Non-Uniform Quantization based Reporting in Cooperative Cognitive Radio

Dhritiman Das and Siddharth Deshmukh
Department of Electronics and Communication Engineering
National Institute of Technology, Rourkela, Odisha, 769008
Email: dhritimandasec2015@hotmail.com, deshmukhs@nitrkl.ac.in

***Abstract*—In this paper we propose a non-uniform quantization technique for reporting the test statistics computed by local cognitive radio (CR) sensors to the fusion center. Local CR sensors are assumed to compute the test statistics based on conventional energy detection technique and fusion center on accumulating the respective test statistics makes final decision about presence or absence of primary user (PU). In order to communicate the test statistics to the fusion center over a band limited channel, the locally computed test statistics are quantized using d bit non-uniform quantizer. The number of bits can be selected on the basis of system specification or amount of backhaul communication that can be supported by the system. The proposed non-uniform quantization is performed on the basis of likelihood function, which is defined as the probability of null and alternate hypothesis when test statistic is known. Next at fusion center the reported local quantized test statistics are combined using optimal weights to get global test statistic. Finally the global test statistic is compared with a threshold to decide for presence or absence of PU. Our simulation results illustrate that the performance of proposed non-uniform quantization is better than conventional uniform quantization.**

I. Introduction

Radio frequency spectrum is identified as one of the most valuable resource for current generation wireless technologies. The rapid advancement of these technologies has led to an exponential growth in bandwidth hungry applications resulting in need for efficient utilization of the spectrum resource. The existing spectrum assignment policy aims in improving reliability in communication; however, the allocation policy leaves a great portion of spectrum severely under-utilized. Thus, there is an urge for a more intelligent and flexible communication technology that can exploit the spectrum resource in a more efficient way. One solution that has gained considerable attention among researchers to address the above challenge is cognitive radio (CR) technology [1], [2]. By definition, a CR is an intelligent device which according to the surrounding radio environment and other user requirements, adapts its transmission power, frequency, modulation technique etc.

The CR technology enables the unlicensed secondary user (SU) to coexist with the licensed primary user (PU) without causing significant interference or very little interference. The secondary user uses a portion of the spectrum, which is unused by the primary user, called spectrum hole, at a particular duration of time. Spectrum hole detection is performed by secondary user and is termed as *spectrum sensing*, [8]. Based on the signal processing approach spectrum sensing can be broadly classified into three major categories: energy detection, matched filter detection and feature detection[4]. Since energy detection approach doesn't require the knowledge of the type of signal from the PU, it is the simplest form of spectrum sensing technique [4], [3]. The CR sensor in case of energy detection based spectrum sensing collects samples from the radio environment, computes the energy and compares it with a threshold to decide for the presence or absence of the PU signal. To further improve the performance of spectrum sensing, cooperative spectrum sensing technique have been studied in [14], [16]. Here a number of CR sensors with different spatial locations are used which individually sense the spectrum and report the decision to the fusion center. Fusion center combines the decision using Soft Combination or Hard Combination technique [5]. In soft combination technique the quantized value of the calculated energy, i.e., the test statistic is sent to the fusion center, where as in hard combination technique the local decisions of the CR sensors are sent. In this work soft combining technique is used as it is more efficient and reliable [5].

Due to limited bandwidth of the reporting channel the exact value of the sensed energy cannot be sent to the fusion center. So, the quantized value of the locally detected energy is reported to the fusion center which is then combined using appropriate combining weights. Based on the system specification or the amount of backhaul communication supported by the system the number of bits for quantization of the test statistic can selected. In [9] a uniform quantization technique for the local test statistic is discussed using Lloyd-Max quantization criterion. [10] proposes a non-uniform quantization technique based on the cumulative distribution function of the presence of PU. It is also shown in [11] that the sensing performance can be increased by increasing the number of bits for quantization. Similarly, in [12] a performance improvement has been observed by reducing the quantization error in the region of uncertainty (the region where no reliable decision can be made) without changing the number of bits. [13] describes a sensing technique where a combination of hard and soft decision is performed. The quantized values of the locally sensed energy is sent to the fusion center when the energy lies in between the two thresholds, otherwise the local decisions are sent. Further in [6], [7] double threshold technique is studied where the sensed energies are ignored when it lies between the two thresholds. All these research work indicate that while reporting the sensed energies from the local CRs, the error should be less in the region of uncertainty. In addition there is an urge to communicate the test statistic in best possible way to the fusion center.

In this paper, we first defined likelihood of hypothesis as the amount of confidence with which a hypothesis can be stated as correct given computed sensed energy. This likelihood function essentially depends on the quality of environment (i.e., fading and noise variance) from which signal samples are sensed. Based on this likelihood function a non-uniform quantization technique for the test statistic is proposed. The combining weights for the local test statistics is then found out by minimizing a cost function, which turns out to be a simpler method than the conventional technique [14], [15]. Simulation results reveal that performance of proposed non-uniform quantization is better than that of the conventional uniform quantization.

II. System Model

Consider a cooperative cognitive radio (CR) sensing scenario in which N CR sensors sense a given narrow band spectrum, as shown in Figure 1. The local CR sensors are similar detectors and are arbitrarily located at different spatial locations such that they experience approximately uncorrelated channel from the primary user. For simplicity in analysis, we assume that all local CR sensors collect L number of samples in a given sensing time duration. Let $x_i(n)$ denote the sample sensed by the i^{th} CR sensor where $i \in \{1, 2, ..., N\}$ at n^{th} time index where $n \in \{0, 1, ..., L-1\}$. The corresponding test statistics computed by i^{th} CR sensor for energy detection based spectrum sensing can be expressed as,

$$T_i = \sum_{n=0}^{L-1} |x_i(n)|^2$$

in which sample $x_i(n)$ take values under two hypotheses,

$$\mathcal{H}_0 : x_i(n) = w_i(n)$$
$$\mathcal{H}_1 : x_i(n) = h_i(n) \cdot s(n) + w_i(n).$$

Here $\mathcal{H}_0$ and $\mathcal{H}_1$ denotes null and alternate hypothesis for absence and presence of primary user (PU) signal, respectively. $h_i(n)$ denotes Rayleigh distributed flat channel fading coefficient for i^{th} CR sensor; $s(n)$ denotes the primary user signal; $w_i(n)$ denotes AWGN noise with zero mean and variance σ_i^2. The expected signal to noise ratio (SNR) η_i for i^{th} CR sensor can be expressed as $\eta_i = \frac{\mathrm{E}\left[|h_i(n)|^2\right] P_s}{\sigma_i^2}$, in which P_s is the power of the primary user signal and $\mathrm{E}[\cdot]$ is expectation operator.

Next, we assume that the number of samples L is large enough such that distribution of test statistics T_i, represented as $\mathcal{P}(T_i)$ is Gaussian distributed. Thus, distribution of T_i under the two respective hypothesis can be expressed as,

$$T_i \overset{\mathcal{H}_0}{\sim} \mathcal{N}\left(\mu_{0,i}, \sigma_{0,i}^2\right) \qquad T_i \overset{\mathcal{H}_1}{\sim} \mathcal{N}\left(\mu_{1,i}, \sigma_{1,i}^2\right) \tag{1}$$

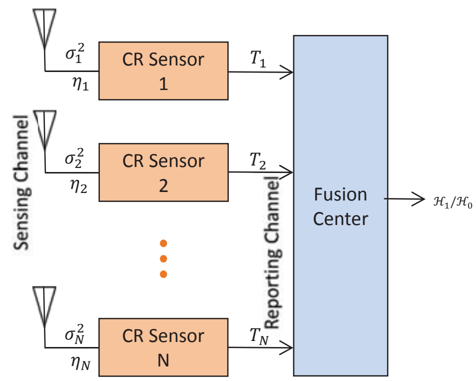

Fig. 1. Block diagram of Cooperative Spectrum Sensing

where respective mean and variance are derived as,

$$\mu_{0,i} = L\sigma_i^2 \qquad \mu_{1,i} = L\sigma_i^2(\eta_i + 1)$$
$$\sigma_{0,i}^2 = 2L\sigma_i^4 \qquad \sigma_{1,i}^2 = 2L\sigma_i^4(2\eta_i + 1)$$

The test statistics computed by the N CR sensors can be arranged into a vector $\overline{T} := \begin{bmatrix} T_1 & T_2 & \ldots & T_N \end{bmatrix}^T$, where T_i is distributed as defined in equation (1). Similarly, under the respective hypothesis we also define SNR vector $\overline{\eta} := \begin{bmatrix} \eta_1 & \eta_2 & \ldots & \eta_N \end{bmatrix}^T$ and noise covariance matrix $\Sigma := \mathrm{diag}\left(\begin{bmatrix} \sigma_1^2 & \sigma_2^2 & \ldots & \sigma_N^2 \end{bmatrix}^T\right)$. It should be noted here that the additive noise term $w_i(n)$ at each local CR sensor is assumed to be spatially uncorrelated and hence the cross terms of Σ are zero.

Since individual elements of $\overline{T}$ are Gaussian distributed, the vector $\overline{T}$ can be defined as multivariate Gaussian random variable, and under respective hypothesis the distribution can be expressed as,

$$\overline{T} \overset{\mathcal{H}_j}{\sim} \mathcal{N}\left(\overline{\mu_j}, \Sigma_j\right) \tag{2}$$

where $j \in \{0, 1\}$ and mean vector and covariance matrix

$$\overline{\mu_j} = \begin{bmatrix} \mu_{j,1} & \mu_{j,2} & \ldots & \mu_{j,N} \end{bmatrix}^T$$
$$\Sigma_j = \mathrm{diag}\left(\begin{bmatrix} \sigma_{j,1}^2 & \sigma_{j,2}^2 & \ldots & \sigma_{j,N}^2 \end{bmatrix}^T\right)$$

Substituting the mean and variance of individual test statistic T_i from equation (1) in above equation, the mean vector and covariance matrix of $\overline{T}$ can be expressed as

$$\overline{\mu_0} = L\Sigma\mathbf{1} \qquad \overline{\mu_1} = L\Sigma(\overline{\eta} + \mathbf{1})$$
$$\Sigma_0 = 2L\Sigma^2 \qquad \Sigma_1 = 2L\Sigma^2\mathrm{diag}(2\overline{\eta} + \mathbf{1})$$

in which $\mathbf{1} = \begin{bmatrix} 1 & 1 & \ldots & 1 \end{bmatrix}^T$. In next section, we discuss quantization techniques required for communicating the test statistics over band limited channels between local CR sensors and the fusion center.

III. Quantization of Test Statistic

Since the communication resource from local CR sensors to the fusion center is band limited, the local sensors need to quantize the test statistics before transmission. For simplicity in analysis, we assume that the reporting channel between local CR sensors and the fusion center are perfect so as there are no error in reporting the quantization bits at the fusion center.

Let us consider quantization for i^{th} sensor. Here we select range of quantization as $(\mu_{0,i} - m_{0,i}\sigma_{0,i},\ \mu_{1,i} + m_{1,i}\sigma_{1,i})$, where $m_{j,i}$, for $j \in \{0,1\}$, is obtained by solving the following inequation,

$$P(|T_i - \mu_{j,i}| \geq m_{j,i}\sigma_{j,i}) \leq \beta \tag{3}$$

The upper limit β is the probability that T_i falls beyond the range of quantization. Since it has been considered earlier that the distribution of the test statistic T_i is Gaussian distribution, so the solution of the above inequality will yield a value independent of hypothesis and communicating CR sensor, i.e., $m_{j,i} = m$ which is dependent only on the value of β. For example, for a typical value of $\beta = 0.0027$, $m = 3$. Next, we divide the range of quantization in $D = 2^d$ quantization levels, where d denotes the number of bits required to represent the quantization level. In the following subsections we first discuss uniform quantization and then propose non-uniform quantization.

A. Uniform Quantization

In case of uniform quantization the region of quantization is divided into D equally spaced intervals to obtain the decision boundaries as $\{b_{k,i}\}_{k=0}^{D}$

$$b_{k,i} = \mu_{0,i} - m\sigma_{0,i} + k\frac{(\mu_{1,i} + m\sigma_{1,i}) - (\mu_{0,i} - m\sigma_{0,i})}{D}$$

Figure 2 shows quantization boundaries for uniform quantization with $d = 3$ and SNR$= -10$dB. The value of β is selected as 0.0027 resulting in $m = 3$. In X axis T_i is normalised using λ_i, which is the point of intersection of distribution functions of T_i for $\mathcal{H}_0$ and $\mathcal{H}_1$ hypothesis.

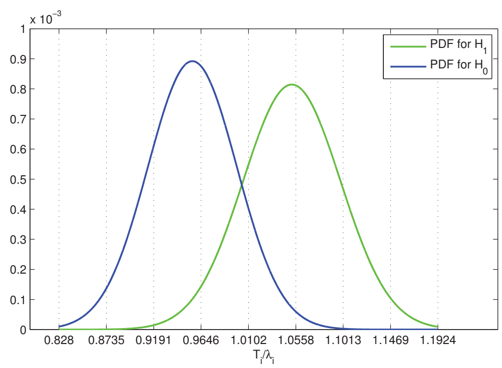

Fig. 2. Quantization boundaries for Uniform Quantization SNR$= -10$dB

The corresponding reconstruction levels $\{\hat{T}_{i,q}\}_{q=0}^{D-1}$ are given by Lloyd-Max quantization criterion [9] and is expressed as

$$\hat{T}_{i,q} = \frac{\int_{b_q}^{b_{q+1}} T_i \mathcal{P}(T_i)}{\int_{b_q}^{b_{q+1}} \mathcal{P}(T_i)} \tag{4}$$

where $\mathcal{P}(T_i)$ is distribution of test statistic for i^{th} sensor and is given by

$$\mathcal{P}(T_i) = P(\mathcal{H}_0)\mathcal{P}(T_i \mid \mathcal{H}_0) + P(\mathcal{H}_1)\mathcal{P}(T_i \mid \mathcal{H}_1). \tag{5}$$

Equation (4) can be simplified by assuming that the quantization intervals are small, such that distribution function $\mathcal{P}(T_i)$ is uniformly distributed within the respective intervals. The reconstruction levels for this simplified case can be stated as,

$$\{\hat{T}_{i,q}\}_{q=0}^{D-1} = \frac{b_q + b_{q+1}}{2}. \tag{6}$$

By quantizing the test statistics, we send specific values of sensed energy to the fusion center. These particular values of sensed energy associate a confidence with which decision can be made [12]. It can be observed from figure 2, that when test statistics T_i takes values around λ_i, the possibility of PU being present or absent is almost same. However, as T_i moves away from λ_i, the confidence on T_i for making decision about presence or absence of PU increases. Thus, confidence of a particular decision is different for different values of T_i. This motivates the idea for non-uniform quantization.

B. Proposed Non-uniform Quantization

In this subsection we propose a non-uniform quantization scheme based on the likelihood of hypothesis. We define likelihood of hypothesis as the probability of null and alternate hypothesis when the test statistic is known, i.e., $P(\mathcal{H}_j \mid T_i)$, where $j \in \{0,1\}$. Using Bayes' rule, likelihood of hypothesis can be mathematically represented as,

$$P(\mathcal{H}_j \mid T_i) = \frac{P(\mathcal{H}_j)\mathcal{P}(T_i \mid \mathcal{H}_j)}{\mathcal{P}(T_i)}$$

where $\mathcal{P}(T_i)$ is defined in equation (5).

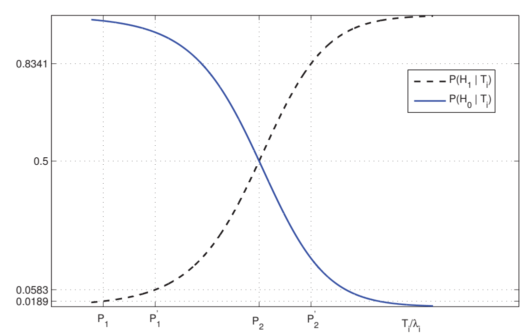

Fig. 3. Likelihood of hypothesis for $\mathcal{H}_1$ and $\mathcal{H}_0$

Figure 3 shows the likelihood of null and alternate hypothesis as a function of T_i for SNR $\eta_i = -12$dB. The X axis T_i is normalised using λ_i (the point of intersection of the distribution functions of T_i for the two hypotheses), as in figure 2. Consider two adjacent values of T_i P_1 and $P_1^{'}$, taken from the region where slope of the likelihood function is very less. Both the values indicate almost same probability of presence of PU; or in other words difference between the likelihood for the two points is very small. In contradictory, if the two adjacent values are taken from the region where the slope is high (e.g., P_2 and $P_2^{'}$ in figure 3) the difference between the likelihood for the two points will be large. A close observation of the likelihood function reveals that, whenever it is required to report the value of the test statistic to the fusion center least error is affordable where the slope of the likelihood function is high. This is because a small change in the value of T_i will cause a significant change in the chance of presence of PU.

Since sum of the likelihood of null and alternate hypotheses is equal to 1, i.e., $\sum_{j\in\{0,1\}} P(\mathcal{H}_j \mid T_i) = 1$, knowledge of one of the likelihood also specifies the value of other likelihood. Thus, the following discussion concentrates only on likelihood of alternate hypothesis.

Assuming *a priori* probability of presence of PU signal as α, i.e., $P(\mathcal{H}_1) = \alpha$ the likelihood function $\mathcal{L}(T_i) := P(\mathcal{H}_1 \mid T_i)$ can be expressed as

$$\mathcal{L}(T_i) = \frac{P(\mathcal{H}_1)\mathcal{P}(T_i \mid \mathcal{H}_j)}{\alpha\mathcal{P}(T_i \mid \mathcal{H}_1) + (1-\alpha)\mathcal{P}(T_i \mid \mathcal{H}_0)} \quad (7)$$

Substituting $\mathcal{P}(T_i \mid \mathcal{H}_1)$ and $\mathcal{P}(T_i \mid \mathcal{H}_0)$ from equation (1) the likelihood can be expressed as $\mathcal{L}(T_i) = 1/(1+\chi)$, where,

$$\chi = \frac{1-\alpha}{\alpha}\sqrt{2\eta_i+1}\exp\left(-\frac{\eta_i}{\sigma_{1,i}^2}\left(T_i^2 - T_i\mu_{0,i} - \frac{\eta_i\mu_{0,i}^2}{2}\right)\right).$$

The quantization levels for a d bit non-uniform quantizer can be obtained by first dividing the Y axis, i.e., likelihood function into $D = 2^d$ equal divisions. The corresponding points are then mapped to the X axis in accordance with likelihood of $\mathcal{H}_1$ to get the quantization boundaries. In figure 4 we show quantization boundaries for 3 bit non-uniform quantizer. As discussed earlier, the range of quantization is given by $(\mu_{0,i} - m\sigma_{0,i},\, \mu_{1,i} + m\sigma_{1,i})$. The corresponding region of likelihood of $\mathcal{H}_1$, i.e., $(\mathcal{L}(\mu_{0,i} - m_{0,i}\sigma_{0,i}),\, \mathcal{L}(\mu_{1,i} + m_{1,i}\sigma_{1,i}))$ is divided into D equally spaced regions to obtain $D+1$ number of values of likelihood of $\mathcal{H}_1$ as $\{\delta_k\}_{k=0}^{D} = \Delta_0 + k\frac{\Delta_1 - \Delta_0}{D}$, where $\Delta_0 = \mathcal{L}(\mu_{0,i} - m_{0,i}\sigma_{0,i})$ and $\Delta_1 = \mathcal{L}(\mu_{1,i} - m_{1,i}\sigma_{1,i})$.

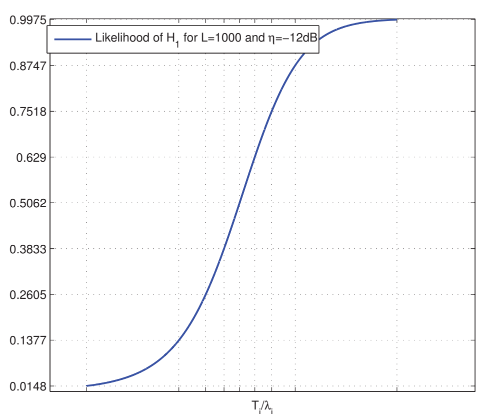

Fig. 4. Quantization boundaries for Non-uniform Quantization

Finally, the non-uniform quantization boundaries are given by $\{b_{k,i}\}_{k=0}^{D}$ as

$$b_{k,i} = \mathcal{L}^{-1}(\delta_k) = \frac{1}{2}\left(\mu_{0,i} + \sqrt{\mu_{0,i}^2 + 2\eta_i\mu_{0,i}^2 + 4\theta(\delta_k)}\right)$$

where $\theta(\delta_k) = \frac{\sigma_{1,i}^2}{\eta_i}\ln\left(\frac{\delta_k(1-\alpha)\sqrt{2\eta_i+1}}{\alpha(1-\delta_k)}\right)$.

The reconstruction levels can be obtained either by equation (4) or (6)

IV. Combining Weights

The received test statistics $\{T_i\}_{i=1}^{N}$ obtained from the local CR sensors are combined together at the fusion center using appropriate combining weights. Let the combining weights be expressed in the form of vector as $\mathbf{w} = \begin{bmatrix} w_1 & w_2 & \dots & w_N \end{bmatrix}^T$. The global test statistic z can be expressed as

$$z = \mathbf{w}^T\overline{T}$$

Since the linear combination of Gaussian random variables is also a Gaussian random variable, the global test statistic z is also a Gaussian random variable with corresponding mean and variance under respective hypotheses as,

$$\mathrm{E}(z \mid \mathcal{H}_0) = \mathbf{w}^T\overline{\mu_0} \qquad \mathrm{E}(z \mid \mathcal{H}_1) = \mathbf{w}^T\overline{\mu_1}$$
$$\mathrm{var}(z \mid \mathcal{H}_0) = \mathbf{w}^T\Sigma_0\mathbf{w} \qquad \mathrm{var}(z \mid \mathcal{H}_1) = \mathbf{w}^T\Sigma_1\mathbf{w}.$$

The combining weights should be selected such that it maximizes the difference between the means of the distributions of z for the two hypotheses and minimizes the individual variances. Thus optimal combining weight $\mathbf{w}^*$ is given by

$$\mathbf{w}^* = \underset{\mathbf{w}}{argmin}\, J$$

$$\begin{aligned} J &= \mathrm{var}(z \mid \mathcal{H}_1) + \mathrm{var}(z \mid \mathcal{H}_0) - (\mathrm{E}(z \mid \mathcal{H}_1) - \mathrm{E}(z \mid \mathcal{H}_0)) \\ &= \mathbf{w}^T\Sigma_1^2\mathbf{w} + \mathbf{w}^T\Sigma_0\mathbf{w} - \mathbf{w}^T\overline{\mu_1} + \mathbf{w}^T\overline{\mu_0}. \end{aligned} \quad (8)$$

J in equation (8) is a convex function. So, differentiating J w.r.t. $\mathbf{w}$ and equating to zero, optimal value $\mathbf{w}^*$ can be obtained as

$$\begin{aligned} \mathbf{w}^* &= \frac{1}{2}(\Sigma_1 + \Sigma_0)^{-1}(\overline{\mu_1} - \overline{\mu_0}) \\ &= \frac{1}{8}\begin{bmatrix} \frac{\eta_1}{\sigma_1^2(\eta_1+1)} & \frac{\eta_2}{\sigma_2^2(\eta_2+1)} & \dots & \frac{\eta_N}{\sigma_N^2(\eta_N+1)} \end{bmatrix}^T \end{aligned} \quad (9)$$

Since norm of $\mathbf{w}^*$ has no effect on the detection performance, it is a convention to make the weighting vector unit norm. So, the final normalized combining vector is given by

$$\mathbf{w}^*_{norm} = \frac{\mathbf{w}^*}{\|\mathbf{w}^*\|}$$

The probability of false alarm and the probability of detection, for threshold λ can be found out by integrating the distribution function of z as

$$P_{fa} = Q\left(\frac{\lambda - \mathrm{E}(z \mid \mathcal{H}_0)}{\sqrt{\mathrm{var}(z \mid \mathcal{H}_0)}}\right) = Q\left(\frac{\lambda - \mathbf{w}^T\overline{\mu_0}}{\sqrt{\mathbf{w}^T\Sigma_0\mathbf{w}}}\right) \quad (10)$$

$$P_d = Q\left(\frac{\lambda - \mathrm{E}(z \mid \mathcal{H}_1)}{\sqrt{\mathrm{var}(z \mid \mathcal{H}_1)}}\right) = Q\left(\frac{\lambda - \mathbf{w}^T\overline{\mu_1}}{\sqrt{\mathbf{w}^T\Sigma_1\mathbf{w}}}\right) \quad (11)$$

The value of threshold λ can be computed for a particular value of false alarm probability P_{fa} using equation (10) to get a detection probability P_d as in equation (11) (Neyman Pearson detection [17]).

V. SIMULATION AND RESULT

In this section we simulate a cooperative cognitive radio scenario sensing a given narrow band spectrum with N local CR sensors. The sensing channel, i.e., the channel between PU and CR sensors is assumed to be Rayleigh distributed flat fading channel. The PU signal is assumed to be BPSK modulated data. We use Neyman Pearson detector, where the primary objective is to satisfy probability of false alarm and probability of detection. The incorporation of *a priori* probability α is meaningful when we deal with minimizing the average probability of sensing error as in the case of *Bayesian detector*[17]. So, due to exclusivity of the individual distribution functions of T_i for $\mathcal{H}_1$ and $\mathcal{H}_0$ hypothesis (as depicted in figure 2) we consider *a priori* probability of occupancy of channel, i.e., $P(\mathcal{H}_1) = \alpha = 0.5$. The channel coefficients observed by the CR sensors are assumed to be uncorrelated. We compare the performance of proposed non-uniform quantization over uniform quantization by plotting the probability of detection versus SNR and the ROC curve.

Figure 5 and 6 shows the plot of P_{fa} versus P_d curve for cooperative CR environment with $N = 6$ local CR sensors, $L = 1000$ number of sensing samples. The local CRs report their test statistics T_i by quantizing with $d = 2$ and $d = 3$ bit quantizer respectively through a perfect reporting channel. The values of SNR at local CRs' front end is taken as $\overline{\eta} = \begin{bmatrix}-15 & -16 & -11 & -14 & -12 & -13\end{bmatrix}^T$ dB. This is in correspondance to different fading environment observed by spatialy distributed CR sensors. The local test statistics are combined using combining vector as formulated in (9). Similarly, figure 7 and 8 shows the plot of SNR versus P_{md} (probability of misdetection) curve for $N = 6$ local CRs. The target probability of false alarm P_{fa} is taken as 0.05. The reporting is done respectively by $d = 2$ and $d = 3$ bit uniform and non-uniform quantization.

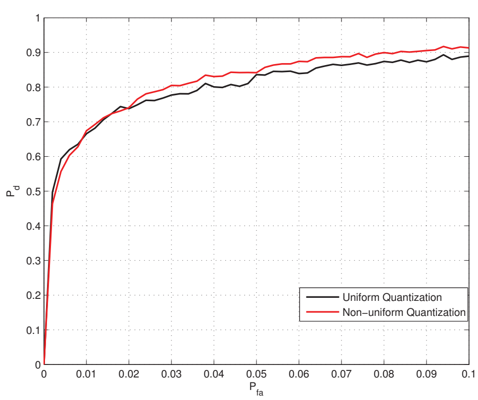

Fig. 5. P_{fa} vs. P_d curve for $d = 2$ bit quantizer

The following inferences can be made from the simulated plots:

- The performance of proposed non-uniform quantization based reporting is better than that of conventional uniform quantization based reporting. This validates our exposition of using non-uniform quantization based on likelihood function.
- As the number of quantization bits are increased the accuracy in reporting the local test statistic increases or in other words quantization error decreases. In such situation performance of both the quantization techniques tend towards the case when exact value of the sensed energy is reported to the fusion center without any quantization error. The lower bound in the values of probability of misdetection P_{md} is shown in figure 7 and 8, in which no

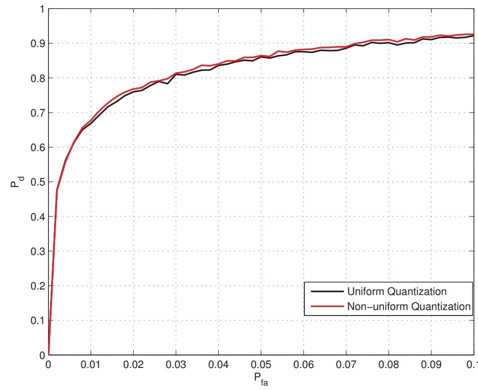

Fig. 6. P_{fa} vs. P_d curve for $d = 3$ bit quantizer

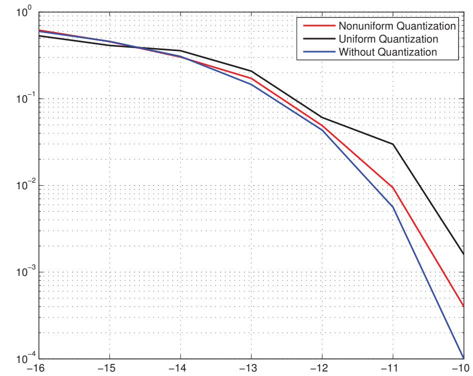

Fig. 7. SNR vs. P_{md} curve for $d = 2$ bit quantizer

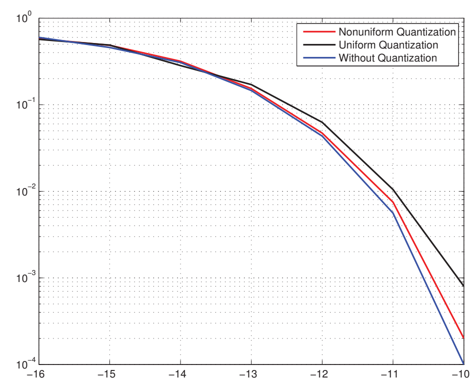

Fig. 8. SNR vs. P_{md} curve for $d = 3$ bit quantizer

quantization is done so that exact value of sensed energy is reported to the fusion center.

- Since the values of sensed energy after quantization can take discrete values the curves shown in figure are not continuous. In the proposed non-uniform quantization the quantization levels are coarsely placed in the region of uncertainty. Since the threshold for energy detection is generally selected around the region of uncertainty, the curves are more continuous for non-uniform quantization than that for the uniform quantization case.

VI. Conclusion

In this paper we have proposed a non-uniform quantization technique for reporting the locally computed test statistics of spatially distributed CR sensors to the fusion center. The non-uniform quantization of the test statistic performed on the basis of likelihood function, which essentially depends on the SNR and noise variance of the environment. It is shown with the help of simulation that the non-uniform quantization based reporting out-performs that of uniform quantization based reporting. For higher number of reporting bits the performance of both the techniques are similar and tends towards the lower bound, i.e., when exact values of the sensed energies are reported. In addition, an optimization problem is formulated to compute optimal weights for combining the test statistics at the fusion center.

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