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Cooperative Spectrum Sensing with Multi-bits Local Sensing Decisions in Cognitive Radio Context

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***Abstract*-There are two important constraints for cooperative spectrum sensing in cognitive radio (CR) context. Firstly, as the CR system can only tolerate low transmitting overhead, the local sensing data must be compressed before transmitting. Secondly, many sophisticated data fusion techniques cannot be used in CR system because of the lack of the signal's prior knowledge. In this paper, we proposed a novel cooperative spectrum sensing scheme which adapts to different overhead tolerance and does not need any prior knowledge. This scheme consists of two main parts: the quantization schemes and the data fusion rule. Two different quantization schemes, according to whether or not the distribution functions of test statistic are known, are proposed. Correspondingly, the optimal data fusion rule of multi-bits decisions is derived. Furthermore, to make the optimal fusion rule more practical, an iterative scheme, which does not need any prior knowledge of the signal, is proposed to estimate the likelihood ratio of local decisions. Simulation results show that our scheme achieves better performance than the schemes with "OR" and "AND" combinations. Furthermore, it is also shown that the proposed scheme could achieve the theoretically optimal performance by only two or three bits quantization.**

I. INTRODUCTION

Spectrum sensing is a key technique in Cognitive Radio (CR) context. By sensing the spectrum environment over a wide frequency band, the channels that do not be occupied by primary users (PU) can be used by a CR system. Generally speaking, given enough sensing time and a proper signal power, most local sensing techniques (*e.g.* energy detection [1], matched filter and cyclostationary feature detection [2]) performed in single sensing node could achieve desirable sensing performance. However, in cognitive radio, we do not have very long sensing time, and the signal power may fluctuate severely because of the multipath fading and shadow effect. Therefore, it is difficult to reach the required performance by only one sensing node. Fortunately, it is confirmed that cooperative spectrum sensing with multi-nodes can achieve better performance than that of single node sensing [3]. In cooperative spectrum sensing, all the local sensing nodes should transmit their sensing data to the central node, then a data fusion rule will be performed to combine these data and the global decisions will be made. Due to the gain from receiver diversity, the global decision is much more reliable than the local decisions.

The most important motivation of cognitive radio is to improve the spectrum efficiency. Therefore, transmitting overhead in CR system cannot be large, which means using a wideband channel to transmit the raw sensing data is not feasible. Hence, all the local sensing data should be quantized into one or several bits before transmitting. In most literatures of cooperative spectrum sensing so far [3] [4], local sensing nodes are assumed to make their own decisions of whether or not the primary users' signal is present (such a process is equivalent to 1-bit quantization). Then in central node, the quantized decisions are combined by simple counting rules, under such a situation, the optimal fusion scheme is the "*k* out of *n*" rule. However, when the number of sensing nodes *n* is not infinite, this scheme is just suboptimal [5]. Ref. [6]-[9] present several optimal quantization schemes in detection process. However, all of these quantization schemes need prior knowledge of the PU's signal, which is not always available in CR system. Furthermore, as another important part of signal detection, the data fusion rule is widely studied in many literatures, and the optimal fusion rules are the well-known Bayes' Criterion, the Neyman-Pearson Criterion, etc. [10]. However, the lack of prior knowledge is still the barrier for these fusion rules.

In this paper, we proposed a novel cooperative spectrum sensing scheme, which comprises of two quantization schemes and an optimal data fusion rule. The first quantization scheme called locally optimal quantization could achieve optimal performance in the low signal-to-noise ratio (SNR) environment, and such a property is very useful for the weak signal detection. Another proposed quantization scheme is more attractive for practical CR systems because no prior knowledge is used in this scheme. Furthermore, the optimal data fusion rule of multi-bits local sensing decisions is derived, which has a form of likelihood ratio test. Meanwhile, in order to make the optimal fusion rule more practical, we propose an iterative scheme to estimate the likelihood ratio of the local sensing decisions.

The rest of this paper is organized as follows. In Section II, we describe the cooperative spectrum sensing system briefly. In Section III, two quantization schemes are introduced, respectively. In Section IV, we derive the optimal fusion rule based on the multi-bits local sensing decisions. And the estimating algorithm of likelihood ration will also be presented in Section V. In Section VI, the simulation results are shown and analyzed. Finally, we conclude this paper in the last section of this paper.

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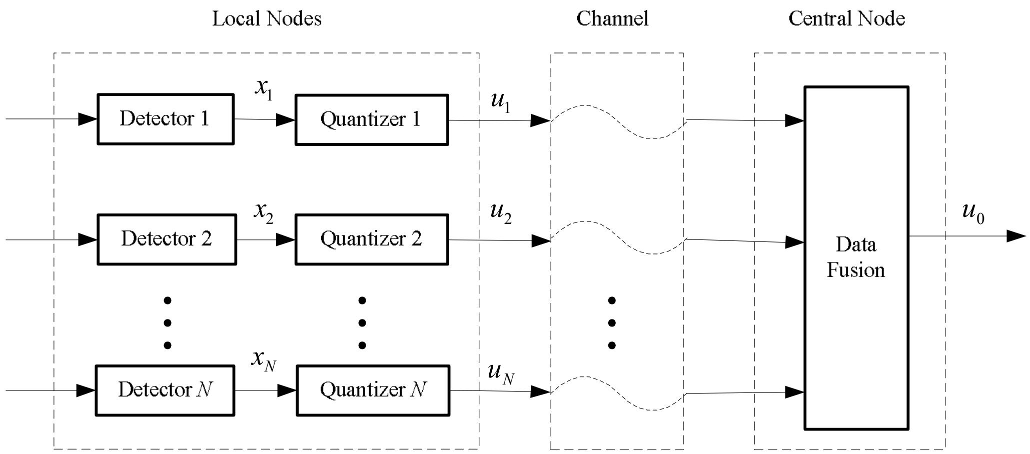

Figure 1 system model of cooperative spectrum sensing

II. System Description

The spectrum sensing problem can be stated in term of a binary hypothesis test between H_0 and H_1. Where H_0 means the situation that only noise exists, while H_1 means that the PU's signal appears. Suppose that there are N uncorrelated sensing nodes in a cooperative spectrum sensing system. The system model is shown in Figure 1. Three main parts comprise the system, including the local sensing nodes, wireless channel, and the central node. The local sensing node includes a detector and a quantizer. The detector senses the candidate frequency bands and outputs the test statistic x_i, where i ($1 \le i \le N$) is the index of sensing nodes. Since the test statistic is usually continual random variant, a quantizer is necessary in order to make the sensing data more suitable for processing and storage. Moreover, another important function of the quantizer is to reduce the data amount of the test statistic, which is more useful in cognitive radio context because of the strict constraint of transmitting overhead. We use a discrete variant u_i to denote the local decision of node i. After being transmitted to the central node, all the local decisions are combined according to some data fusion algorithms, and the global decision u_0 is made. That is, if u_0=1, we decide that the PU's signal is present, and if u_0=0, we decide the PU's signal is absent.

For the local sensing algorithm does not affect the whole cooperative scheme (in other words, our scheme adapts to all local sensing algorithms), we will focus on the quantization scheme and the data fusion scheme in this paper.

III. Quantization Schemes

Assume that x is the quznatizer input and v_l is the quantizer output, the quantization process $Q(\bullet)$ can be expressed as

$$Q(x) = v_l \text{ iff } x \in \Delta_l, l = 1, 2, \cdots, q \quad (1)$$

where q is the number of quantization levels, Δ_l is the quantization interval and Δ_l=[a_l, a_{l+1}). Then the quantizer is completely defined by the number q and the values a_l.

As indicated in [11], if we know the probability density function (PDF) or the distribution function of the signal, the optimal quantization schemes could be found. However, in spectrum sensing, the PDF of test statistic is related with the SNR, which is time-varying and not known to the system. Therefore, it is impossible to develop optimal quantization schemes in spectrum sensing context. In this section, we will introduce two quantization schemes which correspond to the situation that we have partial prior knowledge and do not have any prior knowledge at all, respectively.

A. Locally Optimal Quantization

As discussed above, the bottleneck of the design of optimal quantization schemes is the unknown and time-varying SNR. However, in some situation, the PDF under a given SNR value is possible to obtain. For example, if the local sensing algorithm is energy detection, the PDF under a given SNR can be derived as a chi-squared distribution [1]. Therefore, it is possible to design a locally optimal quantization scheme which is optimal under a given SNR.

In cognitive radio context, in order to avoid the interference to primary systems, it is compulsory to detect the signals which are very weak compared to the noise. The locally optimal quantization scheme is defined as one which has optimal properties only for the lowest SNR required by the system. In fact, strong signal will be detected with acceptable error probability even if the quantization scheme is well below optimal.

In order to find the locally optimal quantization scheme, we will use the deflection criterion [6] defined by

$$D(Q) \triangleq \frac{\left[E_1(Q) - E_0(Q)\right]^2}{V_0(Q)} \quad (2)$$

where E_0 and E_1 denote the expectation values under H_0 and H_1, respectively. And V_0 is the variance under H_0. The deflection reflects the statistical distance between the test statistic under H_0 and H_1. With this criterion, the locally optimal quantization problem can be stated as follows:

Under a given value of SNR (usually is the lowest SNR value of the system required) and a given value of q, one should find the domain Δ_l *and the corresponding value of* v_l ($1 \le l \le q$), *in such a way that the deflection is maximum.*

To solve this problem, we use $P_0(l)$ and $P_1(l)$ to denote the probabilities of $x \in \Delta_l$ under H_0 and H_1, respectively. Then the deflection can be written as

$$D(\Delta, v) = \frac{\left\{\sum_{l=1}^{q} v_l \left[P_1(l) - P_0(l)\right]\right\}^2}{\sum_{l=1}^{q} v_l^2 P_0(l) - \left[\sum_{l=1}^{q} v_l P_0(l)\right]^2}. \quad (3)$$

For a given partition Δ of the observation space, the maximization of $D(\Delta, v)$ is a well-known problem [6], the value of v_i maximizing (3) is

$$v_l = \frac{P_1(l)}{P_0(l)}. \quad (4)$$

The corresponding D is

$$D(\Delta) = l(\Delta) - 1 \quad (5)$$

with

$$l(D) \triangleq \sum_{l=1}^{q} \frac{P_1^2(l)}{P_0(l)}. \quad (6)$$

Then, the optimal partition is defined by

$$\Delta = \arg\max_{\Delta} l(\Delta). \quad (7)$$

In our assumption, the distribution function of test statistic under H_0 is known as $F_0(x)$. And in the situation of H_1, the distribution function under a given SNR is known as $F_1(x)$. The optimal partition can then be written as

$$\Delta = \arg\max_{\Delta} \sum_{l=1}^{q} \frac{\left[F_1(a_{l+1}) - F_1(a_l)\right]^2}{F_0(a_{l+1}) - F_0(a_l)}. \quad (8)$$

Equation (8) can usually be solved numerically. Then the optimal value of a_l can be obtained.

B. Dynamic Range based Uniform Quantization

In some situation, the distribution functions of test statistic $F_0(x)$ and $F_1(x)$ are difficult to obtain. Under such situation, a simple quantization scheme is to divide the observation space uniformly based on the dynamic range of the test statistic. Although this scheme is not optimal under any SNR values, it is more practical because the dynamic range of test statistic is easy to estimate.

Assume that the test statistic at time slot τ is T_τ, $\tau=1,2,\cdots,n$, the maximal value within these n value is T_{max}, and the minimum value is T_{min},. The quantization interval can be written as

$$\Delta = \frac{T_{\max} - T_{\min}}{q}. \quad (9)$$

Then the quantization threshold is give as

$$a_l = T_{\min} + (l-1)\Delta, \; l = 1, 2, \cdots, q+1. \quad (10)$$

IV. Optimal Data Fusion Rule

In order to express the problem conveniently, we use number 1 to q to denote the quantized local decisions. Then the local decisions can be write as

$$u_i = l, \quad l = 1, 2, \cdots, q. \quad (11)$$

where i is the index number of local sensing nodes. In this paper, we assume u_i is perfectly reconstructed in central node without transmission loss.

Subsequently, we use minimum error probability criterion [10] to derive the optimal data fusion rule. The minimum error probability criterion in cooperative spectrum sensing context can be expressed as

$$\frac{P(u_1, \cdots, u_n | H_1)}{P(u_1, \cdots, u_n | H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P(H_1)}{P(H_0)}. \quad (12)$$

The corresponding log-likelihood form is

$$\log \frac{P(u_1, \cdots, u_n | H_1)}{P(u_1, \cdots, u_n | H_0)} + \log \frac{P(H_1)}{P(H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} 0. \quad (13)$$

Since the decisions of the sensing nodes are uncorrelated, we have

$$\begin{aligned} &P(u_1, \cdots, u_n | H_1) = \prod_{i=1}^{N} P(u_i | H_1) \\ &= \prod_{S_1} P(u_i = 1 | H_1) \cdot \prod_{S_2} P(u_i = 2 | H_1) \cdots \cdot \prod_{S_q} P(u_i = q | H_1) \quad (14) \\ &= \prod_{S_l} \prod_{l=1}^{q} P(u_i = l | H_1) \end{aligned}$$

where S_l is the set of all i such that u_i=l. In a similar way, we have the likelihood function under H_0 as

$$P(u_1, \cdots, u_n | H_0) = \prod_{S_l} \prod_{l=1}^{q} P(u_i = l | H_0). \quad (15)$$

By substituting (14) and (15) into (13), we get

$$\begin{aligned} &\log \frac{P(H_1)}{P(H_0)} + \sum_{S_l} \sum_{l=1}^{q} \log \frac{P(u_i = l | H_1)}{P(u_i = l | H_0)} \\ &= \log \Lambda_0 + \sum_{S_l} \sum_{l=1}^{q} \log \Lambda_{il} \underset{H_0}{\overset{H_1}{\gtrless}} 0 \end{aligned} \quad (16)$$

where

$$\Lambda_0 = \frac{P(H_1)}{P(H_0)} \quad (17)$$

and

$$\Lambda_{il} = \frac{P(u_i = l | H_1)}{P(u_i = l | H_0)}. \quad (18)$$

Λ_{il} can be seen as the likelihood ratio of the sensing node i whose quantized decision is l. In practical applications, both Λ_0 and Λ_{il} are not readily available. In the next section, we will propose a scheme to estimate the likelihood ratio.

V. The Estimation of Likelihood Ratio

If we consider H_1, H_0, $\{u_i = l|\mathrm{H}_1\}$, and $\{u_i = l|\mathrm{H}_0\}$ as four random events, then the probabilities $P(\mathrm{H}_1)$, $P(\mathrm{H}_0)$, $P(u_i = l|\mathrm{H}_1)$, and $P(u_i = l|\mathrm{H}_0)$ can be calculated by simply counting the number of times that these random events occur. However, in cognitive radio, the exact information of whether the PU's signal appears is not known. In fact, to acquire this information is just the goal of spectrum sensing. Therefore, the exact values of $P(\mathrm{H}_1)$, $P(\mathrm{H}_0)$, $P(u_i = l|\mathrm{H}_1)$, and $P(u_i = l|\mathrm{H}_0)$ can not be obtained.

However, in cooperative spectrum sensing, the global decision usually has high reliability. Which means $P(\mathrm{H}_1)$, $P(\mathrm{H}_0)$, $P(u_i = l|\mathrm{H}_1)$, and $P(u_i = l|\mathrm{H}_0)$ can be calculated with acceptable validity if we use the global decision instead of the real information of the existence of the PU's signal. Let D_1 denote the random event that the global decision is H_1, while D_0 is the random event that the global decision is H_0. Then, we get

$$P(D_j) \approx P(\mathrm{H}_j), \quad j = 0,1 \tag{19}$$

and

$$P(u_i = l|D_j) \approx P(u_i = l|\mathrm{H}_j), \quad j = 0,1. \tag{20}$$

Now, we focus on the calculation of $P(D_1)$, $P(D_0)$, $P(u_i = l|D_1)$, and $P(u_i = l|D_0)$. Let $S(k)$ denote the decision state (including local decisions and global decisions) at time slot k, then we get

$$S(k) \in \{s_{lj} | l = 1,2,\cdots,q;\ j = 0,1\} \tag{21}$$

where $\{s_{lj}\}$ denotes the possible value space of $S(k)$, l is the quantized local decision, and j indicates the global decisions. Let $J(n)$ denote the cumulant of $S(k)$ at time slot n, we get

$$J(n) = \sum_{k=1}^{n} S(k) = \sum_{l=1}^{q}\sum_{j=0}^{1} N_{lj}(n) s_{lj} \tag{22}$$

where N_{lj} denotes the number of times of s_{lj}. (22) can also be written in an iterative form, *i.e.*,

$$J(n) = J(n-1) + S(n) \tag{23}$$

Then, we can estimate the likelihood ratio as

$$\Lambda_0 = \frac{P(\mathrm{H}_1)}{P(\mathrm{H}_0)} \approx \frac{P(D_1)}{P(D_0)} = \frac{\sum_{l=1}^{q} N_{l1}(n)}{\sum_{l=1}^{q} N_{l0}(n)} \tag{24}$$

and

$$\Lambda_{il} = \frac{P(u_i = l|\mathrm{H}_1)}{P(u_i = l|\mathrm{H}_0)} \approx \frac{P(u_i = l|D_1)}{P(u_i = l|D_0)} = \frac{N_{l1}(n) \cdot \sum_{l=1}^{q} N_{l0}(n)}{N_{l0}(n) \cdot \sum_{l=1}^{q} N_{l1}(n)}. \tag{25}$$

Before we start the iterative algorithm, the initial values of N_{lj} must be set. In order to enable the iterative algorithm converge faster and more accurately, we need to set the initial values closer to the real values as far as possible. Meanwhile, in order to mitigate the latency of the iterative algorithm, the initial values should not be set too large. Under normal circumstances, Λ_{il} is a value between 0 and infinite, and it increases along with the quantization level l. Therefore, after setting the initial values of Λ_{il} reasonably, the initial values of N_{lj} could be derived according to the corresponding Λ_{il}.

It must be noted that the values of Λ_0 and Λ_{il} are time-varying as a result of the time-varying sensing environment in practical environments. However, as the estimation algorithm depends on the cumulant of the decision states within a relative long period, lots of "outdated" data which reflect the former state are taken into account in the processing. Therefore, the estimated value may not converge to the accurate values of Λ_0 and Λ_{il} if the sensing environment changes. We will then introduce two methods to suppress the outdated decisions and improve the adaptability of the estimation algorithm.

A. Limited Memory

Rewrite (22) as

$$J(n) = \sum_{k=n-M+1}^{n} S(k) \tag{26}$$

where M is the memory length. With the operation of (26), only the M latest decisions are used to estimate Λ_0 and Λ_{il}. After processing like this, the earliest outdated decisions are excluded from the cumulant, therefore the estimated values will be more close to the accurate values of Λ_0 and Λ_{il}.

B. Forgetting Factor

Rewrite (23) as

$$J(n) = \gamma J(n-1) + S(n) = \sum_{k=1}^{n} \gamma^{n-k} S(k) \tag{27}$$

where γ is the forgetting factor which is usually a number between 0.9 and 1. Then, the contribution of the former decision state to $J(n)$ becomes weaker along with time. Therefore, this method can also reduce the impact of the outdated decisions.

VI. Simulation Results

In our simulations, we assume that all the sensing nodes are operating in severe sensing environment, which means the SNR at each node may be very low. If the sensing scheme could achieve good performance in such severe environment, it will certainly perform better in some better environment. In our simulation, we generate the SNR value uniformly within the range between –19dB and –21dB at each sensing node (–20dB is approximately the lowest SNR that the IEEE 802.22 WRAN system required [12]). All the local sensing nodes have the same detector and quantizer. The local sensing algorithm is energy detection, and the sensing time is the length of 10000 samples.

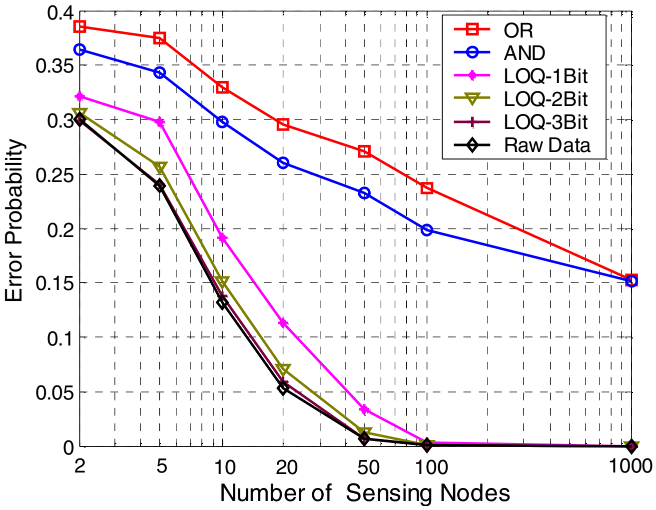

Figure 2 The Error Probabilities vs. the Number of Sensing Nodes under Different Quantization Results. (Where LOQ Means the Locally Optimal Quantizer).

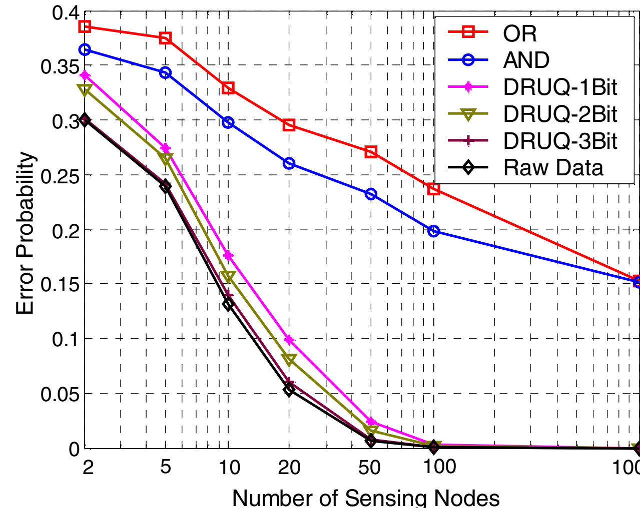

Figure 3 The Error Probabilities vs. the Number of Sensing Nodes under Different Quantization Results. (Where DRUQ Means the Dynamic Range based Uniform Quantizer).

For energy detection, the distribution functions of test statistic under different channels are presented in [13]. In our simulations, we assume that the channel is AWGN, and the lowest required SNR of the system is –20dB. Then the distribution function of the statistic under H_0 and H_1 are:

$$Y \sim \begin{cases} \chi_N^2, & H_0 \\ \chi_N^2(2\gamma), & H_1 \end{cases} \tag{28}$$

where Y is the test statistic of energy detection, χ_N^2 denotes the central chi-squared distribution with N degrees of freedom, and $\chi_N^2(2\gamma)$ denotes the noncentral chi-squared distribution with N degrees of freedom and a noncentrality parameter 2γ, where N is the number of samples used in detection and γ is a value that depends on the SNR value. Substituting the distribution functions in (8) and solving it numerically, the locally optimal quantization scheme could be found.

We use the error probability to evaluate the performance of the cooperative spectrum sensing schemes. The error probability P_e can be expressed as

$$P_e = P(H_1)P_{GM} + P(H_0)P_{GF} \tag{29}$$

where P_{GM} is the global probability of missed detection, P_{GF} is the global probability of false alarm. For the sake of comparison, we also provide the performance of the schemes with the “OR” and “AND” combination.

As in our previous work [14], the convergence and the adaptability of the estimation algorithm have been proved, therefore in this paper, we assume that the iterative algorithm has already converged and the values of the likelihood Λ_0 and Λ_{il} are obtained. The simulation results are shown in Figure 2 and Figure 3. In these two figures, the curves that marked by “Raw Data” represent the scheme that the unquantized test statistic were transmitted to the central node, and the Bayes’s criterion is performed to combine the decisions. This curve is the theoretical lower bound of the error probability. In figure 2, the abbreviation “LOQ-xBit” means x-bit(s) quantization by Locally Optimal Quantizer. And the abbreviation “DRUQ-xBit” in figure 3 means x-bit(s) quantization by Dynamic Range based Uniform Quantizer.

As shown in these figures, the error probabilities of our proposed schemes decrease rapidly along with the number of sensing nodes increasing. The error probability can achieve an acceptable value (less than 0.1) by just 30 sensing nodes, while the quantization result is only 1 bit. On the other hand, if we use “OR” or “AND” combination, the error probability decreases very slowly. Even if the number of sensing nodes increases to 1000, the error probability is still at a high level (about 0.15) for the schemes with “OR” or “AND” combination. Furthermore, using our schemes, the error probability could achieve the theoretical low bound by only 2 or 3 bits quantization. This result indicates that more quantization levels do not brings more performance gain and more than 4 bits quantization is not necessary. In fact, only 2 bits quantization is enough.

VII. Conclusions

In this paper, we have proposed a cooperative spectrum sensing scheme with multi-bits local sensing decisions. This scheme provides an approach to adapt to different requirements of transmitting overhead and achieving better performance. Compared with the “OR” and “AND” combination, this scheme has obvious advantage at the cost of marginal extra overhead.

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