A Novel Cluster-Based Cooperative Spectrum Sensing with Double Adaptive Energy Thresholds and Multi-Bit Local Decision in Cognitive Radio

Hiep-Vu Van and Insoo Koo
The School of Electrical Engineering, University of Ulsan
680-749 San 29, Muger 2-dong, Ulsan, Republic of Korea
[e-mail: vvhiep@gmail.com, iskoo@ulsan.ac.kr]
*Corresponding author: Insoo Koo

Received August 15, 2009; revised September 27, 2009; accepted October 3, 2009; published October 30, 2009

Abstract

The cognitive radio (CR) technique is a useful tool for improving spectrum utilization by detecting and using the vacant spectrum bands in which cooperative spectrum sensing is a key element, while avoiding interfering with the primary user. In this paper, we propose a novel cluster-based cooperative spectrum sensing scheme in cognitive radio with two solutions for the purpose of improving in sensing performance. First, for the cluster header, we use the double adaptive energy thresholds and a multi-bit quantization with different quantization interval for improving the cluster performance. Second, in the common receiver, the weighed HALF-voting rule will be applied to achieve a better combination of all cluster decisions into a global decision.

Keywords: Cognitive radio, cooperative spectrum sensing, optimal data fusion, adaptive energy threshold, multi-bit quantization

DOI: 10.3837/tiis.2009.05.003

1. Introduction

Nowadays, the rapid development of the applications of wireless technologies increases the requirement for more frequency band, which is a limited resource. In fact, most frequency bands that serve licensed users are scarce. However, frequency bands' capabilities have not been fully utilized. Especially, in some cases, this utilization is only a few percents of the full capability [1]. The CR technology has recently been proposed to reuse the available vacant frequency bands of licensed users in order to more effectively utilize frequency bands. The licensed user is often called the Primary User (PU) and the unlicensed user, who reuses the vacant frequency from the PU, is called the Cognitive Radio User (CU).

In the process of reusing frequency, if the vacant frequency of the PU is detected, then it will be used by the CU. On the other hand, if the presence of the PU is detected, then the CU should vacate their occupied frequency. The best sensing performance will let every CU know exactly whether or not a PU is present in order to use the vacant frequency of the PU without any harmful influence. Therefore, in a CR network, sensing the status of the PU is a prerequisite step.

In practice, there are some common detection methods that are used to sense the presence of the PU such as the matched filter detection, energy detection, feature detection, and so on [2], [3]. In those detection methods, if the CU has limited information about the signals of the PU (e.g., only the local noise power is known), then the energy detection is the optimal method [3]. In the energy detection method, the radio frequency energy of the sensing channel is received through a fixed bandwidth W over an observation time window T, and the energy is compared with the energy threshold to decide whether or not the channel is being utilized. However, in a CR network, the signal power may severely fluctuate because of the multipath and shadow effect. Thereby, it is difficult to achieve good performance with only one CU. Fortunately, the problem can be solved by allowing some CUs to perform the cooperative spectrum sensing [4][5][6].

In the cooperative spectrum sensing, we rely on the variability of the signal strength at various locations of the CUs for improving the sensing performance of the network with a large number of CUs [7]. Cooperative spectrum sensing often takes 3 steps: sensing, reporting and making a decision. In the sensing step, the CUs individually perform the sensing to make local decisions, and all local decisions will be transmitted to the common receiver later in the reporting step. Finally, in the decision making step, the common receiver uses a data fusion rule to combine all local observations together as a global decision in the absence or the presence of the PU.

More accurate detection can be achieved when some CUs coordinate to perform cooperative spectrum sensing. However, the sensing performance can be severely degraded when the local observations are forwarded to a common receiver through fading channels. In order to overcome this problem, Sun et al. have proposed a cluster-based cooperative sensing method. In this method, few CUs with the same SNR are collected into a cluster. In the cluster, the favorable user is selected to be the cluster header that receives local sensing information from all CUs to make the cluster decision and to later report to the common receiver. This approach really improves the sensing performance in comparison with the conventional method. However, in [8], the authors have considered OR-rule with only one threshold for making the global decision.

We propose a novel cluster-based cooperative spectrum sensing with double adaptive energy thresholds and multi-bit local decisions for improving the sensing performance. In this method, all the CUs perform local observations by using the energy detection method with double adaptive energy thresholds and multi-bit quantization. The adaptive energy threshold is the changeable energy threshold that's dependent on the optimal energy threshold of one threshold case and the received energy. In the energy detection method with double adaptive energy thresholds, the collected energy will be compared with double energy thresholds. If the collected energy is between double energy thresholds, then it will be quantized with multi-bit. Otherwise, the local decision will be made in the absence or presence of the PU. After one sensing time, all the CUs in the same cluster report one of two kinds of information to the cluster header, that is, local decisions or multi-bit local quantization decisions. All multi-bit local quantization decisions will be combined together at the final quantization decision according to the optimal data fusion rule [9], which is based on the likelihood ratio test. After that, the cluster decision will be made by integrating all of its local decisions with the final quantization decision. Cluster decisions from all clusters will be sent to a common receiver to make the global decision by using the weighed HALF-voting rule that depends on the SNR of each cluster.

2. System Description

In this paper, we consider a CR network that includes k clusters with $n_j\ (j=1,2,...,k)$ CUs for each cluster, and we consider the common receiver that functions as a base station and manages the CR network and all the associated CUs. We assume that all CUs in the same cluster have the same channel as the PU (same SNR, γ), as is shown in **Fig. 1**, and all CUs cooperate to perform spectrum sensing to decide between two hypotheses as follows:

$$\begin{cases} \mathrm{H}_0: \text{ primary user is absent} \\ \mathrm{H}_1: \text{ primary user is in operation} \end{cases} \tag{1}$$

We assume that each CU performs local sensing by independently using the energy detector in which the sensing channel is time-invariant during the sensing process. For the $i^{th}\ (i=1,2,...,n_j)$ CU in the $j^{th}\ (j=1,2,...,k)$ cluster, the local spectrum sensing is to decide between the two following hypotheses:

$$\begin{cases} H_0: x_i(t) = n_i(t) \\ H_1: x_i(t) = h_i s(t) + n_i(t) \end{cases} \tag{2}$$

where $x_i(t)$ is the received signal at the i^{th} CU, $s(t)$ is the PU's signal, $n_i(t)$ is the additive white Gaussian noise (AWGN) and h_i is the complex channel gain of the sensing channel between the i^{th} CU and the PU.

In order to perform energy detection, each CU collects the energy of the frequency domain that's denoted by E_i and has the following distribution [10], [11]:

$$\begin{cases} H_0: E_i = \chi^2_{2u} \\ H_1: E_i = \chi^2_{2u}(2\gamma_i) \end{cases} \tag{3}$$

where χ^2_{2u} denotes a central chi-square distribution with *2u* degrees of freedom, and $\chi^2_{2u}(2\gamma_i)$ denotes a non-central chi-square distribution with *2u* degrees of freedom and a non-centrality parameter $2\gamma_i$. The instantaneous SNR of the received signal at the i^{th} CU is γ_i, and $u = TW$ is the time-bandwidth product. The collected energy will be compared with the energy threshold to make the local decision in the presence or absence of the PU.

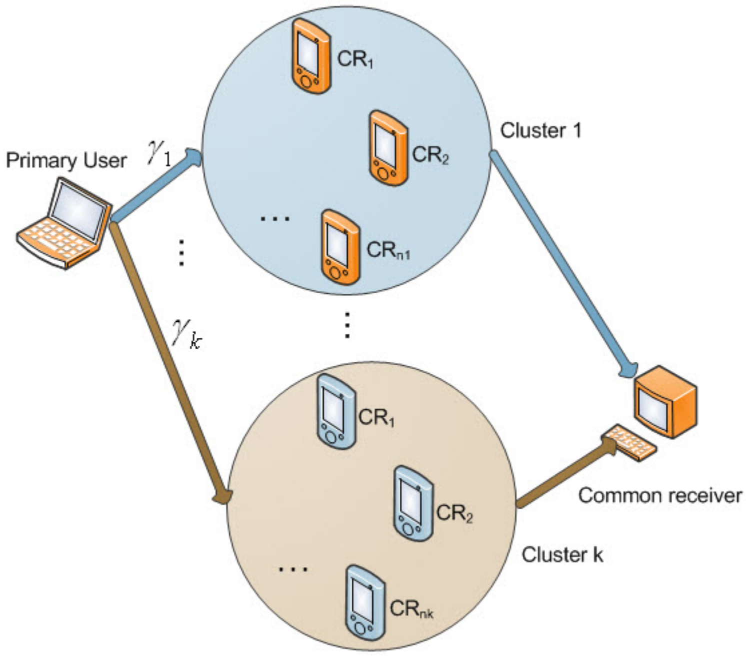


Fig. 1. System model

3. Double Adaptive Energy Thresholds and Multi-bit Local Decisions

In this paper, we propose a novel cooperative spectrum sensing method based on double adaptive energy thresholds and multi-bit local decisions for improving sensing performance. Our scheme takes 3 steps as below:

- **Step 1:** All the CUs in the j^{th} cluster perform local observation and send the information of local observation to the cluster header.
- **Step 2:** The cluster header receives this information, and later makes a cluster decision.
- **Step 3:** The cluster decisions of each cluster are reported to the common receiver by their cluster header, and a global decision is then made.

3.1 Local Decision with Double Adaptive Thresholds

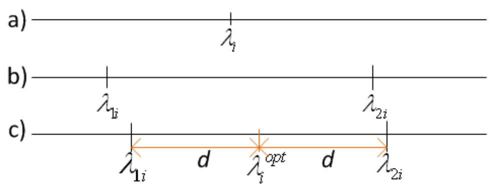
In the previous work [12], the authors have proposed double fixed energy thresholds of the energy detection method and they proved that double energy thresholds can improve sensing performance. However, the double fixed energy thresholds are not adaptive to the change in the signal. In order to solve this problem and improve the reliability of the sensing process, we propose that all the CUs use the energy detection method with double adaptive energy thresholds as shown in **Fig. 2(c)**. In this paper, the double adaptive energy thresholds are set based on the optimal energy threshold according to the function below:

$$\begin{cases} \lambda_{1i} = \lambda_i^{opt} - \Delta \\ \lambda_{2i} = \lambda_i^{opt} + \Delta \end{cases} \tag{4}$$

where Δ is the *adaptive interval* of quantization. In this paper, we presume that Δ is a function of the distance between the *max* and the min values of the collected energy in the CUs, and we set Δ as $\eta(E(i,j)_{\max} - E(i,j)_{\min})$ where $E(i,j)$ is the collected energy of the i^{th} CU in the j^{th} cluster, $E(i,j)_{\max}$ and $E(i,j)_{\min}$ the *max* and *min* values of $E(i,j)$, and η takes a value between 0.3 and 0.5. In practice, Δ will be set as a constant in each cluster, and λ_i^{opt} is the optimal energy threshold of the singe threshold case with which we can minimize the error probability Q_e, that is, $\lambda_i^{opt} = \arg\min_{\lambda_i}(Q_e)$ where Q_e can be given as follows:

$$\begin{aligned} Q_e &= Q_f + Q_m \\ &= \text{Prob}\{E(i,j) > \lambda_i \,|\, H_0\} + (1 - \text{Prob}\{E(i,j) > \lambda_i \,|\, H_1\}) \\ &= \frac{\Gamma(u, \frac{\lambda_i}{2})}{\Gamma(u)} + 1 - Q_u(\sqrt{2\gamma_i}, \sqrt{\lambda_i}) \end{aligned} \tag{5}$$

where γ_i is the SNR between the i^{th} CU and the PU.



a) One energy threshold; b) Double energy thresholds; c) Double adaptive energy thresholds
Fig. 2. Illustration of the energy detection method

In order to make local decisions, all CUs sense the presence of the PU by using the energy detection method with double adaptive energy thresholds. The local decision *G(i, j)* will be made by following the logic function rule:

$$\begin{cases} G(i,j) = 0 \ \text{ if } \ E(i,j) < \lambda_{1i} \\ G(i,j) = 1 \ \text{ if } \ E(i,j) \geq \lambda_{2i} \\ \mathit{Quantization} \ \text{otherwise} \end{cases} \tag{6}$$

where *E(i, j)* is the collected energy of the i^{th} CU in the j^{th} cluster with $i = 1, 2, ..., n_j$ and $j = 1, 2, ..., k$.

Consequently, the CUs make two kinds of decisions, which are the local decision $G \in [0,1]$ and the quantization decision. After that, the CUs send their local decision or quantization decision to the cluster header The multi-bit quantization scheme will be explained in *subsection 3.2.*

3.2 Multi-bit Quantization

In the proposed scheme, when the collected energy is between λ_{1i} and λ_{2i}, it will be quantized with a different quantization interval. Here, we define $u(i,j)$ as the quantization decision and $E(i,j)$ as the quantization input. The quantization process $Q(.)$ can be expressed as:

$$Q(E(i,j)) = u(i,j) \;\text{ if }\; E(i,f) \in \Delta_q,\; q = 1,2,...,l \tag{7}$$

where l is the number of quantization levels, $\Delta_q = [a_q,\; a_{q+1})$ is the quantization interval.

We set up the quantization with a different interval as follows:

$$\begin{aligned}
&\Delta_l = \frac{l}{2}d = [\lambda_i^{opt} + (\frac{l-2}{4})\frac{l}{2}d,\; \lambda_i^{opt} + (\frac{l}{2}+1)\frac{l}{4}d) \\
&\ldots \\
&\Delta_{l/2+3} = 2d = [\lambda_i^{opt} + d,\; \lambda_i^{opt} + 3d) \\
&\Delta_{l/2+2} = d = [\lambda_i^{opt},\; \lambda_i^{opt} + d) \\
&\Delta_{l/2+1} = d = [\lambda_i^{opt} - d,\; \lambda_i^{opt}) \\
&\Delta_{l/2} = 2d = [\lambda_i^{opt} - 3d,\; \lambda_i^{opt} - d) \\
&\ldots \\
&\Delta_1 = \frac{l}{2}d = [\lambda_i^{opt} - (\frac{l}{2}+1)\frac{l}{4}d,\; \lambda_i^{opt} - (\frac{l-2}{4})\frac{l}{2}d)
\end{aligned} \tag{8}$$

where

$$\begin{cases} \lambda_{1i} = \lambda_i^{opt} - (\frac{l}{2}+1)\frac{l}{4}d \\ \lambda_{2i} = \lambda_i^{opt} + (\frac{l}{2}+1)\frac{l}{4}d \end{cases} \tag{9}$$

Based on above function, d can be calculated as follows:

$$d = \frac{\lambda_{2i} - \lambda_i^{opt}}{(\frac{l}{2}+1)\frac{l}{4}} \tag{10}$$

Fig. 3 for example, shows a two-bit quantization with double adaptive energy thresholds.

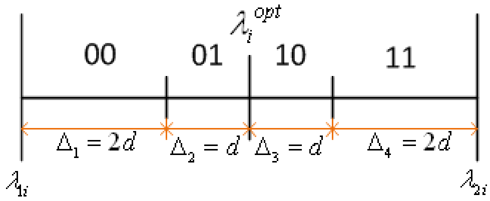


Fig. 3. Example of a two-bit quantization

After making the decision, all the CUs will transmit the local decisions $G \in [0,1]$ or the quantization decisions $u \in [1,2,...,l]$ to the cluster header where the cluster decision will be made through two steps that will be explained in the next subsection.

3.3 The Cluster Decision

In the cluster header, we have two types of information for making the cluster decision, namely, local decisions and quantization decisions. First, we combine all quantization decisions by using the optimal data fusion rule [9] to make final quantization decision $u_0(j)$ as follows:

$$\begin{cases} u_0(j)=1 \ \text{ if } \ w_0+\sum_{q=1}^{l}\sum_{S_q} w_{iq} \geq 0 \\ u_0(j)=0 \ \text{ othrewise} \end{cases} \tag{11}$$

where S_q is the set of all i such that $u(i,j)=q$, and w_0 and w_{iq} are pinpointed as follows:

$$\begin{cases} w_0=\log\dfrac{P(H_1)}{P(H_0)} \\ w_{iq}=\log\dfrac{P(u(i,j)=q|H_1)}{P(u(i,j)=q|H_0)} \end{cases} \tag{12}$$

After making the final quantization decision, the cluster decision will be made by combining all local decisions and the final quantization decision that's given as follows:

$$\begin{cases} B(j)=1 \ \text{ if } \ D_0+D_{au}+\sum_{\Omega_g} D_{ai} \geq 0 \\ B(j)=0 \ \text{ Otherwise} \end{cases} \tag{13}$$

where Ω_g is the set of all i such that the CUs make local decisions and D_0, D_{au} and D_{ai} can be computed according to the following equation:

$$\begin{cases} D_0=\log\dfrac{P(H_1)}{P(H_0)} \\ D_{au}=\log\dfrac{P(u_0(j)=a|H_1)}{P(u_0(j)=a|H_0)} \quad \begin{matrix} \textit{if } u_0(j)=a \\ \textit{with } a\in[0,1] \end{matrix} \\ D_{ai}=\log\dfrac{P(G(i,j)=a|H_1)}{P(G(i,j)=a|H_0)} \quad \begin{matrix} \textit{if } G(i,j)=a \\ \textit{with } a\in[0,1] \end{matrix} \end{cases} \tag{14}$$

Generally, it is difficult to calculate the exact value of w_0, w_{iq}, D_0, D_{au} and D_{ai} because we can not know exact information of whether or not the PU's signal appears. Hence, we consider an algorithm to estimate those values. To do this, let $D(j)$ denote the estimate of the status of the PU's signal that can be given as follows:

$$\begin{cases} D(j)=1 \text{ if } (\frac{l}{2}+1)\mathrm{n}_{g0}+\frac{l}{2}n_1+(\frac{l}{2}-1)n_2+\ldots+n_{\frac{l}{2}} \\ \qquad \geq n_{(\frac{l}{2}+1)}+2n_{(\frac{l}{2}+2)}+\ldots+\frac{l}{2}n_l+(\frac{l}{2}+1)\mathrm{n}_{g1} \\ D(j)=0 \text{ otherwise} \end{cases} \tag{15}$$

where n_q is the number of CUs that make the quantization decision, $u(i,j)=q$ with $q=1,\ 2,\ldots,\ l$ and n_{g0} and n_{g1} are the numbers of CUs that make local decision $G=0$ and $G=1$, respectively.

By using the estimated status of PU's signal $D(j)$, we can estimate w_0, w_{iq}, D_0, D_{au} and D_{ai} according to the following:

- Estimating the value of w_0 and D_0

  We define n_{H_1} and n_{H_0} as the time that event $D(j)=1$ and $D(j)=0$ occur, respectively. Thereby, we can estimate the values of w_0 and D_0 as follows:

$$w_0=D_0=\log\frac{P(H_1)}{P(H_0)}=\log\frac{n_{H_1}}{n_{H_0}} \tag{16}$$

- Estimating the value of w_{iq}

  For the i^{th} CU, we define Q_{q1} and Q_{q0} as the state of the current quantization decisions $u(i,j)$ which can be expressed as follows:

$$\begin{cases} Q_{q1}: u(i,j)=q \text{ and } D(j)=1 \\ Q_{q0}: u(i,j)=q \text{ and } D(j)=0 \end{cases} \quad i\in S_q \ \ with\ q=1,\ 2,\ \ldots,\ l \tag{17}$$

  and d_{q1} and d_{q0} are the times that Q_{q1} and Q_{q0} appear. From that, we can estimate the value of w_{iq} as follows:

$$w_{iq}=\log\frac{P(u(i,j)=q|H_1)}{P(u(i,j)=q|H_0)}=\log\frac{d_{q1}.n_{H_0}}{d_{q0}.n_{H_1}} \tag{18}$$

- Estimating the value of D_{au}

  For the j^{th} cluster, we define Q_{au1} and Q_{au0} as the state of the current final quantization decision $u_0(j)$ that's expressed as follows:

$$\begin{cases} Q_{au1}: u_0(j)=a \text{ and } D(j)=1 \\ Q_{au0}: u_0(j)=a \text{ and } D(j)=0 \end{cases} \quad with\ a=[1,0] \tag{19}$$

and d_{au1} and d_{au0} are the times that Q_{au1} and Q_{au0} appear. From that, we can estimate the value of D_{au} as follows:

$$D_{au} = \log \frac{P(u(j)=u \mid H_1)}{P(u(j)=u \mid H_0)} = \log \frac{d_{au1}.n_{H_0}}{d_{au0}.n_{H_1}} \text{ with } a=[0,1] \tag{20}$$

- Estimating the value of D_{ai}

For the i^{th} CU, we define Q_{ai1} and Q_{ai0} as the states of the current local decision $G(i,j)$ that can be expressed as follows:

$$\begin{cases} Q_{ai1} : G(i,j)=a \text{ and } D(j)=1 \\ Q_{ai0} : G(i,j)=a \text{ and } D(j)=0 \end{cases} \quad with \quad \begin{matrix} a=[1,0] \\ i \in \Omega_g \end{matrix} \tag{21}$$

and d_{ai1} and d_{ai0} are the times that Q_{ai1} and Q_{ai0} appear. From that, we can estimate the value of D_{ai} with the following equation:

$$D_{ai} = \log \frac{P(G(i,j)=a \mid H_1)}{P(G(i,j)=a \mid H_0)} = \log \frac{d_{ai1}.n_{H_0}}{d_{ai0}.n_{H_1}} \tag{22}$$

Finally, all cluster decisions $B(j)$ with $j=1, 2,..., k$ will be reported to the common receiver to make a global decision.

3.4 Global Decision at the Common Receiver

In the common receiver, the higher the SNR cluster, the more reliable cluster; therefore, we propose a weighed HALF-voting rule where the weight values of clusters in the common receiver are determined by the corresponding clusters' SNR to make global decision *H*. The proposed global decision rule will be expressed as follows:

$$\begin{cases} H=1 \text{ if } \sum_{j=1}^{k} \rho_j B(j) \ge \frac{1}{2} \sum_{j=1}^{k} \rho_j \\ H=0 \text{ otherwise} \end{cases} \tag{23}$$

where ρ_j is the weight value that can be calculated as follows:

$$\rho_j = \frac{\gamma_j}{\sum_{j=1}^{k} \gamma_j} \tag{24}$$

where γ_j is the SNR of the j^{th} cluster.

It can be seen that the HALF-voting rule is the special case of the weighed HALF-voting rule when all ρ_j is set to be *1*.

4. Simulation Results

The simulation results are presented in this section to demonstrate the performance of the proposed scheme in both the cluster header and the common receiver. For the cluster performance, we consider the j^{th} cluster with *10 CUs (nj = 10)* and assume that all CUs have SNR within the range of $-20dB$ to $-10dB$. For the sake of comparison, we provide the sensing performance of the four following cases:

- *Method 1*, proposed scheme 1; we use double adaptive energy threshold and two-bit quantization with a different quantization interval in each of the CUs and the optimal fusion rule [9] is used in the cluster header.
- *Method 2*, proposed scheme 2; "Same Quantization Interval", a double adaptive energy threshold and a two-bit quantization with the same quantization interval are used in each of the CUs and the optimal fusion rule [9] is used in the cluster header.
- *Method 3*, proposed scheme 3; "Double Fixed Threshold", double fixed energy thresholds and two-bit quantization with different quantization interval are used in each of the CUs and the optimal fusion rule [9] is used in the cluster header.
- *Method 4*, "One optimal threshold", we use one optimal energy threshold in each of the CUs and the optimal fusion rule [9] is used in the cluster header.

Fig. 4 shows the cluster performance in terms of the probabilities of detection P_{dc} and false alarm P_{fc} according to the aforementioned four methods.

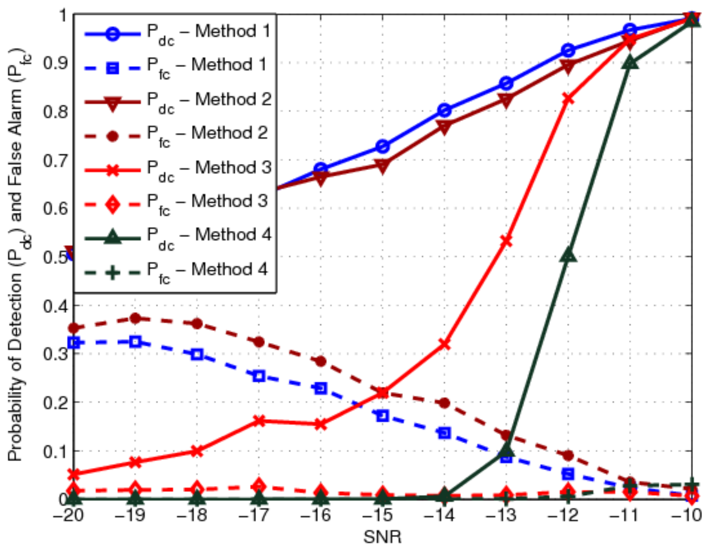


Fig. 4. The cluster performance of the proposed scheme in terms of the probabilities of detection and false alarm

It is observed that *method 1* achieves the best result with a stable increase of P_{dc} and a decrease of P_{fc}. Besides that, based on the difference in results between *method 1* and *method 2*, we can observe that the quantization process with a *different interval* as the proposed scheme has better sensing performance when compared to that of the quantization process with the *same interval*. Furthermore, the difference between *method 1* and *method 3* can also prove the outstanding sensing performance of the *double adaptive thresholds* compared to the *double fixed thresholds*.

The conclusions from **Fig. 4** are more clearly represented by **Fig. 5**, which shows the probability of error (P_{ec}) of four considered methods in the cluster header. Here, the probability of error in the cluster header is defined by the following equation:

$$\begin{aligned} P_{ec} &= P(B(j)=1 | H_0) + P(B(j)=0 | H_1) \\ &= P_{fc} + (1 - P_{dc}) \end{aligned} \tag{25}$$

The best result of *method 1* is also achieved as shown in **Fig. 5** that once again demonstrates a better effect of quantization with a *different interval* compared to that of the quantization with the *same interval*, and an improved outcome of the *double adaptive thresholds* compared to the *double fixed thresholds*.

Consequently, the simulation results, which are illustrated by **Fig. 4** and the **Fig. 5**, prove that the proposed scheme can get the best sensing performance with combining the *double adaptive energy thresholds* and the multi-bit *quantization with the difference quantization interval*.

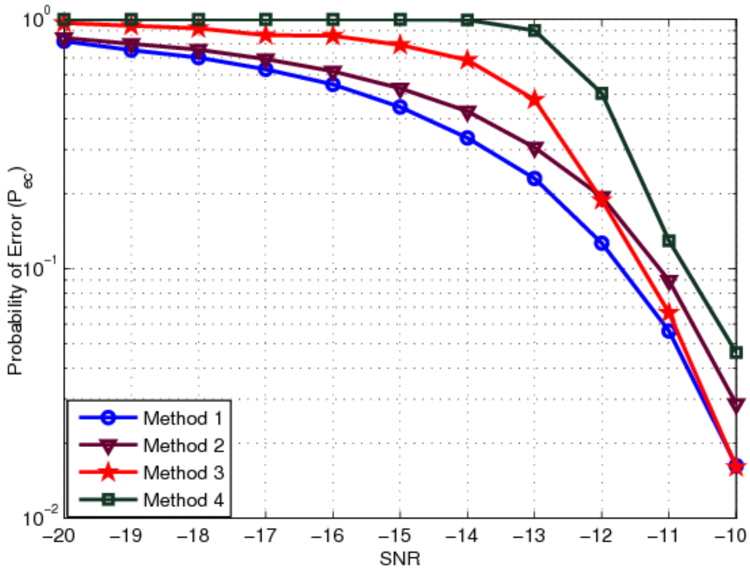


Fig. 5. The cluster performance of the proposed scheme in terms of the probability of error

For the sensing performance in the common receiver, we assume that the cognitive radio network includes *7* clusters and *10* CUs for each cluster, and that *method 1* is applied to all cluster headers. The weighed HALF-voting rule is applied to the common receiver as the global decision rule. For the aim of comparison, in the simulation, the sensing performance of other combination rules will be provided such as AND rule, OR rule and HALF-voting rule.

Fig. 6 shows the probability of detection P_d and false alarm P_f of the proposed scheme in the common receiver versus the three referred schemes in which the proposed scheme achieves the best result with a very high P_d approximating *1* and a very low P_f approximating

0 when an average SNR of *-16dB*. On the other hand, P_d and P_f values of the HALF-voting rule are approximately 0.9 and 0.02, respectively.

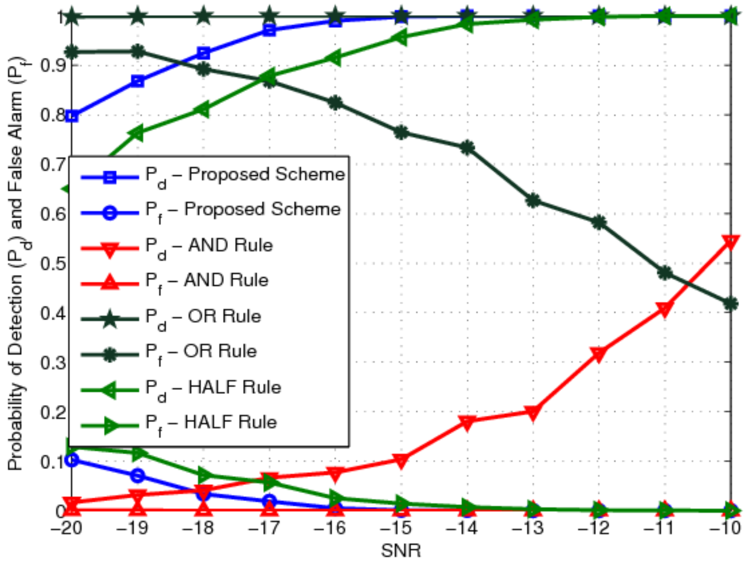


Fig. 6. The global performance of the proposed scheme at the common receiver in terms of the probabilities of detection and false alarm

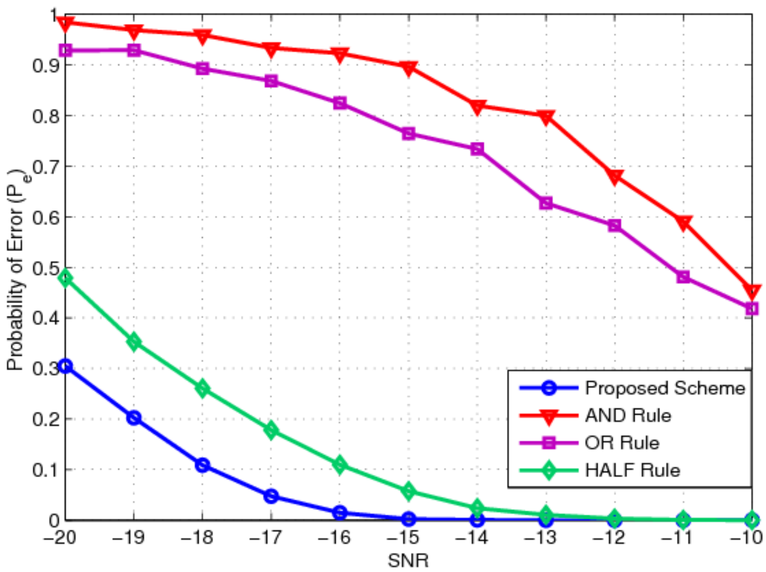


Fig. 7. The global performance of the proposed scheme at the common receiver in terms of the probability of error

The illustration in **Fig. 7** demonstrates that in the common receiver, the proposed scheme with the smallest value of error probability has an outstanding sensing performance compared with that of the other data fusion rules such as AND rule, OR rule and HALF-voting rule. Here the probability of error in the common receiver is defined as follows:

$$\begin{aligned} P_e &= P(H=1|H_0) + P(H=0|H_1) \\ &= P_f + (1-P_d) \end{aligned} \tag{26}$$

Admittedly, the simulation results in this section prove that the proposed scheme has the ability to significantly improve the sensing performance in a CR network.

5. Conclusion

In this paper, we propose a scheme that aims to improve the sensing performance of CR networks. The simulation results show that our proposed scheme can achieve improved performance in both the cluster header and the common receiver. Furthermore, under the same conditions, the proposed double adaptive energy thresholds can obtain some enhanced results compared with the double fixed thresholds. In addition, the simulation results also prove that the quantization process with the difference quantization interval can enhance the reliability of sensing performance comparison to quantization with the same quantization interval. In the common receiver, the weighed HALF-voting rule is really the best combination rule among the considered rules such as AND Rule, OR Rule and HALF Rule.

References

[1] Federal Communications Commission, *Spectrum Policy Task Force*, Rep. ET Docket no. 02-135, Nov. 2002.

[2] Y. Hur, J. Park, W. Woo, K. Lim, C.-H. Lee, H. S. Kim, and J. Laskar, “A wideband analog multi-resolution spectrum sensing (MRSS) technique for cognitive radio (CR) systems,” *Proc. IEEE Int. Symp. Circuit and System*, Greece, pp. 4090-4093, May 2006.

[3] A. Sahai, N. Hoven, and R. Tandra, “Some fundamental limits on cognitive radio,” *Proc. Allerton Conf. on Communications, control, and computing*, Monticello, Oct. 2004.

[4] G. Ganesan and Y. G. Li, “Cooperative spectrum sensing in cognitive radio networks,” *Proc. IEEE Symp. New Frontiers in Dynamic Spectrum Access Networks* (*DySPAN05*), Baltimore, USA, pp. 137-143, Nov. 2005.

[5] A. Ghasemi and E. S. Sousa, “Collaborative spectrum sensing for opportunistic access in fading environments,” *Proc. IEEE Symp. New Frontiers in Dynamic Spectrum Access Networks* (*DySPAN05*), Baltimore, USA, pp. 131-136, Nov. 2005.

[6] S. M. Mishra, A. Sahai, and R. Brodersen, “Cooperative sensing among cognitive radios,” *Proc. IEEE Int. Conf. Commun.*, Turkey, vol. 4, pp. 1658-1663, June 2006.

[7] D. Cabric, S. M. Mishra, and R. W. Brodersen, “Implementation issues in spectrum sensing for cognitive radios,” *Proc. of Asilomar Conf. on Signals, Systems and Computers*, Pacic Grove, CA, USA, pp. 772-776, Nov. 2004.

[8] C. Sun, W. Zhang, and K. B. Letaief, “Cluster-based cooperative spectrum sensing for cognitive radio systems,” *Proc. IEEE Int. Conf. Commun.*, Glasgow, Scotland, UK, pp. 2511-2515, June 2007.

[9] Z. Chair, P. K. Varshney, “Optimal data fusion in multiple sensor detection systems,” *IEEE Trans. Aerospace Electron. Syst.*, pp. 98-101, Jan. 1986.

[10] V. I. Kostylev, "Energy detection of a signal with random amplitude," *Proc. IEEE Int. Conf. Commun.*, New York, pp. 1606-1610, Apr.-May 2002.

[11] F. F. Digham, M.-S. Alouini, and M. K. Simon, "On the energy detection of unknown signals over fading channels," *Proc. IEEE Int. Conf. Commun.*, Anchorage, AK, USA, pp. 3575-3579, May 2003.

[12] Jiang Zhu, Zhengguang Xu, Furong Wang, Benxiong Huang, Bo Zhang, "Double Threshold Energy Detection of Cooperative Spectrum Sensing in Cognitive Radio," *3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications* 2008 (*CrownCom 2008*), vol., no., pp. 1-5, May 2008.

[13] Lei Chen; Jun Wang; Shaoqian Li, "Cooperative Spectrum Sensing with multi-bit Local Sensing Decisions in Cognitive Radio Context," *Wireless Communications and Networking Conference, 2008* (*WCNC 2008*) pp. 570-575, Mar.-Apr. 2008,.

Hiep-Vu Van received the B.E. degree in Electronics & Telecommunications Engineering from Ton Duc Thang University, Vietnam in 2005 and the B. degree in Business Administration from University of Economy Ho ChiMinh city, Vietnam in 2007, respectively. Since 2008 he has been involved in the combined degree programs (Master's and Ph.D.) in University of Ulsan, Korea. His current research interests include cognitive radio and next generation wireless communication systems.

Insoo Koo received the B.E. degree from the Kon-Kuk University, Seoul, Korea, in 1996, and received the M.S. and Ph.D. degrees from the Gwangju Institute of Science and Technology (GIST), Gwangju, Korea, in 1998 and 2002, respectively. From 2002 to 2004, he was with Ultrafast Fiber-Optic Networks (UFON) research center in GIST, as a research professor. For one year from September 2003, he was a visiting scholar at Royal Institute of Science and Technology, Sweden. In 2005, he joined University of Ulsan where he is now associate professor. His research interests include next generation wireless communication systems and wireless sensor networks