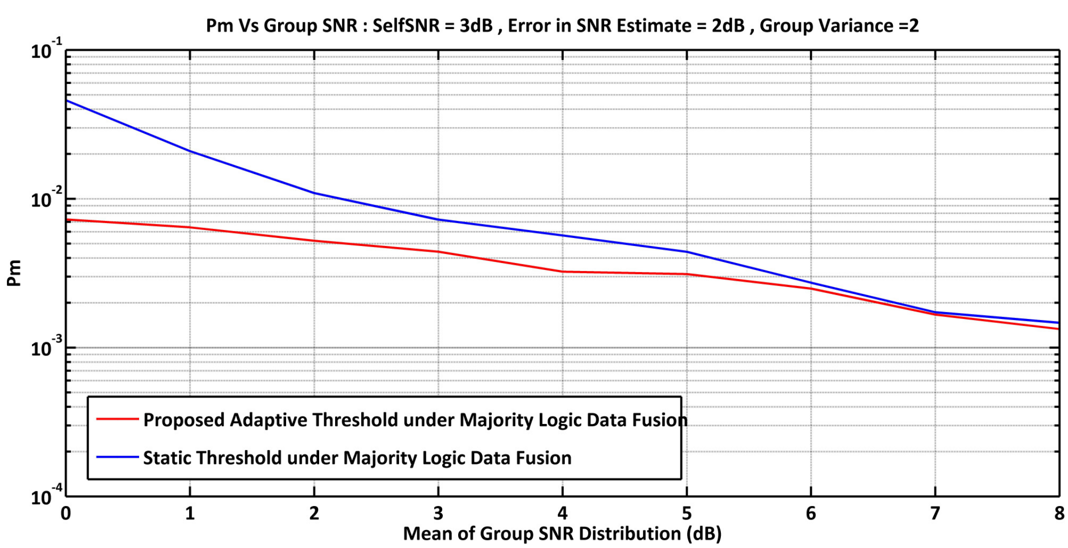

Figure 14. P_m Vs Mean SNR of the Group at SNR at Self SU=3dB

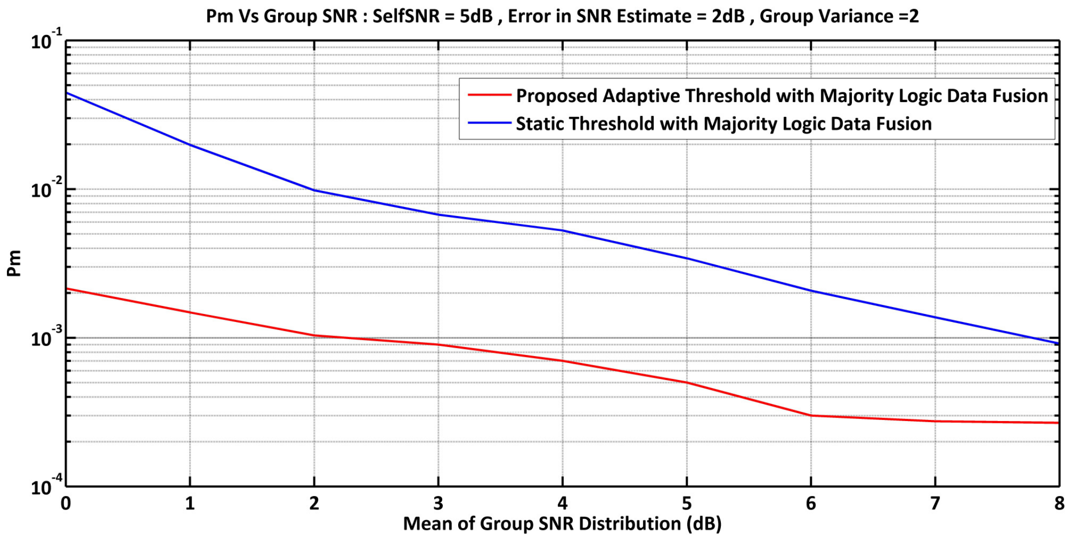

Figure 15. P_m Vs Mean SNR of the Group at SNR at Self SU=5dB

4. CONCLUSIONS

In this paper, we have applied the concepts of group intelligence to cognitive radio networks. Each SU in the group is operating in fading channel conditions with varying noise conditions. Reliability of energy detection devices used for spectral detection is known to be low at sub zero SNR conditions. As a result, decisions made by the SU are not always reliable. Adapting each SU to follow the group, will increase the channel awareness, cognition of each SU is such a way that it behaves more like the group. It is possible that if one SU is intelligent (a CR in a low fading, low noise zone), the inputs from other not-so-intelligent SUs (CRs in large fading) will make it behave less intelligently. However, this is always true with group dynamics, this case being no different. A technique to identify the intelligent SU in the group would ensure that using group knowledge will only benefit an SU and not harm it in anyway. Techniques referred to as “censoring” to limit the number SUs that are broadcasting and the SUs that are used to update the group knowledge are currently being investigated. Another source of error would arise from errors in the control channel used to broadcast information [17]. The group intelligence based adaptation is expected to perform better in this case since it relies on only the hard decisions from other SUs and the measurements are expected to be noisy. Group behaviour under this situation is also being explored.

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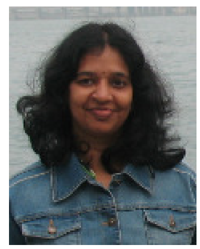

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