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Research Article

Cooperative Spectrum Sensing for Cognitive Heterogeneous Networking Using Iterative Gauss-Seidel Process

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Heterogeneous networks with dense deployment of small cells can employ cognitive features to efficiently utilize the available spectrum resources. Spectrum sensing is the key enabler for cognitive radio to detect the unoccupied channels for data transmission. In order to deal with shadowing and multipath fading in sensing channels, cooperative spectrum sensing is designed to increase the accuracy of the sensed signal. In this paper, an optimized local decision rule is implemented for the case that the received data from primary users are possibly correlated due to the sensing channel impairments. Since the prior information is unavailable in the real systems, Neyman-Pearson criterion is used as the cost function. Then, a discrete iterative algorithm based on Gauss-Seidel process is applied to optimize the local cognitive user decision rules under a fixed fusion rule. This method with low complexity can minimize the cost using the golden section search method in a finite number of iterations. ROC curves are depicted using the achieved probability of detection and false alarm by numerical examples to illustrate the efficiency of the proposed algorithm. Simulation results also confirm the superiority of the proposed method compared to the conventional topologies and decision rules.

1. Introduction

Heterogeneous networks are the next generation of cellular networks with densely deployed low power small cells that may reuse spectrum resources across the space. Since heterogeneous networks may experience spectral crowding, the main challenge is to coexist efficiently with other licensed users. According to the Federal Communication Commissions (FCC) frequency allocation chart, the spectrum bands dedicated to the licensed or primary user (PU) are highly underutilized [1]. Cognitive radio features may equip heterogeneous networks with spectrum sensing within the small cells to acquire available channels and enhance their operations [2]. Cognitive radio can provide opportunistic spectrum access for unlicensed or secondary users and optimize the spectral efficiency [3, 4]. The most critical requirement of cognitive radio is the sensing mechanism to exploit the spectrum holes while suppressing the mutual interference with PUs [4–6].

An optimal spectrum sensing mechanism is necessary for cognitive radios to maximize detection probability of the PUs' signal subject to the constraint of the limited probability of false alarm. Among various signal detection schemes, energy detection has been recognized with low computational complexity to be used for spectrum sensing. This method is based on measuring and comparing the received signal strength from the PUs with a threshold, within the channels and a certain sensing time [7]. However, the performance of energy detector is degraded with sensing channel impairments which leads to attenuation and variations of the sensed signal. Multipath fading, path loss, shadowing, and hidden node problem inevitably compromise the sensing reliability. An effective approach to overcoming these uncertainty problems and improving the performance is cooperative sensing [8–11].

Cooperative sensing can be used to acquire information of an intelligent wireless network with various applications including radar and sensor networks [12, 13]. The design of cooperative sensing can increase the reliability, flexibility, speed, and coverage area of the sensing network. In a cognitive radio with large number of sensing nodes, cooperative spectrum sensing can increase the detection probability of primary users and the channel utilization. Cooperative spectrum sensing can enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located secondary users which transmit their sensing information to a fusion center for final decision. It has been shown that increasing the number of cooperative users can decrease the required detector sensitivity and sensing time. Moreover, a cooperative approach needs lower communication bandwidth and is more robust to channel fading [14–16].

The drawback of the feedback overhead of spectrum sensing is overcome in [14] by using a fixed number of common feedback channels so that each node compares the sensing result with a threshold and selects the appropriate data to be sent to the fusion center. In [15], a sensor selection strategy is proposed to minimize the energy consumption for cooperative spectrum sensing under satisfactory primary user detection performance. A decentralized spectrum sensing approach is proposed in [16] to reduce the overall overhead and power consumption of the network by eliminating the need for fusion center node. In this scheme, each secondary user communicates only with its adjacent nodes via one-hop transmissions within several rounds to reach global convergence. The performance of cooperative spectrum sensing over Rayleigh fading channel is improved in [17] using an adaptive linear combiner with weights to secondary user decisions.

In this paper, a cooperative spectrum sensing is deployed for cognitive heterogeneous network with a parallel approach instead of centralized topology that needs wideband channels. With correlated local sensing observations, a numerical algorithm is proposed to optimize the local decisions of local cognitive users (LCUs) and send the information to a common cognitive user (CCU) as fusion center. The design of parallel topology increases the reliability, flexibility, speed, and coverage area of the sensing network. Based on Bayesian optimality criteria with independent observations, the optimized rule for decision making of each LCU is likelihood ratio test (LRT) [18–20]. Since the prior probabilities of hypotheses and accurate illustration of cost coefficients are not available in real systems, common Bayesian method for maximizing LRT is not practical. Therefore, Neyman-Pearson criterion is adopted for optimum local decision rule (OLDR) so that the probability of false alarm is limited to a desired value while the probability of missed detection is minimized [21].

The rest of this paper is organized as follows. Section 2 describes cooperative sensing schemes and Section 3 illustrates the system model. The proposed iterative algorithm for decision making at LCUs is described in Section 4. Then, this method is simulated and the results are analyzed in Section 5. The paper is concluded in Section 6 and the open issues for future researches are addressed.

2. Cooperative Sensing Schemes

Various cooperative sensing schemes by LCUs depending on the decision making methods of the fusion center can be used to carry out PU detection. In a centralized network approach, local sensors send the raw sensing information to a fusion center which decides on the presence or absence of the PU. However, the transmission of these unprocessed observations does not efficiently utilize the bandwidth. Cooperative sensing methods perform some preliminary data processing at each sensor to condense the information [21]. The major cooperative configurations include parallel, serial, and tree topologies as shown in Figure 1.

In a parallel sensing model, each LCU can decide independently based on its sensed information and pass the quantized local decision to a CCU whose role as a fusion center is to make a final decision on PU existence according to the spatially collected results. Even though extensive investigations have been done for cooperative sensing schemes to increase the sensing accuracy, most of the research assumed that the sensed information is independent and identically distributed within the local sensors [22]. This assumption is practically unrealistic as shadowing is highly correlated when several cognitive users are geographically proximate with similar shadowing effects. Spatially correlated shadowing which exponentially depends on the distance can bound the achievable gain of cooperative sensing [23].

For optimal PU detection, Bayesian criterion with maximizing LRT is the most common method in signal detection theory. For a given set of observations, $Y = [y_1, \dots, y_N]$, it has been shown that when the prior information of probabilities is known, LRT is the optimized detection method in which the likelihood ratio is calculated for the received signals and compared to a threshold θ as $\Lambda(Y) = P(Y \mid H_1)/P(Y \mid H_0) < \theta$, where θ is a function of prior probabilities of p_0 and p_1 and the cost function c_{ij} of H_i decision while H_j has been true, so we have $\theta = (c_{10} - c_{00})p_0/(c_{01} - c_{11})p_1$. In many cases, it is difficult to know these cost coefficients and prior probabilities. Instead, Neyman-Pearson cost function F is replaced under a condition that false alarm probability P_f is less than a certain value α as $F = \lambda(P_f - \alpha) + P_m$, where λ is the Lagrange multiplier, P_f is the probability of false alarm, and P_m is the probability of detection, respectively. To provide the final relations for P_d and P_f, note that $P_d = 1 - \int_\Omega P(Y \mid H_1)dY$ and $P_f = 1 - \int_\Omega P(Y \mid H_0)dY$, where Ω is decision region of H_0 determined due to the type of local decision rules and fusion rules.

In the case of Bayesian criterion for centralized network, as shown in Figure 1(a), there are N sensors that send their observations directly to one fusion center before processing and the final decision U_f is made based on a fusion rule as $G(Y)$ while

$$U_f = \begin{cases} 0, & H_0 \text{ decision, if } G(Y) \leq 0 \\ 1, & H_0 \text{ decision, if } G(Y) > 0. \end{cases} \tag{1}$$

The region of final decision based on H_0 is $\Omega_{\mathrm{CN}} = \{Y : G(Y) \leq 0\}$. The fusion rule $G(Y)$ is defined while minimizing

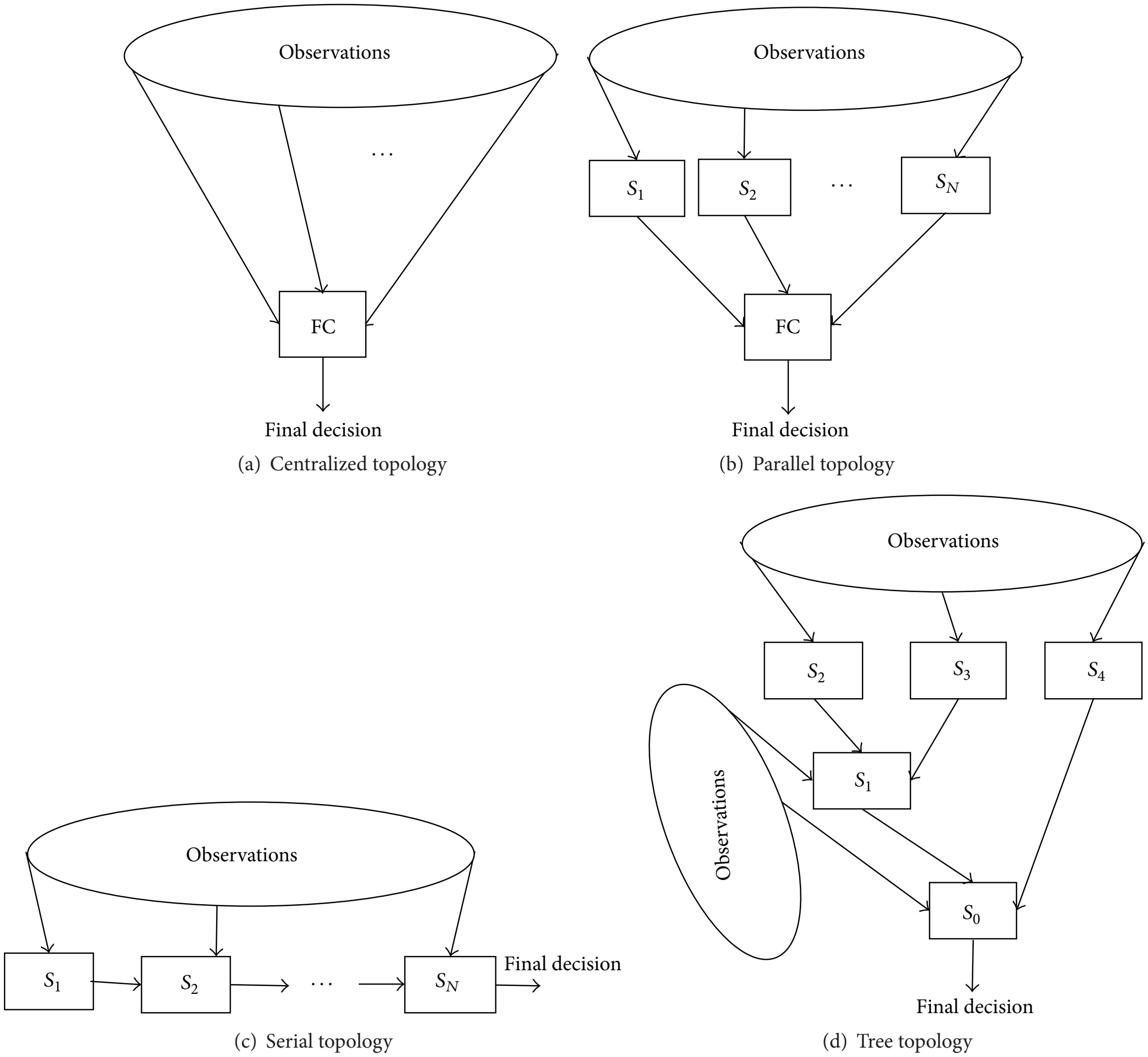

Figure 1: Major topologies of cooperative sensing networks.

the cost function of $F = c + \int_{\Omega_{\mathrm{CN}}} f(Y)dY$, where $c = (p_0 c_{10} + p_1 c_{11})$, $f(Y) = a_1 P(Y \mid H_1) - a_0 P(Y \mid H_0)$, with $a_1 = (c_{01} - c_{11})p_1$, and $a_0 = (c_{10} - c_{00})p_0$. Therefore, the optimum decision region of centralized network is $\Omega_{\mathrm{CN}} = \{y_i : \Lambda(Y) < \theta_{\mathrm{CN}},\ i = 1, \ldots, N\}$, where $\Lambda(Y) = P(Y \mid H_1)/P(Y \mid H_0)$, θ_{CN} is the threshold of decision making for centralized network, and N is the number of sensors.

In parallel topology with distributed local observations as shown in Figure 1(b), Bayesian criterion leads to LRT for local decision rule. For a network with N receivers and OR fusion rule, it can be written that $\Omega_{\mathrm{LRT,OR}} = \{y_i : \Lambda(y_i) \le \theta_i,\ i = 1, \ldots, N\}$, where θ_i is the threshold for the ith receiver. Meanwhile, for AND fusion rule, it is given that $\Omega_{\mathrm{LRT,AND}} = S - \{y_i : \Lambda(y_i) > \theta_i,\ i = 1, \ldots, N\}$, where S is the whole decision region. Based on Neyman-Pearson criterion, the values of thresholds θ_i can be achieved by minimizing the cost function of F, which in the case of OR fusion rule is

$$F_{\mathrm{LRT,OR}} = \gamma + \int_{\Omega_{\mathrm{LRT,OR}}} f(Y)\, dY \tag{2}$$

and for AND fusion rule is

$$F_{\mathrm{LRT,AND}} = \gamma + \int_{\Omega_{\mathrm{LRT,AND}}} f(Y)\, dY, \tag{3}$$

where $\gamma = \lambda(1 - \alpha)$, $f(Y) = P(Y \mid H_1) - \lambda P(Y \mid H_0)$.

The region of decision making for parallel sensing approach under cognitive radio channels is discussed in the next section. The local decision rules of local cognitive users and fusion rule are formulated to design an optimal algorithm with Neyman-Pearson criterion.

3. System Model

In this work, a cellular network scenario so called as heterogeneous network is considered for densely populated areas such that macrocells are mixed with low power cells. The small cells of heterogeneous networks can increase the signal coverage for the areas that are not accessible by macrobase stations to optimize the reliability and data rate. However, in

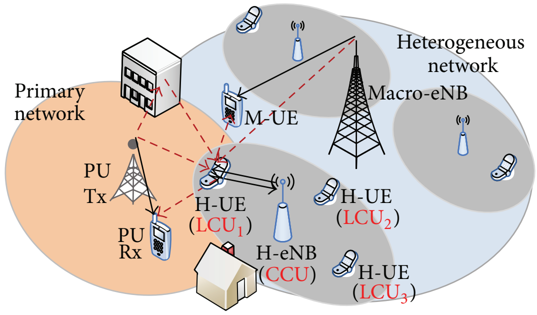

Figure 2: A heterogeneous network overlapping with primary network.

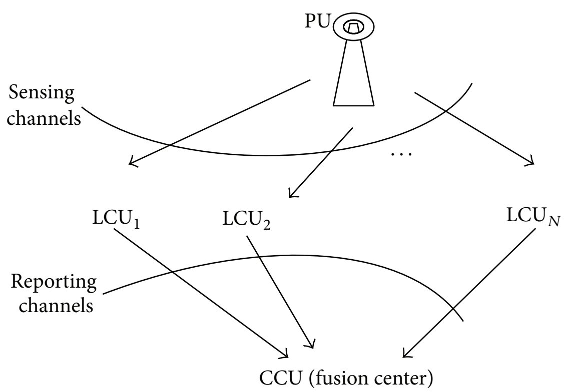

Figure 3: Parallel cooperative spectrum sensing.

this network, the coverage areas of small cells and primary systems can be overlapped. This mutual interference occurs when they are using the same time-frequency resources while spatially located in a certain distance apart from each other as shown in Figure 2. The frequency reusing of adjacent macrocell user equipment (M-UE) or other primary systems by small cells can create interferences to heterogeneous user equipment (H-UE). Hence, H-UE which operates as secondary users needs to transmit under a certain power level, which is acceptable by the licensed users, PUs, and at the same time mitigates the interference from the primary system.

The decision making on the presence or absence of PU signals is a critical part of spectrum sensing procedure at cognitive H-UE. In practice, each cognitive piece of H-UE plays a role same as distributed LCUs that is equipped with spectrum sensing by energy detection to locally measure the PU signal transmission power and frequencies. The local decisions are the output of certain local rules, at these distributed pieces of H-UEs that will be sent to H-eNB with the capability of a CCU to process the received information and produce the final decision based on the embedded fusion rule. Then, in the presence of PU signals, pieces of H-UE adapt their configurations to avoid mutual interferences with primary network. Since the channel impairments affect the input observations of each energy detector at H-UE, the assumption of independency is not correct any more and a cooperative decision making is required as the solution. Cognitive features enable the secondary users to analyze interference using the spectrum sensing mechanism that is mainly performed in LCUs, whereas the decision is made for the cooperative network. Let us consider N distributed LCUs as shown in Figure 3. In this figure, the ith LCU is shown as LCU_i that receives the observation signals, y_i, from the PU through the sensing channels. Each LCU_i sends its local binary decision, u_i, to the fusion center, the CCU, to make the final decision using the fusion rule. The metrics of probability of detection, $P_{d,i}$, and probability of false alarm, $P_{f,i}$, for local decision at the ith LCU_i are derived to be employed for the performance evaluation. Assuming that during the sensing time CUs do not broadcast and there is no mutual interference between them, the vector of the received signal through the sensing channels is defined as

$$Y = H \cdot S_p + V, \tag{4}$$

where S_p denotes PU's transmitted signal, $H = [h_1, \ldots, h_i, \ldots, h_N]$ states the sensing channel gain vector, and $Y = [y_1, \ldots, y_i, \ldots, y_N]$ shows the observation vector in which y_i denotes the received signal at LCU_i. The vector of additive white Gaussian noise (AWGN) at LCU receivers is $V = [v_1, \ldots, v_i, \ldots, v_N]$. The observations of PU's signal are received through the sensing channels at LCU_i. In this scenario, the correlated channels lead to correlated sensing observations at the LCU receivers that analyze the data as a binary hypothesis testing form. H_0 and H_1 are the binary hypotheses which define the absence and presence of PU, respectively. Then, the general form of the received signal at the spectrum sensing part of LCU is

$$\begin{aligned} H_1 &: y_1 = h_1 \cdot S_p + v_1, \ldots, y_N \\ &\quad = h_N \cdot S_p + v_N, \\ H_0 &: y_1 = v_1, \ldots, y_N = v_N. \end{aligned} \tag{5}$$

Given that y_i denotes the available observation of PU signal at LCU_i receiver, the local decision rule $g_i(y_i)$ is employed by LCU_i to make a binary decision u_i about the existence of PU signal. Based on a set of local decision rules as $G(Y) = [g_1(y_1), \ldots, g_i(y_i), \ldots, g_N(y_N)]$, the fusion center, CCU, receives the local decision as

$$u_i = \begin{cases} 0, & g_i(y_i) \le 0, \\ 1, & g_i(y_i) > 0. \end{cases} \tag{6}$$

The CCU follows a fusion rule as $Q(U)$ which is a Boolean function and whenever $Q(U) = 0$ the final decision is taken as H_0; otherwise it is H_1. The local decision rule maps the observation set $Y = y_1, \ldots, y_N$ to a local decision set $U = u_1, \ldots, u_i, \ldots, u_N$, where $u_i \in \{0, 1\}$, $i = 1, \ldots, N$. The combination of local binary decisions u_i results in 2^N states. Thus, the 2^{2^N} is the total number of states for final decision $u_f = Q(U)$ and

$$Q(U) = \left\{ Q_n, u_i = \mathrm{mod}\left(\frac{n-1}{2^{(i-1)}}, 2\right), \ 1 \le n \le 2^N \right\}, \tag{7}$$

where $\mathrm{mod}(A, 2)$ is the division remaining of $A/2$ and $u_i = \mathrm{mod}((n-1)/2^{(i-1)}, 2)$ is the ith bit of n. Hence, $Q(U) = \{Q_n, n = \sum_{i=1}^{N} u_i 2^{i-1} + 1\}$. Consider two different sets as $S_0 = \{n : Q_n = 0\}$ and $S_1 = \{n : Q_n = 1\}$ such that $S_0 \cup S_1 = \{1, 2, \ldots, 2^N\}$; then $\Omega_{\mathrm{OLDR}} = \{y_i : Q_n = 0,\ n \in S_0\}$, where Ω_{OLDR} defines the region of optimal decision making for parallel cooperative cognitive network which leads to the final decision of H_0. With a given set of S_0, the fusion rule $Q(U)$ is deterministic and constant and, for every n belonging to S_0, nth composition will result in a decision on H_0. For a fixed fusion rule, the region of final decision is $\Omega_{\mathrm{OLDR}} = \bigcup_{n\in S_0} \Omega_n$, where Ω_n denotes the region of nth combination of Q as

$$\Omega_n = \left\{ Y : u_i = \mathrm{mod}\left(\frac{n-1}{2^{(i-1)}}, 2\right),\ Q = Q_n \right\}. \tag{8}$$

In the next section, the optimization problem for parallel local decision rules is reduced to solve a set of fixed point integral equations that minimizes the Neyman-Pearson cost function. The decision rules are digitized for simplicity, and Gauss-Seidel algorithm [24] and Golden Section search [25] are applied to find the final solutions.

4. OLDR Algorithm with Gauss-Seidel Process

Each distributed H-UE/LCU$_i$ performs the spectrum sensing by energy detection to detect the initial PU signal observation, y_i. This distributed information from all LCUs is used by the OLDR algorithm to cooperatively optimize local decision rules, g_i, according to the fix central fusion rule at H-eNB/CCU, AND/OR, and achieve the final minimized P_f with Gauss-Seidel process. Based on the Neyman-Pearson criterion, the optimum local decision rule is defined to minimize the corresponding cost function F:

$$F(G; Q) = \lambda(1-\alpha) + \int_{\Omega_{\mathrm{OLDR}}} f(Y)\, dY, \tag{9}$$

where Q is the Boolean fusion function, Y denotes local observations, and $f(Y) = P(Y \mid H_1) - \lambda P(Y \mid H_0)$. Given that $\gamma = \lambda(1-\alpha)$, according to the above relations, it can be concluded that

$$\begin{aligned} F(G; Q) &= \gamma + \int_{Y\in\Omega_{\mathrm{OLDR}}} f(Y)\, dY = \gamma \\ &+ \left(\int_{g_i(y_i)\le 0} \left(\int_{\bigcup_{n\in S_{01,i}} \Omega_{n/i}} - \int_{\bigcup_{n\in S_{02,i}} \Omega_{n/i}} \right) + \int_{y_i} \int_{\bigcup_{n\in S_{02,i}} \Omega_{n/i}} \right) \\ &\cdot f(Y)\, dY, \end{aligned} \tag{10}$$

where $\Omega_{n/i}$ is Ω_n excluding y_i, $S_{01,i}$, $S_{02,i}$ are two subsets of S_0 such that $S_{01,i} \cup S_{02,i} = S_0$. $S_{01,i}$ is a subset of n belonging to S_0 with $u_i = 0$, $S_{01,i} = \{n : Q_n = 0, u_i = 0\}$, and similarly $S_{02,i}$ is a subset of n belonging to S_0 with $u_i = 1$, $S_{02,i} = \{n : Q_n = 0, u_i = 1\}$. The set of optimum local decision rules that minimizes the F function in (10) can be defined as $\overline{G} = (\overline{g}_1, \ldots, \overline{g}_N)$ [26]:

$$\overline{g}_i(y_i) = \left(\int_{\bigcup_{n\in S_{01,i}} \overline{\Omega}_{n/i}} - \int_{\bigcup_{n\in S_{02,i}} \overline{\Omega}_{n/i}} \right) \cdot \frac{f(Y)\, dY}{dy_i}, \tag{11}$$

where $\overline{\Omega}_{n/i} = \{(y_1, \ldots, y_{i-1}, y_{i+1}, \ldots, y_N) : \phi(\overline{g}_i, u_i) \le 0\}$, and $\phi(\overline{g}_i, u_i) = (1/2 - u_i)\overline{g}_i$. Consequently, each set of optimum local decisions is derived by solving several fixed point integral equations as

$$\Gamma_Q(G) = \begin{bmatrix} \left(\int_{\bigcup_{n\in S_{01,1}} \Omega_{n}/1} - \int_{\bigcup_{n\in S_{02,1}} \Omega_{n/1}} \right) \dfrac{f(Y)\, dY}{dy_1} \\ \vdots \\ \left(\int_{\bigcup_{n\in S_{01,i}} \Omega_{n/i}} - \int_{\bigcup_{n\in S_{02,i}} \Omega_{n/i}} \right) \dfrac{f(Y)\, dY}{dy_i} \\ \vdots \\ \left(\int_{\bigcup_{n\in S_{01,N}} \Omega_{n/N}} - \int_{\bigcup_{n\in S_{02,N}} \Omega_{n/N}} \right) \dfrac{f(Y)\, dY}{dy_N} \end{bmatrix}. \tag{12}$$

Therefore, the problem of optimum cooperative sensing is essentially reduced to optimizing a set of $G = (g_1, \ldots, g_N)$ that satisfies the integral equations. An iterative algorithm based on Gauss-Seidel process can approximate the solution of the above equations [26]. This method is used for solving a matrix of linear equations when the number of system parameters is too high to find a solution by common PLU techniques. The initial requirement is that the diagonal elements of the matrix of equations must be nonzero and convergence is provided when this matrix is either diagonally dominant or symmetric and positive definite [24]. Let us consider the local decision rule in jth iteration stage of the algorithm as $G^{(j)}$ and the initial set as $G^{(0)}$. Gauss-Seidel process for optimum local decision rules can be defined as

$$G^{(j+1)} = \Gamma_Q\left(G^{(j)}\right), \quad \forall j = 0, 1, 2, \ldots, \tag{13}$$

where

$$g_i^{(j+1)}(y_i) = \left(\int_{\bigcup_{n\in S_{01,i}} \Omega_n/i} - \int_{\bigcup_{n\in S_{02,i}} \Omega_n/i}\right) \cdot \frac{f(Y)\,dY}{dy_i}. \tag{14}$$

To reduce the computation complexity, the discrete variables t_i are extracted from y_i as $T = \{t_1, \dots, t_i, \dots, t_N\}$ and (14) can be described as

$$g_i^{j+1}(t_i) = \left(\sum_{\bigcup_{n\in S_{01,i}} \Omega_n/i} - \sum_{\bigcup_{n\in S_{02,i}} \Omega_n/i}\right) \frac{f(T)\,\Delta T}{\Delta t_i}. \tag{15}$$

Hence, the discrete local decision rules are defined as:

$$Z_i(t_i) = I\left(g_i(t_i)\right), \quad I(x) = \begin{cases} 0, & x \le 0, \\ 1, & x > 0. \end{cases} \tag{16}$$

Accordingly, the cost function F is approximated as

$$F\left(Z;Q\right) = \gamma + \sum_{n\in S_0}\left(\sum_{\{t_1:Z_1=u_1\}}\sum_{\{t_i:Z_i=u_i\}}\sum_{\{t_N:Z_N=u_N\}} f(T)\,\Delta T\right). \tag{17}$$

Therefore,

$$g_i^{j+1}(t_i) = \left(\sum_{n\in S_{01,i}} - \sum_{n\in S_{02,i}}\right) \sum_{t_1}\cdots\sum_{t_{i-1}}\sum_{t_{i+1}}\cdots\sum_{t_N}\prod_{L=1}^{i-1}\left(1-\left|\operatorname{mod}\left(\frac{n-1}{2^{(L-1)}},2\right) - Z_L^{(j+1)}(t_L)\right|\right)\prod_{L=i+1}^{N}\left(1-\left|\operatorname{mod}\left(\frac{n-1}{2^{(L-1)}},2\right) - Z_L^{(j)}(t_L)\right|\right)\frac{f(T)\,\Delta T}{\Delta y_i}. \tag{18}$$

For the simplicity of computations, discrete local decision rules $Z_i(t_i)$ are substituted instead of $g_i(t_i)$ as both of them have the same region of decision making. Note that the iterative process converges when absolute relative approximate error $|(Z_i^{(j+1)}(t_i) - Z_i^{(j)}(t_i))/Z_i^{(j+1)}(t_i)| \times 100 \ll \varepsilon$, where $\varepsilon > 0$ is prespecified tolerance parameter. For each positive value of Δt_i and initial selection of Z_i^0, the algorithm is converged after a certain number of iterations to a set of Z_i^j that satisfies the convergence condition. Figure 4 presents the flowchart of the developed optimization algorithm based on the golden section search method for Neyman-Pearson criterion. Golden section ratio of golden section search is applied with $\varphi = 0.618$ or symmetrically $(1 - 0.618) = 0.382$ to condense the width of the range in each step [25].

5. Simulation and Discussion

For the performance evaluation of the proposed OLDR algorithm and compared to the other methods, the receiver operating characteristic (ROC) curve is depicted as a graph of P_d versus P_f. To depict ROC curves for the OLDR algorithm, in each iteration, the values of P_d and P_f are provided based on the OLDR rules. As a benchmark, the simulation results are compared to centralized network and parallel network with LRT local decision rule.

When normal pdf is assumed for the sensed signals, the conditional pdf's under both hypotheses H_0 and H_1 are defined as $p(y_1, y_2, \dots, y_N \mid H_0) = N(\mu_0, C_0)$ and $p(y_1, y_2, \dots, y_N \mid H_1) = N(\mu_1, C_1)$, where C_0 and C_1 are the covariance matrices under H_0 and H_1, respectively. With correlation coefficient $-1 \le \rho \le 1$, the covariance matrix is written as $C(y_1, y_2, \dots, y_N) = [\sigma_1^2, \rho_{12}\sigma_1\sigma_2, \dots, \rho_{1N}\sigma_1\sigma_N; \dots; \rho_{N1}\sigma_N\sigma_1, \rho_{N2}\sigma_N\sigma_2, \dots, \sigma_N^2]$. The performance of OLDR algorithm for cooperative spectrum sensing is shown in this section. Centralized network (CN) with a fusion center is considered as the optimum benchmark for the evaluation of the proposed method. Numerical results are analyzed for both OLDR and LRT local decision rules with AND/OR fusion rules. Then, the effect of various correlation coefficients (ρ) on ROC curves is investigated with correlated sensed signals.

In the first case, a cooperative spectrum sensing with two local cognitive users is considered. Given that the received observations from PU are random Gaussian signal $H \cdot S_p$ with mean $\mu_{H\cdot S_p} = 2$ and variance $\sigma_{H\cdot S_p}^2 = 1$, added to n_1 and n_2 as independent zero mean Gaussian noises such that $\sigma_{n_1}^2 = 2$ and $\sigma_{n_2}^2 = 1$, then the conditional pdf's under both hypotheses, H_0 and H_1, are $p(y_1, y_2 \mid H_0) = N(\mu_0, C_0)$ and $p(y_1, y_2 \mid H_1) = N(\mu_1, C_1)$. Therefore, $\mu_0 = [0; 0]$, $C_0 = [2, 0; 0, 1]$, $\mu_1 = [2; 2]$, $C_1 = [3, 1; 1, 2]$.

Figure 5 compares the performance of OLDR and LRT with centralized network. As illustrated in this figure, OLDR with AND fusion rule outperforms the other techniques since

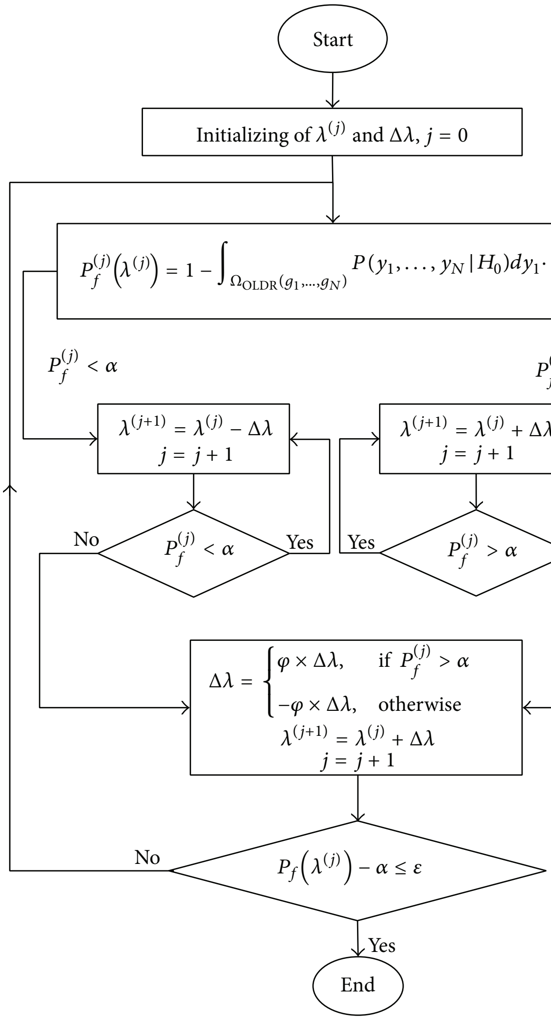

FIGURE 4: The proposed optimization algorithm (OLDR).

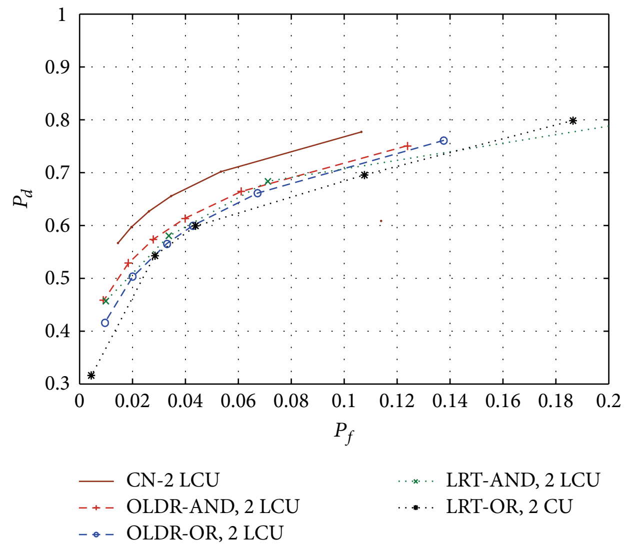

FIGURE 5: ROC comparison for Gaussian received signal in independent Gaussian noise with two LCUs.

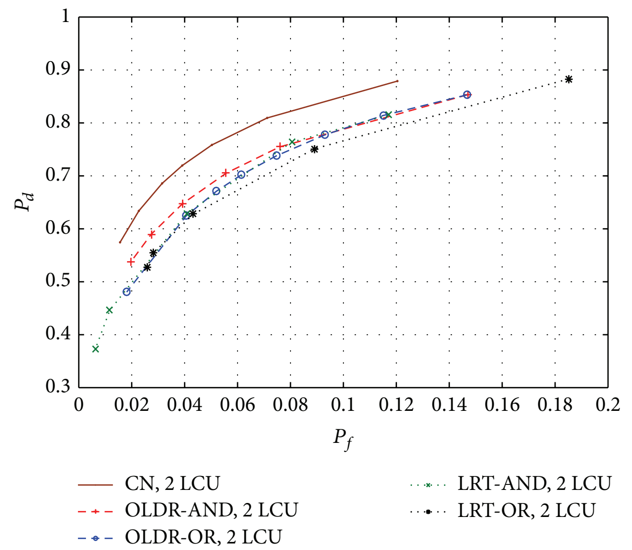

FIGURE 6: ROC comparison for deterministic received signal in correlated Gaussian noises with two LCUs.

it is closer to the CN curve. Meanwhile, OLDR performs better than LRT with the same fusion rules; for example, at $P_f = 0.02$, OLDR shows 4% improvement in P_d compared to the LRT with the same fusion rules.

In the second case, parallel spectrum sensing with two local cognitive users are considered with correlated received signals as $\mu_0 = [0; 0]$, $\mu_1 = [2; 2]$, $C_0 = C_1 = [\sigma_1^2, \rho\sigma_1\sigma_2; \rho\sigma_1\sigma_2, \sigma_2^2]$. The results of simulations with $\rho = 0.1$ are presented in Figure 6 which illustrates that the OLDR with AND fusion rule is more proximate to the CN curve and achieves a better performance than OR fusion rule; for instance, at $P_f = 0.02$ the improvement is about 4%.

The performance of the same network for various values of correlation coefficient (ρ) is shown in Figure 7. According to these results, the performance is enhanced by the reduction of the correlation coefficient (ρ).

Now a network of three local cognitive users with Gaussian signal observations is considered with mean $\mu_{H\cdot S_p} = 2$ and variance $\sigma^2_{H\cdot S_p} = 1$, added to zero mean independent noises with $\sigma^2_{n_1} = 3$, $\sigma^2_{n_2} = 2$, and $\sigma^2_{n_3} = 1$. Thus, the covariance matrices under H_0 and H_1 are described as $C_0 = [3, 0, 0; 0, 2, 0; 0, 0, 1]$ and $C_1 = [4, 1, 1; 1, 3, 1; 1, 1, 2]$.

Figures 8 and 9 show that increasing the number of local cognitive users enhances the performance of the network. For Gaussian received signals with independent Gaussian noise at $P_f = 0.02$, the P_d is enhanced about 3% for OLDR with three LCUs comparing to OLDR with two LCUs.

From these results, it is concluded that, for a fixed fusion rule, OLDR algorithm shows a superior performance of local decision rules to detect primary users compared to LRT method. Apparently, the probability of primary user detection is increased with the number of cooperative local cognitive users equipped with spectrum sensing. When the sensing channels are correlated, results show performance degradation in higher correlation coefficients.

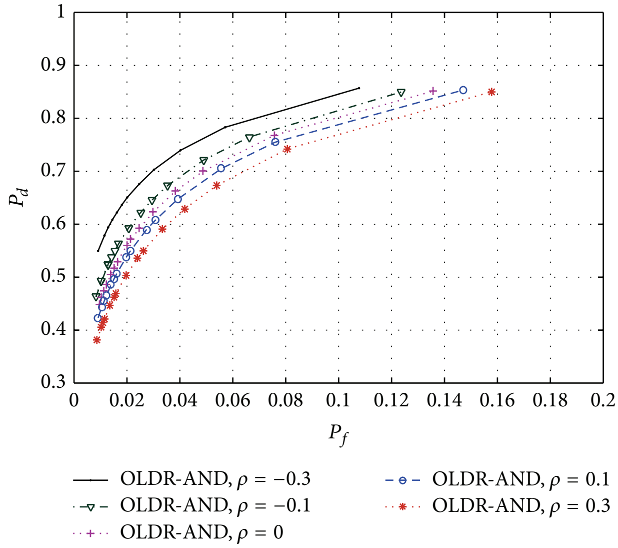

FIGURE 7: ROC comparison for deterministic received signal in correlated Gaussian noise with different correlation coefficients (ρ).

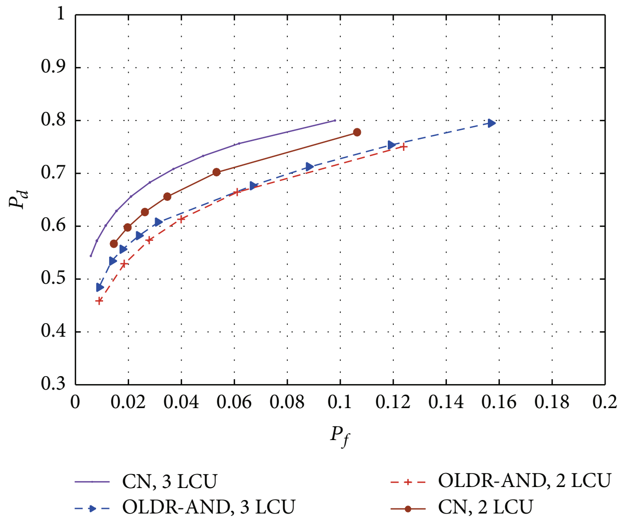

FIGURE 8: ROC comparison for Gaussian received signal in independent Gaussian noises with different numbers of LCUs.

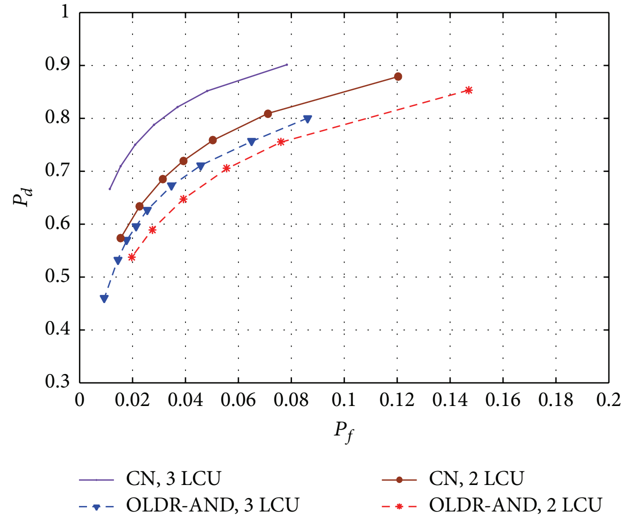

FIGURE 9: ROC comparison for deterministic signal in correlated Gaussian noises with different numbers of LCUs.

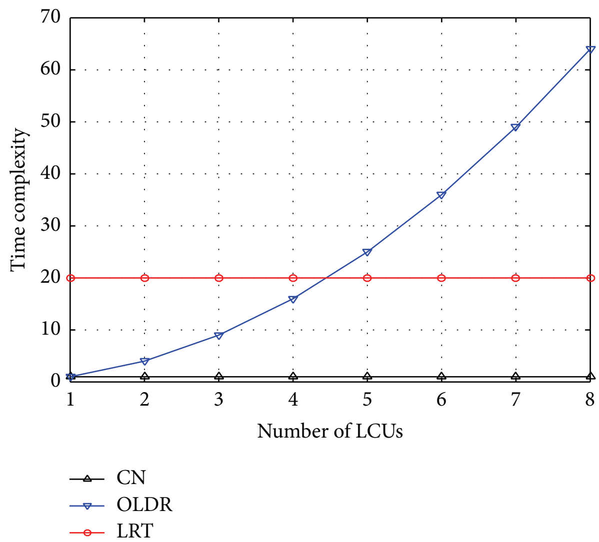

FIGURE 10: Time complexity comparison of local decision rules.

OLDR method is a low complexity solution for the problem of (11) which is reduced to optimizing a set of local decision rules, $G = (g_1, \ldots, g_N)$, that satisfies the integral equations (12). In addition, the computation complexity of (14) has been reduced by considering discrete variables for the observations y_i, as well as local decision rules g_i, to t_i, and Z_i, respectively. For the centralized network, there is no local decision rule, and the local decision rule of LRT method is defined as $\Lambda(y_i) \leq \theta_i$, where θ_i is the threshold for the ith receiver. In each iteration of the algorithm with LRT, $\Lambda(Y_i)$ is calculated for all observations, y_i, and compared with threshold θ_i. For the initial threshold within a range of M levels, the time complexity of each local decision rule can be written as $O(M)$. According to (18), the local decision rule of OLDR algorithm, g_i^{j+1}, has to be updated at each iteration with the time complexity of $O(N^2)$ compared to the other local decision rules. The time complexity comparison of local decision rules for $M = 20$ is shown in Figure 10 which describes the increase of the calculations number proportional to the number of the receivers, N. However, since CN method consumes too large bandwidths for sending the data to the fusion center and LRT method assumes independent observations, they cannot be considered as optimum solution for cooperative cognitive users with correlated sensed signals.

6. Conclusion

In this paper, the cooperative spectrum sensing for cognitive heterogeneous network has been designed with a parallel configuration. An optimum algorithm for local decision rule based on Neyman-Pearson criterion with correlated observations from PUs has been proposed. This scheme, based on a discrete Gauss-Seidel iterative algorithm, leads to a low complexity method of finding an optimum solution for LCU's decision rules. The performance evaluation shows the efficiency of this algorithm with fixed fusion rules in which AND rule outperforms the OR fusion rule. Furthermore, with lower correlation coefficients, a better performance is achieved. The experimental measurements and implementation of OLDR algorithm for a distributed heterogeneous cognitive network are a challenging open area for the future work. Meanwhile, optimizing the fusion rule simultaneously with the local decision rules, study of different topologies of cooperative cognitive networks, the performance analysis of multilevel decision rules, and shadowing in reporting channels are among the other suggestions for the future exploration.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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