Cooperative Spectrum Sensing Strategies for Cognitive Radio Mesh Networks

Qian Chen, *Student Member, IEEE*, Mehul Motani, *Member, IEEE*, Wai-Choong (Lawrence) Wong, *Senior Member, IEEE*, and Arumugam Nallanathan, *Senior Member, IEEE*

***Abstract*—In this paper, we consider the cooperative spectrum sensing problem for a cognitive radio (CR) mesh network, where secondary users (SUs) are allowed to share the spectrum band which is originally allocated to a primary users' (PUs) network. We propose two new cooperative spectrum sensing strategies, called *amplify-and-relay* (AR) and *detect-and-relay* (DR), aiming at improving the detection performance with the help of other eligible SUs so as to agilely vacate the channel to the primary network when the neighboring PUs switch to active state. AR and DR strategies are periodically executed during the spectrum sensing phase which is arranged at the beginning of each MAC frame. Based on AR and DR strategies, we derive the closed-form expressions of false alarm probability and detection probability for both single-relay and multi-relay models, with or without channel state information (CSI). Simulation results show that our proposed strategies achieve better performance than a non-cooperative (or non-relay) spectrum sensing method and an existing cooperative detection method. As expected, we observe that the detection performance improves as the number of eligible relay SUs increases, and furthermore, it is better for the known-CSI case than that of the unknown-CSI case.**

***Index Terms*—Amplify-and-relay, cognitive radio (CR), cooperative spectrum sensing, detect-and-relay.**

I. Introduction

COGNITIVE radio (CR) [1]–[3] solves the spectrum congestion problem by allowing secondary users (SUs) to use the spectrum band which is originally allocated to primary users (PUs). In traditional spectrum management mechanism, most of the spectrum bands are exclusively allocated to a few particular customers, which results in the exhaustion of limited frequency resource as wireless applications grow. However, in contrast to spectrum scarcity, spectrum utilization is often very low. Measurement results show that, in the U.S., only 2% of the spectrum is used at any given time and location [4]. Moreover, the spectrum utilization efficiency in Singapore is 5% only [5]. Even when PUs are active, there still exists an abundance of access opportunities for SUs at the slot time level.

One feasible solution to alleviate the spectrum scarcity is opportunistic spectrum access (OSA), envisioned by the DARPA XG program [6], by which SUs can use the PUs' spectrum band but they are required to detect the PUs' states before their transmissions. Here, the detection function is fulfilled by spectrum sensing technique. If PUs are detected, SUs will defer their transmissions and vacate the channel to PUs, then try again later after a predefined *blocking time*. Otherwise, if PUs are undetected, SUs are allowed to start their transmission.

Generally, three different spectrum sensing methods are widely used in application: matched filter, energy detection, and cyclostationary feature detection [7]–[10]. In [10], the advantages and disadvantages of these three techniques were discussed in detail. However, the authors in [10], [11] showed that the performances of these techniques are influenced by the received signal strength, and would be severely degraded due to multi-path fading and shadowing. Later, collaboration methods were proposed in, e.g., [10]–[14] to improve the overall detection probability by using either a centralized or a distributed manner which is based on the decision fusion policy. In a centralized manner, each SU receives the signals from PUs, independently makes its local decision, and then send the decision result to an anchor node or a base station (BS). Next, BS makes a global decision and immediately response to SUs once PUs have been detected. However, BS may locate far away from SUs, so that it is inapplicable to implement this global fusion mechanism. Moreover, this centralized fusion method would be easily compromised by an attacker. On the other hand, for a distributed manner, each SU only collects the neighboring SUs' decisions and makes a local decision by itself. From the description above, we see that no matter which manner is adopted, this majority logic-based decision fusion policy actually cannot improve the individual detection probability. Thus, the authors in [15] and [16] considered a relay model and proposed a cooperative spectrum sensing strategy using data fusion policy to improve the detection performance: the secondary transmitter first sends a message to the secondary relay SUs, then listens to the following response signal that consists of the messages replied by the secondary relay SUs and the signals transmitted by the neighboring PUs, and finally makes the detection decision based on this message interaction. Also, they concluded that SU with higher independent detection probability can act as a relay to help other SUs.

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Q. Chen, M. Motani, and W.-C. L. Wong are with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore 118622 (e-mail: chenqian@nus.edu.sg; motani@nus.edu.sg; elewwcl@nus.edu.sg).

A. Nallanathan is with the Department of Electronic Engineering, King's College London, Strand, London WC2R 2LS, U.K. (e-mail: arumugam.nallanathan@kcl.ac.uk).

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In this paper, we adopt the energy detection technique and apply the data fusion policy to cooperative spectrum sensing under a CR mesh network, where SUs are self-organized by a mesh network topology detailed in IEEE 802.16 [17], [18], and allowed to use the spectrum band which is originally allocated to a PUs' network. To protect the PUs' operations, SUs must agilely vacate the channel when PUs are detected to be active. Here, the agility of vacating the channel is scaled by a parameter called detection probability which is the probability that a SU can correctly detect the active state of its neighboring PUs when PUs are working. Considering a CR mesh network, we propose two cooperative spectrum sensing strategies called *amplify-and-relay* (AR) and *detect-and-relay* (DR) to improve the detection performance in this paper. In AR strategy, the relay SU amplifies the received signal from PU and then directly forwards to the secondary transmitter. On the other hand, DR strategy not only amplifies and forwards the signal, but also involves its independent detection results to decide whether it should relay or not. For both AR and DR, the secondary transmitter finally makes its decision based on the resultant signals sent by the relay SUs or PUs or both, which will be detailed in later sections. Note that the concepts of AR and DR proposed in this paper are implemented for energy detection, which is different with the concepts of *amplify-and-forward* (AF) and *decode-and-forward* (DF) for cooperative transmission diversity. We analyze the performances of AR and DR for both single-relay [19] and multi-relay models, with or without channel state information (CSI). Moreover, we design a suitable MAC frame structure that consists of two consecutive durations called spectrum sensing phase and transmission phase, during which the AR or DR is implemented in spectrum sensing phase, and the following transmission phase is the same as the conventional packet transmission process standardized in IEEE 802.16, except that the decision whether or not to transmit is determined by the outcome of spectrum sensing.

This paper is organized as follows. Section II introduces the system model and the details of our proposed AR and DR strategies. In Sections III and IV, considering the unknown-CSI case, we derive the closed-form expressions of false alarm probability and detection probability for non-cooperative (or non-relay), single-relay, and multi-relay models, respectively, and also compare the performances among them. Then, we compute the performance achieved by each method for the known-CSI case in Section V. Finally, simulation results are shown in Section VI and conclusions are drawn in Section VII.

II. System Model

The CR mesh network organized by SUs is shown in Fig. 1, where a secondary transmitter or a mesh subscriber station (MSS) named in IEEE 802.16, denoted by $\mathbb{U}_0$, and M number of relay MSSs, denoted by $\mathbb{U}_i$, $i = 1 \cdots M$, share the same spectrum band with carrier frequency f_c and bandwidth W which is originally allocated to another network organized by PUs. We assume that the PUs' network consists of only one service provider, e.g., a TV or a radio station, denoted by $\mathbb{P}_t$, and several service users, e.g., TV or radio receivers denoted by $\mathbb{P}_r$'s. Note that the results obtained in this paper can be easily extended to the multi-PU case.

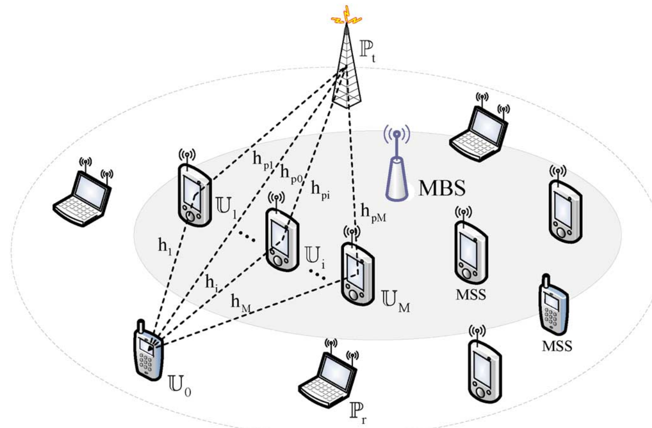


Fig. 1. Cooperative spectrum sensing model.

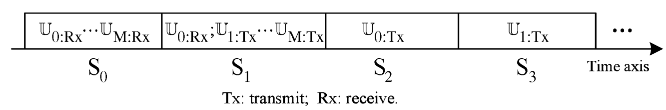


Fig. 2. MAC frame structure for our proposed strategies.

As seen in Fig. 1, since $\mathbb{U}_0$ locates outside the coverage area of a secondary access point (AP) or a mesh base station (MBS) called in IEEE 802.16, it cannot directly communicate with this MBS, and must transmit through one or more relay MSSs. On the other hand, $\mathbb{U}_0$ is far away from $\mathbb{P}_t$, so that its transmission may influence the neighboring $\mathbb{P}_r$'s operation due to its poor detection performance. In this case, based on the CR mesh network and the relay model under consideration, we propose two cooperative spectrum sensing strategies called AR and DR to improve $\mathbb{U}_0$'s detection probability and well-protect the operations of the PUs' network. We assume that SUs operate in a fixed time division multiple access (TDMA) manner, thus spectrum sensing can be periodically executed in the spectrum sensing phase of each frame before the data transmission. As seen in Fig. 2, the spectrum sensing phase consists of two time slots S_0 and S_1, and the transmission phase proceeds in the following slots. In S_0, all the $\mathbb{U}_i$'s listen in the desired band and receive the signal from $\mathbb{P}_t$. Next, in S_1, each relay MSS $\mathbb{U}_i$ works according to two different strategies:

1) $\mathbb{U}_i$ amplifies its received signal during S_0 and directly relays to $\mathbb{U}_0$ by maximum transmission power constraint, which is called *amplify-and-relay* (AR);
2) $\mathbb{U}_i$ firstly detects the $\mathbb{P}_t$'s states by the received signal in S_0. If $\mathbb{P}_t$ is undetected, $\mathbb{U}_i$ keeps quiet during S_1. Otherwise, if $\mathbb{P}_t$ is detected, $\mathbb{U}_i$ proceeds to relay the received signal, which is the same as AR. In this paper, we call this detection strategy *detect-and-relay* (DR).

Here, the signal sent by relay SU during S_1 may interfere with the neighboring $\mathbb{P}_r$'s receiving. However, since the duration of S_1 in the spectrum sensing process is relatively short, we assume that this influence can be ignored. Finally, using the signals received from $\mathbb{U}_i$'s and $\mathbb{P}_t$ during S_1, $\mathbb{U}_0$ makes its own decision by energy detection technique. After that, $\mathbb{U}_0$ broadcasts a message containing $\mathbb{P}_t$'s state information to notify its neighboring $\mathbb{U}_i$'s. If $\mathbb{P}_t$ is deemed to be active, the following data transmission will be suspended; otherwise, the transmission phase will proceed as usual.

III. Cooperative Detection Strategies for Single-Relay Model

In this section, we consider the single-relay model with unknown-CSI, which means that only one relay SU, denoted by $\mathbb{U}_1$, helps $\mathbb{U}_0$ improve its detection probability. Suppose[1] the received signal-to-noise ratio (SNR) at $\mathbb{U}_1$ is greater than that of $\mathbb{U}_0$. In addition, we consider the Rayleigh fading channels and assume that they are independent with each other.

A. Overview of Non-Cooperative Detection Method

We first introduce the non-cooperative (or non-relay) detection method, where each SU detects the PU's states by itself. In this case, the received signal y_i at $\mathbb{U}_i$ during a slot S_j can be expressed as

$$y_i = \theta h_{pi} x_{p,j} + n_i \tag{1}$$

where θ denotes the $\mathbb{P}_t$'s state, h_{pi} is the instantaneous channel fading gain from $\mathbb{P}_t$ to $\mathbb{U}_i$, $x_{p,j}$ refers to the signal sent by $\mathbb{P}_t$ during the T_j (using QPSK, BPSK or some other modulations), and n_i is the complex white Gaussian noise with zero mean and variance $\sigma^2_{n_i} = N_i$.

Suppose that the signal set of $x_{p,j}$ is given and $\mathbf{E}\{|x_{p,j}|^2\} = E_s$. Moreover, we assume for simplicity that h_{pi} is determined by both distance-dependent average path loss and fading, i.e., $h_{pi} = h'_{pi}/\sqrt{d^3_{pi}}$, where d_{pi} is the distance between $\mathbb{P}_t$ and $\mathbb{U}_i$, path-loss exponent equates to 3, i.e., a typical of a flat rural environment, and the fading coefficient h'_{pi} is a complex Gaussian random variable (CGRV) with zero mean and unit variance. Thus, the variance of h_{pi} is given by $\sigma^2_{h_{pi}} = \mathbf{E}\{|h'_{pi}/\sqrt{d^3_{pi}}|^2\} = 1/d^3_{pi}$. Let E_i denote the signal received from $\mathbb{P}_t$ when $\mathbb{P}_t$ is active during S_0, then we have

$$E_i = \mathbf{E}\left\{|h_{pi}x_{p,0}|^2\right\} = E_s/d^3_{pi}. \tag{2}$$

For energy detection, a threshold T_i must be properly selected to detect the $\mathbb{P}_t$'s state θ, where $\theta = 1$ indicates the active case, and $\theta = 0$ is the inactive case. Let $\hat{\theta}_i$ be an estimated result of θ at $\mathbb{U}_i$. Thus, if the power of y_i denoted by Y_i, satisfies that $Y_i \geq T_i$, we have $\hat{\theta}_i = 1$; otherwise, $\hat{\theta}_i = 0$.

For non-cooperative case, $\mathbb{U}_i$ makes a decision from standard testing with two hypotheses: H_0 (i.e., $\theta = 0$) and H_1 (i.e., $\theta = 1$). From (1), it is easily verified that Y_i follows an exponential distribution. Let $\sigma_{i,j}$ denote the expected power of y_i under H_j. Using (2), we have

$$\begin{cases} \sigma_{i,0} = N_i, & H_0 \\ \sigma_{i,1} = E_i + N_i, & H_1. \end{cases} \tag{3}$$

By definition, the false alarm occurs when $\mathbb{U}_i$ claims the active of $\mathbb{P}_t$ under H_0. On the other hand, detection means that $\mathbb{U}_i$ can correctly detect the active state of $\mathbb{P}_t$ under H_1. We use $P_{f,i}$ and $P_{d,i}$ to denote the false alarm probability and detection probability of $\mathbb{U}_i$, respectively. Thus, $P_{f,i}$ is given by

$$\begin{aligned} P_{f,i} &= P\{\hat{\theta}_i = 1|H_0\} = P\{Y_i \geq T_i|H_0\} \\ &= \int_{T_i}^{\infty} \frac{1}{\sigma_{i,0}} e^{-\frac{t}{\sigma_{i,0}}} dt = e^{-\frac{T_i}{N_i}}. \end{aligned} \tag{4}$$

Suppose that $P_{f,i}$ is fixed at a constant value α $(0 < \alpha < 1)$. From (4), the corresponding T_i is obtained as

$$T_i = -\ln \alpha^{N_i}. \tag{5}$$

Furthermore, the detection probability $P_{d,i}$ can be derived by

$$\begin{aligned} P_{d,i} &= P\{\hat{\theta}_i = 1|H_1\} = P\{Y_i \geq T_i|H_1\} \\ &= \int_{T_i}^{\infty} \frac{1}{\sigma_{i,1}} e^{-\frac{t}{\sigma_{i,1}}} dt = \alpha^{\sigma_{i,0}/\sigma_{i,1}} = \alpha^{\frac{1}{1+\gamma_i}}. \end{aligned} \tag{6}$$

where $\gamma_i = E_i/N_i$ is the received SNR of $\mathbb{U}_i$. Suppose that all the N_i's are fixed as one in this paper; thus, we have $P_{d,i} = \alpha^{1/(1+E_i)}$.

From (6), we can define a parameter $\Gamma_i = \sigma_{i,1}/\sigma_{i,0}$ as the expected power ratio of the received signal y_i under H_1 to that of value under H_0. Therefore, we see that the higher γ_i, the greater Γ_i, which results in the better $P_{d,i}$ for the non-cooperative (or non-relay) case.

B. Performance of AR

AR strategy has been introduced in Section II. From (1), we know that the received signal y_1 at $\mathbb{U}_1$ during the slot S_0 is given by

$$y_1 = \theta h_{p1} x_{p,0} + n_1. \tag{7}$$

Next, $\mathbb{U}_1$ amplifies the signal y_1 and then relays to $\mathbb{U}_0$ during S_1. We use β'_i to denote the amplification factor of $\mathbb{U}_i$. According to maximum power constraint, β'_i is chosen as

$$\beta'_i = \frac{\tilde{E}_i}{E_i + N_i} = \frac{\tilde{E}_i}{E_s/d^3_{pi} + N_i} \tag{8}$$

in order to accommodate both cases H_0 and H_1, where $\tilde{E}_i$ is the maximum transmit power of $\mathbb{U}_i$.

Finally, the resultant signal received at $\mathbb{U}_0$ is given by

$$\begin{aligned} y_0 &= \sqrt{\beta'_1} h_1 (\theta h_{p1} x_{p,0} + n_1) + \theta h_{p0} x_{p,1} + n_0 \\ &= \theta \left(h_{p0} x_{p,1} + \sqrt{\beta'_1} h_1 h_{p1} x_{p,0}\right) + n_0 + \sqrt{\beta'_1} h_1 n_1 \end{aligned} \tag{9}$$

where $h_i = h'_i/\sqrt{d^3_i}$ is the instantaneous channel gain from $\mathbb{U}_i$ to $\mathbb{U}_0$, and the fading coefficient h'_i is a CGRV with zero mean and unit variance.

For a given h_1, y_0 is a CGRV with zero mean since that h_{pi}'s and n_i's are all CGRVs with zero mean. Thus, it is easily veri-

[1]This kind of information can be known *a priori* through different ways, e.g., received signal strength indication (RSSI) based location tracking method, etc.

fied that the power of y_0, denoted by Y_0, follows an exponential distribution. For computational simplicity, we define

$$G_i \triangleq \mathbf{E}\left\{|h_i|^2\right\} = 1/d_i^3 \tag{10}$$

as the expected channel gain from $\mathbb{U}_i$ to $\mathbb{U}_0$, where d_i is the distance from $\mathbb{U}_i$ to $\mathbb{U}_0$. Also, we define that

$$\beta_i = \beta_i' G_i \quad \text{and} \quad g_i = |h_i|^2/G_i. \tag{11}$$

Obviously, g_i is an exponential random variable with failure rate $\lambda_i = 1$, i.e., $g_i \sim Exponential(1)$.

Therefore, from (9), the mean value of Y_0 for a given g_1 can be expressed as

$$\begin{cases} \sigma_{0,0} = N_0 + \beta_1 N_1 g_1, & H_0 \\ \sigma_{0,1} = N_0 + E_0 + \beta_1 (N_1 + E_1) g_1, & H_1. \end{cases} \tag{12}$$

Let $P_{f,0}^{(1)}$ denote the false alarm probability obtained by AR strategy, thus we have

$$\begin{aligned} P_{f,0}^{(1)} &= P\{Y_0 \geq T_0 | H_0\} = \int_0^\infty P\{Y_0 \geq T_0 | H_0, g_1\} f(g_1) dg_1 \\ &= \int_0^\infty \left(\int_{T_0}^\infty \frac{1}{\sigma_{0,0}} e^{-\frac{t}{\sigma_{0,0}}} dt \right) e^{-g_1} dg_1 \\ &= \int_0^\infty e^{-g_1 - \frac{T_0}{N_0 + \beta_1 N_1 g_1}} dg_1. \end{aligned} \tag{13}$$

For notation simplicity, we define

$$\phi_1(t;\eta) = \int_0^\infty e^{-g_1 - \frac{t}{N_0 + \eta N_1 g_1}} dg_1 \tag{14}$$

as the function of t with a parameter η, where the subscript 1 refers to the AR strategy. Therefore, if $P_{f,0}^{(1)}$ is the same as the value α given in the non-cooperative case, the detection threshold for AR is given by

$$T_0^{(1)} = \phi_1^{-1}(\alpha; \beta_1) \tag{15}$$

where the superscript (1) refers to AR, and ϕ_1^{-1} is the inverse function of ϕ_1.

In a similar way, $P_{d,0}^{(1)}$ is given by

$$\begin{aligned} P_{d,0}^{(1)} &= P\left\{Y_0 \geq T_0^{(1)} | H_1\right\} \\ &= \int_0^\infty P\left\{Y_0 \geq T_0^{(1)} | H_1, g_1\right\} f(g_1) dg_1 \\ &= \int_0^\infty \left(\int_{T_0^{(1)}}^\infty \frac{1}{\sigma_{0,1}} e^{-\frac{t}{\sigma_{0,1}}} dt \right) e^{-g_1} dg_1 \\ &= \int_0^\infty e^{-g_1 - \frac{T_0^{(1)}}{N_0 + E_0 + \beta_1 (N_1 + E_1) g_1}} dg_1. \end{aligned} \tag{16}$$

We define

$$\varphi_1(t;\eta) = \int_0^\infty e^{-g_1 - \frac{t}{N_0 + E_0 + \eta (N_1 + E_1) g_1}} dg_1. \tag{17}$$

Then, we have

$$P_{d,0}^{(1)} = \varphi_1\left(T_0^{(1)}; \beta_1\right) = \varphi_1\left(\phi_1^{-1}(\alpha;\beta_1);\beta_1\right). \tag{18}$$

Finally, we compare the performances of our proposed AR strategy with another cooperative detection method proposed in [15] and [16]. This method is briefly summarized as follows. In time slot S_0, $\mathbb{U}_0$ transmits a message to $\mathbb{U}_1$. In S_1, $\mathbb{U}_1$ amplifies the received message by the maximum power constraint, and then relay back to $\mathbb{U}_0$. At last, $\mathbb{U}_0$ makes its own decision based on this message interaction at the end of S_1.

Let $P_{f,0}'$ and $P_{d,0}'$ denote the false alarm probability and the detection probability in [15] and [16], respectively. Using the functions defined in (14) and (17), we can rewrite $P_{f,0}'$ and $P_{d,0}'$ as

$$P_{f,0}' = \phi_1\left(T_0'; \delta_0\right) = \alpha; \quad P_{d,0}' = \varphi_1\left(\phi_1^{-1}(\alpha;\delta_0);\delta_1\right) \tag{19}$$

where $\delta_0 = \tilde{E}_1 G_1/(N_1 + E_m G_1)$, $\delta_1 = \tilde{E}_1 G_1/(N_1 + E_1 + E_m G_1)$, E_m is the power of the message sent from $\mathbb{U}_0$ to $\mathbb{U}_1$, and T_0' is the corresponding threshold in [15], [16]. It is obvious that δ_0 is greater than δ_1, i.e., the amplification factor under H_0 is greater than the value under H_1.

Given the same value of false alarm probability α, we have

$$\alpha = \phi_1\left(T_0^{(1)}; \beta_1\right) = \phi_1\left(T_0'; \delta_0\right). \tag{20}$$

Theorem 1: If $\delta_1 \leq \beta_1 \leq \delta_0$, then $P_{d,0}^{(1)}$ is greater than or equal to $P_{d,0}'$.

Proof: Note that $\phi_1(t;\eta)$ is an increasing function of η but is a decreasing function of t. If $\beta_1 \leq \delta_0$, from (20), we know that $T_0^{(1)} \leq T_0'$ for the same α.

On the other hand, for $\beta_1 \geq \delta_1$, we can easily see that $\varphi_1(T_0^{(1)};\beta_1) \geq \varphi_1(T_0';\delta_1)$ since the characteristic of function φ_1 is the same as ϕ_1. Therefore, $P_{d,0}^{(1)} \geq P_{d,0}'$ holds. ∎

Remark 1: Theorem 1 only provides a sufficient condition for $P_{d,0}^{(1)} \geq P_{d,0}'$. From the simulation results, we can observe that for a large β_1, $P_{d,0}^{(1)}$ is still much higher than $P_{d,0}'$. That numerically proves the better performance of our proposed AR strategy.

C. Performance of DR

We consider the DR strategy and analyze its performance in this section.

As mentioned in Section II, $\mathbb{U}_1$ first detects the $\mathbb{P}_t$'s states, and then relays only when it claims that $\hat{\theta}_i = 1$. In this case, the resultant signal received by $\mathbb{U}_0$ at the end of S_1 is given by

$$\begin{aligned} y_0 &= \hat{\theta}_1 \sqrt{\beta_1'} h_1 (\theta h_{p1} x_{p,0} + n_1) + \theta h_{p0} x_{p,1} + n_0 \\ &= \theta \left(h_{p0} x_{p,1} + \hat{\theta}_1 \sqrt{\beta_1'} h_1 h_{p1} x_{p,0}\right) \\ &\quad + n_0 + \hat{\theta}_1 \sqrt{\beta_1'} h_1 n_1. \end{aligned} \tag{21}$$

For given g_1 and $\hat{\theta}_1$, the mean value of Y_0 is equal to

$$\begin{cases} \sigma_{0,0} = N_0 + \hat{\theta}_1 \beta_1 N_1 g_1, & H_0 \\ \sigma_{0,1} = N_0 + E_0 + \hat{\theta}_1 \beta_1 (N_1 + E_1) g_1, & H_1. \end{cases} \quad (22)$$

From (22), the false alarm probability of DR strategy denoted by $P_{f,0}^{(2)}$, is given by

$$\begin{aligned} P_{f,0}^{(2)} &= P\{Y_0 \geq T_0 | H_0\} \\ &= P\{Y_0 \geq T_0 | \hat{\theta}_1 = 1, H_0\} \cdot P\{\hat{\theta}_1 = 1 | H_0\} \\ &\quad + P\{Y_0 \geq T_0 | \hat{\theta}_1 = 0, H_0\} \cdot P\{\hat{\theta}_1 = 0 | H_0\} \\ &= \alpha \phi_1(T_0; \beta_1) + (1-\alpha)\phi_1(t; 0). \end{aligned} \quad (23)$$

To simplify the expression of $P_{f,0}^{(2)}$, we define a function as

$$\phi_2(t;\eta) = \alpha \phi_1(t;\eta) + (1-\alpha)\phi_1(t;0) \quad (24)$$

where the subscript 2 refers to DR strategy. Suppose that the false alarm probabilities for both $\mathbb{U}_0$ and $\mathbb{U}_1$ are given by the same value α. Then, the detection threshold for DR is calculated by

$$T_0^{(2)} = \phi_2^{-1}(\alpha; \beta_1) \quad (25)$$

where ϕ_2^{-1} is the inverse function of ϕ_2. Then, the detection probability corresponding to DR strategy is given by

$$\begin{aligned} P_{d,0}^{(2)} &= P\left\{Y_0 \geq T_0^{(2)} | H_1\right\} \\ &= P\left\{Y_0 \geq T_0^{(2)} | \hat{\theta}_1 = 1, H_1\right\} \cdot P\{\hat{\theta}_1 = 1 | H_1\} \\ &\quad + P\left\{Y_0 \geq T_0^{(2)} | \hat{\theta}_1 = 0, H_1\right\} \cdot P\{\hat{\theta}_1 = 0 | H_1\} \\ &= \alpha^{\frac{1}{1+E_1}} \varphi_1\left(T_0^{(2)}; \beta_1\right) \\ &\quad + \left(1 - \alpha^{\frac{1}{1+E_1}}\right) \varphi_1\left(T_0^{(2)}; 0\right). \end{aligned} \quad (26)$$

Moreover, we define that

$$\varphi_2(t;\eta) = \alpha^{\frac{1}{1+E_1}} \varphi_1(t;\eta) + \left(1 - \alpha^{\frac{1}{1+E_1}}\right) \varphi_1(t;0) \quad (27)$$

thus $P_{d,0}^{(2)}$ can be expressed as

$$P_{d,0}^{(2)} = \varphi_2\left(T_0^{(2)}; \beta_1\right) = \varphi_2\left(\phi_2^{-1}(\alpha;\beta_1);\beta_1\right). \quad (28)$$

Now, we compare the detection performances between our proposed AR strategy and DR strategy. From (15), we have

$$\begin{aligned} \alpha &= \phi_1\left(T_0^{(1)}; \beta_1\right) \\ &= \alpha\phi_1\left(T_0^{(1)}; \beta_1\right) + (1-\alpha)\phi_1\left(T_0^{(1)}; \beta_1\right) \\ &\geq \alpha\phi_1\left(T_0^{(1)}; \beta_1\right) + (1-\alpha)\phi_1\left(T_0^{(1)}; 0\right) \\ &= \phi_2\left(T_0^{(1)}; \beta_1\right). \end{aligned} \quad (29)$$

On the other hand, from (25), we have $\alpha = \phi_2(T_0^{(2)}; \beta_1)$. Obviously, ϕ_2 is a monotonically decreasing function of t; therefore, we can conclude that $T_0^{(1)} \geq T_0^{(2)}$.

Comparing (18) and (26), we see that the first term $\varphi_1(T_0^{(2)}; \beta_1)$ is greater than $\varphi_1(T_0^{(1)}; \beta_1)$; however, the second term $\varphi_1(T_0^{(2)}; 0)$ is not directly comparable to $\varphi_1(T_0^{(1)}; \beta_1)$. Therefore, the comparison between the detection probabilities of AR in (18) and DR in (28) is not straightforward. However, if E_1 is large enough, the factor $\alpha^{1/(1+E_1)}$ goes to 1. Then, the first term $\alpha^{1/(1+E_1)}\varphi_1(T_0^{(2)}; \beta_1)$ will be the dominant part, so that higher $P_{d,0}^{(2)}$ than $P_{d,0}^{(1)}$ can be expected. In fact, the simulation results in later sections also demonstrate that DR strategy outperforms AR strategy even when E_1 is relatively small.

IV. Cooperative Detection Strategies for Multi-Relay Model

In this section, we extend our proposed cooperative detection AR and DR strategies to multi-relay model with unknown-CSI. More than one relay SUs with higher received SNR from $\mathbb{P}_t$ and better channel gain to $\mathbb{U}_0$ are competent for helping $\mathbb{U}_0$ to improve its $P_{d,0}$.

A. AR for Multi-Relay Model

Considering the AR strategy, the received signal from $\mathbb{P}_t$ during S_0 at each $\mathbb{U}_i$ has been given in (1). Therefore, the resultant signal by $\mathbb{U}_0$ at the end of S_1 can be expressed as

$$\begin{aligned} y_0 &= \sum_{i=1}^{M} \left[\sqrt{\beta_i'} h_i (\theta h_{pi} x_{p,0} + n_i)\right] + \theta h_{p0} x_{p,1} + n_0 \\ &= \theta \left(h_{p0} x_{p,1} + \sum_{i=1}^{M} \sqrt{\beta_i'} h_i h_{pi} x_{p,0} \right) \\ &\quad + n_0 + \sum_{i=1}^{M} \sqrt{\beta_i'} h_i n_i. \end{aligned} \quad (30)$$

In a similar way, for given g_i's, the mean value of Y_0 is given by

$$\begin{cases} \sigma_{0,0} = N_0 + \sum_{i=1}^{M} \beta_i N_i g_i, & H_0 \\ \sigma_{0,1} = N_0 + E_0 + \sum_{i=1}^{M} \beta_i (N_i + E_i) g_i, & H_1. \end{cases} \quad (31)$$

Therefore, the false alarm probability $P_{f,0}^{(1)}$ for the multi-relay case is given by

$$\begin{aligned} P_{f,0}^{(1)} &= P\{\hat{\theta}_0 = 1 | \theta = 0\} = P\{Y_0 \geq T_0 | H_0\} \\ &= \int_0^\infty \cdots \int_0^\infty P\{Y_0 > T_0 | H_0, g_1, \cdots, g_M\} \cdot f(g_1|H_0) \\ &\qquad \cdots f(g_M|H_0) dg_1 \cdots dg_M \\ &= \int_0^\infty \cdots \int_0^\infty e^{-\left(\sum_{i=1}^{M} g_i + \frac{T_0}{N_0 + \sum_{i=1}^{M} \beta_i N_i g_i}\right)} \\ &\qquad \times dg_1 \cdots dg_M \end{aligned} \quad (32)$$

and the corresponding detection probability $P_{d,0}^{(1)}$ is given by

$$\begin{aligned} P_{d,0}^{(1)} &= P\{\hat{\theta}_0 = 1|\theta = 1\} = P\{Y_0 \geq T_0|H_1\} \\ &= \int_0^\infty \cdots \int_0^\infty P\{Y_0 \geq T_0|H_1, g_1, \cdots, g_M\} \cdot f(g_1|H_1) \\ &\qquad \cdots f(g_M|H_1)dg_1 \cdots dg_M \\ &= \int_0^\infty \cdots \int_0^\infty e^{-\left(\sum_{i=1}^M g_i + \frac{T_0}{N_0+E_0+\sum_{i=1}^M \beta_i(N_i+E_i)g_i}\right)} \\ &\qquad \times dg_1 \cdots dg_M. \end{aligned} \tag{33}$$

Obviously, the expressions of $P_{f,0}^{(1)}$ in (32) and $P_{d,0}^{(1)}$ in (33) cannot be computed straightforward since its complexity grows exponentially with the number M. To simplify the computation, we will derive the closed-form expressions of $P_{f,0}^{(1)}$ and $P_{d,0}^{(1)}$ as follows.

First, we rewrite $P_{f,0}^{(1)}$ and $P_{d,0}^{(1)}$ as the expectations over g_i's such that

$$\begin{aligned} P_{f,0}^{(1)} &= \mathbf{E}_{g_1,\ldots,g_M}\left[P\{Y_0 \geq T_0|H_0, g_1, \cdots, g_M\}\right] \\ &= \mathbf{E}_{g_1,\ldots,g_M}\left[e^{-\frac{T_0}{N_0+\sum_{i=1}^M \beta_i N_i g_i}}\right] \end{aligned} \tag{34}$$

and

$$\begin{aligned} P_{d,0}^{(1)} &= \mathbf{E}_{g_1,\ldots,g_M}\left[P\{Y_0 \geq T_0|H_1, g_1, \cdots, g_M\}\right] \\ &= \mathbf{E}_{g_1,\ldots,g_M}\left[e^{-\frac{T_0}{N_0+E_0+\sum_{i=1}^M \beta_i(N_i+E_i)g_i}}\right]. \end{aligned} \tag{35}$$

Then, we define two variables:

$$R = \sum_{i=1}^M k_i g_i \quad \text{and} \quad V = \sum_{i=1}^M l_i g_i. \tag{36}$$

where $k_i = \beta_i N_i$ and $l_i = \beta_i(N_i + E_i)$. Note that $k_i > 0$ and $l_i > 0$, and suppose that no two k_i's or l_i's are equal.

Since each g_i follows the common standard exponential distribution with failure rate $\lambda_i = 1$, and they are mutually independent of each other, the probability density functions (pdfs) of R and V are given by

$$f_R(r) = \sum_{i=1}^M \left[\prod_{j\neq i}(k_i - k_j)^{-1}\right] k_i^{M-2} e^{-r/k_i} \tag{37}$$

and

$$f_V(v) = \sum_{i=1}^M \left[\prod_{j\neq i}(l_i - l_j)^{-1}\right] l_i^{M-2} e^{-v/l_i} \tag{38}$$

respectively.

Substituting (37) and (38) into (34) and (35), $P_{f,0}^{(1)}$ and $P_{d,0}^{(1)}$ are rewritten as

$$\begin{aligned} P_{f,0}^{(1)} &= \int_0^\infty e^{-\frac{T_0}{N_0+r}} f_R(r)dr \\ &= \sum_{i=1}^M \left[\prod_{j\neq i}(k_i - k_j)^{-1}\right] k_i^{M-2} \\ &\quad \times \int_0^\infty e^{-\frac{T_0}{N_0+r} - \frac{r}{k_i}} dr \end{aligned} \tag{39}$$

and

$$\begin{aligned} P_{d,0}^{(1)} &= \int_0^\infty e^{-\frac{T_0}{N_0+v}} f_V(v)dv \\ &= \sum_{i=1}^M \left[\prod_{j\neq i}(l_i - l_j)^{-1}\right] l_i^{M-2} \\ &\quad \times \int_0^\infty e^{-\frac{T_0}{N_0+v} - \frac{v}{l_i}} dv. \end{aligned} \tag{40}$$

Since k_i's and l_i's are constant, for notational simplicity, we define Φ_1 and Ψ_1 as the functions of T_0 in (39) and (40), respectively. Then, we have $P_{f,0}^{(1)} = \Phi_1(T_0)$ and $P_{d,0}^{(1)} = \Psi_1(T_0)$.

To protect $\mathbb{P}_t$, we assume that the target $P_{f,0}^{(1)}$ is fixed at α. For AR strategy with M relay SUs, the corresponding threshold is given by $T_0^{(1)} = \Phi_1^{-1}(\alpha)$. Substituting $T_0^{(1)}$ into Ψ_1, the detection probability $P_{d,0}^{(1)}$ is obtained as $P_{d,0}^{(1)} = \Psi_1(\Phi_1^{-1}(\alpha))$.

Theorem 2: In contrast to the non-cooperative (or non-relay) detection method, $\mathbb{U}_0$ receives higher $\Gamma_0^{(1)}$ by using the AR strategy.

Proof: See Appendix I. ■

Therefore, it is reasonable to expect that AR strategy achieves better detection performance, compared to the non-cooperative (or non-relay) detection approach.

B. DR for Multi-Relay Model

We consider the DR strategy under multi-relay model. In S_0, each $\mathbb{U}_i$ receives the signal y_i from $\mathbb{P}_t$ given by (1). Based on the DR strategy, $\mathbb{U}_i$ independently makes its own decision $\hat{\theta}_i$ by comparing the power of y_i with the threshold T_i which is calculated by (5), and the corresponding $P_{d,i}$ is given by (6). Then, if $\hat{\theta}_i = 1$, $\mathbb{U}_i$ will amplify and relay y_i to U_0. On the contrary, if $\hat{\theta}_i = 0$, $\mathbb{U}_i$ will keep quiet in S_1. Finally, the resultant signal at $\mathbb{U}_0$ can be written as

$$\begin{aligned} y_0 &= \sum_{i=1}^M \hat{\theta}_i \sqrt{\beta_i'} h_i(\theta h_{pi} x_{p,0} + n_i) + \theta h_{p0} x_{p,1} + n_0 \\ &= \theta\left(h_{p0} x_{p,1} + \sum_{i=1}^M \hat{\theta}_i \sqrt{\beta_i'} h_i h_{pi} x_{p,0}\right) \\ &\quad + n_0 + \sum_{i=1}^M \hat{\theta}_i \sqrt{\beta_i'} h_i n_i. \end{aligned} \tag{41}$$

Using (41), for given g_i's and $\hat{\theta}_i$'s, the mean value of Y_0 is obtained as

$$\begin{cases} \sigma_{0,0} = N_0 + \sum_{i=1}^{M} \hat{\theta}_i \beta_i N_i g_i, & H_0 \\ \sigma_{0,1} = N_0 + E_0 + \sum_{i=1}^{M} \hat{\theta}_i \beta_i (N_i + E_i) g_i, & H_1. \end{cases} \quad (42)$$

From (42), the pdf of Y_0 under H_0 denoted by $f_{Y_0|H_0}(t)$ is

$$\begin{aligned} f_{Y_0|H_0}(t) &= f_{Y_0|H_0,\hat{\theta}_1=0,\cdots\hat{\theta}_M=0}(t) \\ &\quad \cdot P\{\hat{\theta}_1 = 0, \cdots, \hat{\theta}_M = 0 | H_0\} + \\ &\quad \cdots + f_{Y_0|H_0,\hat{\theta}_1=1,\cdots\hat{\theta}_M=1}(t) \\ &\quad \cdot P\{\hat{\theta}_1 = 1, \cdots \hat{\theta}_M = 1 | H_0\} \\ &= \sum_{\hat{\theta}_1=0}^{1} \cdots \sum_{\hat{\theta}_M=0}^{1} \frac{\prod_{i=1}^{M} \alpha^{\hat{\theta}_i}(1-\alpha)^{1-\hat{\theta}_i}}{N_0 + \sum_{i=1}^{M} \hat{\theta}_i \beta_i N_i g_i} \\ &\quad \cdot e^{-\frac{t}{N_0 + \sum_{i=1}^{M} \hat{\theta}_i \beta_i N_i g_i}} \end{aligned} \quad (43)$$

and the pdf of Y_0 under H_1 denoted by $f_{Y_0|H_1}(t)$ is

$$\begin{aligned} f_{Y_0|H_1}(t) &= f_{Y_0|H_1,\hat{\theta}_1=0,\cdots\hat{\theta}_M=0}(t) \\ &\quad \cdot P\{\hat{\theta}_1 = 0, \cdots, \hat{\theta}_M = 0 | H_1\} + \\ &\quad \cdots + f_{Y_0|H_1,\hat{\theta}_1=1,\cdots\hat{\theta}_M=1}(t) \\ &\quad \cdot P\{\hat{\theta}_1 = 1, \cdots \hat{\theta}_M = 1 | H_1\} \\ &= \sum_{\hat{\theta}_1=0}^{1} \cdots \sum_{\hat{\theta}_M=0}^{1} \frac{\prod_{i=1}^{M} \left(\alpha^{\frac{1}{1+E_i}}\right)^{\hat{\theta}_i} \left(1-\alpha^{\frac{1}{1+E_i}}\right)^{1-\hat{\theta}_i}}{N_0 + E_0 + \sum_{i=1}^{M} \hat{\theta}_i \beta_i (N_i + E_i) g_i} \\ &\quad e^{-\frac{t}{N_0 + E_0 + \sum_{i=1}^{M} \hat{\theta}_i \beta_i (N_i + E_i) g_i}}. \end{aligned} \quad (44)$$

As seen in (43) and (44), both $f_{Y_0|H_0}(t)$ and $f_{Y_0|H_1}(t)$ consist of 2^M possible cases that relate to $\hat{\theta}_i$'s. Next, we will derive the closed-form expressions of $P_{f,0}^{(2)}$ and $P_{d,0}^{(2)}$ as follows.

Define $\hat{\boldsymbol{\theta}} = [\hat{\theta}_1, \cdots, \hat{\theta}_M]$ as the decision vector of $\mathbb{U}_i$'s in S_0. Since there exists 2^M possible cases, $\hat{\boldsymbol{\theta}}$ varies from $[0, \cdots, 0]$ to $[1, \cdots, 1]$. Let j denote the index number of each case, so that $j \in [1, 2^M]$. Also, we use $\hat{\boldsymbol{\theta}}^{(j)} = [\hat{\theta}_1^{(j)}, \cdots, \hat{\theta}_M^{(j)}]$ to denote the decision vector of the jth case.

Obviously, $f_{Y_0|H_0}(t)$ and $f_{Y_0|H_1}(t)$ can be expressed as the mixture of exponential distributions, which is composed of 2^M sub populations in proportions $\mathcal{P}_j$ ($\mathcal{P}_1 + \mathcal{P}_2 + \cdots + \mathcal{P}_{2^M} = 1$) within each of which there is a constant hazard rate denoted by λ_j. Therefore, $f_{Y_0|H_0}(t)$ under H_0 can be rewritten as

$$f_{Y_0|H_0}(t) = \sum_{j=1}^{2^M} \frac{\mathcal{P}_{j|H_0}}{\lambda_{j|H_0}} e^{-\frac{t}{\lambda_{j|H_0}}} \quad (45)$$

where $\mathcal{P}_{j|H_0} = \prod_{i=1}^{M} [(P_{f,i})^{\hat{\theta}_i^{(j)}} (1 - P_{f,i})^{1-\hat{\theta}_i^{(j)}}]$ denotes the occurrence probability of the jth case under H_0, and $\lambda_{j|H_0} = N_0 + \sum_{i=1}^{M} \hat{\theta}_i^{(j)} \beta_i N_i g_i$ denotes the corresponding λ_j under H_0. For given g_i's, $P_{f,0}^{(2)}$ is a survival function of Y_0 under H_0; thus, we have

$$P_{f,0}^{(2)} = 1 - F_{T_0}(t|H_0) = \sum_{j=1}^{2^M} \mathcal{P}_{j|H_0} e^{-\frac{T_0}{\lambda_{j|H_0}}}. \quad (46)$$

Similarly, the pdf of Y_0 under H_1 is given by

$$f_{Y_0|H_1}(t) = \sum_{j=1}^{2^M} \frac{\mathcal{P}_{j|H_1}}{\lambda_{j|H_1}} e^{-\frac{t}{\lambda_{j|H_1}}} \quad (47)$$

where $\mathcal{P}_{j|H_1} = \prod_{i=1}^{M} [(P_{d,i})^{\hat{\theta}_i^{(j)}} (1 - P_{d,i})^{1-\hat{\theta}_i^{(j)}}]$ and $\lambda_{j|H_1} = N_0 + E_0 + \sum_{i=1}^{M} \hat{\theta}_i^{(j)} \beta_i (N_i + E_i) g_i$. Then, we have

$$P_{d,0}^{(2)} = 1 - F_{T_0}(t|H_1) = \sum_{j=1}^{2^M} \mathcal{P}_{j|H_1} e^{-\frac{T_0}{\lambda_{j|H_1}}}. \quad (48)$$

Now, we remove the conditions on g_i's. From (46) and (48), we see that only λ_j relates to g_i's. Therefore, we define two variables R_j and V_j as

$$R_j = \sum_{m=1,\hat{\theta}_m^{(j)} \neq 0}^{M} k_m g_m \quad \text{and} \quad V_j = \sum_{m=1,\hat{\theta}_m^{(j)} \neq 0}^{M} l_m g_m \quad (49)$$

where k_m and l_m are defined similarly to k_i and l_i as before. Thus, we have

$$\begin{aligned} \mathbf{E}_{g_1,\cdots,g_M}\left[e^{-\frac{T_0}{\lambda_{j|H_0}}}\right] &= \sum_{m=1,\hat{\theta}_m^{(j)} \neq 0}^{M} \left[\prod_{n \neq m, \hat{\theta}_n^{(j)} \neq 0} (k_m - k_n)^{-1}\right] \\ &\quad \times k_m^{\sum_{m=1}^{M} \hat{\theta}_m^{(j)} - 2} \cdot \int_0^{\infty} e^{-\frac{T_0}{N_0 + r_j} - \frac{r_j}{k_m}} dr_j \end{aligned} \quad (50)$$

and

$$\begin{aligned} \mathbf{E}_{g_1,\cdots,g_M}\left[e^{-\frac{T_0}{\lambda_{j|H_1}}}\right] &= \sum_{m=1,\hat{\theta}_m^{(j)} \neq 0}^{M} \left[\prod_{n \neq m, \hat{\theta}_n^{(j)} \neq 0} (l_m - l_n)^{-1}\right] \\ &\quad \times l_m^{\sum_{m=1}^{M} \hat{\theta}_m^{(j)} - 2} \cdot \int_0^{\infty} e^{-\frac{T_0}{N_0 + v_j} - \frac{v_j}{l_m}} dv_j. \end{aligned} \quad (51)$$

Combining (46), (48), (50), and (51), the expressions of $P_{f,0}^{(2)}$ and $P_{d,0}^{(2)}$ can be given by

$$\begin{aligned} P_{f,0}^{(2)} &= \sum_{j=1}^{2^M} \mathcal{P}_{j|H_0} \sum_{m=1,\hat{\theta}_m^{(j)} \neq 0}^{M} \left[\prod_{n \neq m, \hat{\theta}_n^{(j)} \neq 0} (k_m - k_n)^{-1}\right] \\ &\quad \cdot k_m^{\sum_{m=1}^{M} \hat{\theta}_m^{(j)} - 2} \int_0^{\infty} e^{-\frac{T_0}{N_0 + r_j} - \frac{r_j}{k_m}} dr_j \end{aligned} \quad (52)$$

and

$$\begin{aligned} P_{d,0}^{(2)} &= \sum_{j=1}^{2^M} \mathcal{P}_{j|H_1} \sum_{m=1,\hat{\theta}_m^{(j)} \neq 0}^{M} \left[\prod_{n \neq m, \hat{\theta}_n^{(j)} \neq 0} (l_m - l_n)^{-1}\right] \\ &\quad \cdot l_m^{\sum_{m=1}^{M} \hat{\theta}_m^{(j)} - 2} \int_0^{\infty} e^{-\frac{T_0}{N_0 + v_j} - \frac{v_j}{l_m}} dv_j. \end{aligned} \quad (53)$$

Similar to the analysis in AR strategy, we define Φ_2 and Ψ_2 as the functions of T_0 given by (52) and (53), respectively; thus, we have $P_{f,0}^{(2)} = \Phi_2(T_0)$ and $P_{d,0}^{(2)} = \Psi_2(T_0)$. Then, the threshold

T_0 for DR strategy can be computed by $T_0^{(2)} = \Phi_2^{-1}(\alpha)$. Substituting $T_0^{(2)}$ into Ψ_2, we have $P_{d,0}^{(2)} = \Psi_2(\Phi_2^{-1}(\alpha))$.

Theorem 3: The value of the received $\Gamma_0^{(2)}$ using DR strategy is greater than that of $\Gamma_0^{(1)}$ by AR strategy.

Proof: See Appendix II. ∎

From *Theorem 3*, DR strategy is expected to perform better than AR strategy, which can be validated by numerical method later.

V. Cooperative Detection Strategies With Known-CSI

In this section, we assume that CSI is known *a priori* by SUs, which can be obtained by channel estimation technique via training signals. For both AR and DR strategies, each relay $\mathbb{U}_i$ not only amplifies its received signal y_i by the factor β_i', but also multiplies by a complex phase w_i which is associated with the channel coefficients h_{pi} and h_i. Therefore, the signals received from $\mathbb{U}_i$'s are co-phased. We rewrite h_{pi}' and h_i' as a polar form that $h_{pi}' = r_{pi}e^{j\omega_{pi}}$ and $h_i' = r_i e^{j\omega_i}$, where r_{pi} and r_i are known and $\mathbf{E}\{|r_{pi}|^2\} = \mathbf{E}\{|r_i|^2\} = 1$. Thus, w_i must be chosen as the complex conjugate of the phase $e^{j(\omega_{pi}+\omega_i)}$, i.e., $w_i = e^{-j(\omega_{pi}+\omega_i)}$ and $|w_i|^2 = 1$.

In this case, y_0 for AR strategy is given by

$$y_0 = \theta\left(h_{p0}x_{p,1} + \sum_{i=1}^{M}\sqrt{\beta_i/d_{pi}^3}r_{pi}r_i x_{p,0}\right) + n_0 + \sum_{i=1}^{M}\sqrt{\beta_i}r_i n_i e^{-j\omega_{pi}}. \quad (54)$$

As $\theta = 0$, the received power Y_0 under H_0 follows an exponential distribution; on the other hand, for $\theta = 1$, Y_0 under H_1 is a noncentral chi-square distributed variable with 2 degrees of freedom and a non-centrality parameter of $2\gamma_0^{(1)}$, where $\gamma_0^{(1)}$ is the received SNR at $\mathbb{U}_0$ by using AR strategy. Therefore, the mean value of Y_0 is given by

$$\begin{cases} \sigma_{0,0}{=}N_0{+}\sum_{i=1}^{M}\beta_i N_i, & H_0 \\ \sigma_{0,1}{=}N_0{+}\sum_{i=1}^{M}\beta_i N_i{+}E_0{+}\left(\sum_{i=1}^{M}\sqrt{\beta_i/d_{pi}^3}\right)^2 E_s, & H_1. \end{cases} \quad (55)$$

Considering the fading channels, $\gamma_0^{(1)}$ is an exponentially distributed variable with failure rate $\Lambda^{(1)} = [E_0 + (\sum_{i=1}^{M}\sqrt{\beta_i/d_{pi}^3})^2 E_s]/(N_0 + \sum_{i=1}^{M}\beta_i N_i)$. Thus, the corresponding $P_{d,0}^{(1)}$ for the known-CSI case is given by

$$P_{d,0}^{(1)} = \int_{0}^{\infty}\int_{-2\ln\alpha}^{\infty}\frac{1}{\Lambda^{(1)}}f_{Y_0}(y;2,2\gamma)e^{-\frac{\gamma}{\Lambda^{(1)}}}dyd\gamma \doteq \alpha^{1/\Gamma_0^{(1)}} \quad (56)$$

where $f_{Y_0}(y;q,v) = (1/2)e^{-(y+v)/2}(y/v)^{q/4-1/2}I_{q/2-1}(\sqrt{vy})$ is the pdf of Y_0, $I_\alpha(z)$ is a modified Bessel function of the first kind, and $\Gamma_0^{(1)}$ can be calculated by definition using (55).

On the other hand, we consider the DR strategy with known-CSI. In this case, y_0 is given by

$$y_0 = \theta\left(h_{p0}x_{p,1} + \sum_{i=1}^{M}\hat{\theta}_i\sqrt{\beta_i/d_{pi}^3}r_{pi}r_i x_{p,0}\right) + n_0 + \sum_{i=1}^{M}\hat{\theta}_i\sqrt{\beta_i}r_i n_i e^{-j\omega_{pi}} \quad (57)$$

and the mean value of Y_0 is given by

$$\begin{cases} \sigma_{0,0} = N_0 + \sum_{i=1}^{M}P_{f,i}\beta_i N_i, & H_0 \\ \sigma_{0,1} = N_0 + E_0 + \sum_{i=1}^{M}P_{d,i}\beta_i(N_i+E_i) \\ \qquad + \sum_{i=1}^{M-1}\sum_{j>i}^{M}2P_{d,i}P_{d,j}\sqrt{\beta_i\beta_j E_i E_j}, & H_1. \end{cases} \quad (58)$$

From (58), we obtain $\Lambda^{(2)} = (E_0 + \sum_{i=1}^{M}P_{d,i}\beta_i E_i + \sum_{i=1}^{M-1}\sum_{j>i}^{M}2P_{d,i}P_{d,j}\sqrt{\beta_i\beta_j E_i E_j})/(N_0 + \sum_{i=1}^{M}P_{d,i}\beta_i N_i)$. In a similar way, $P_{d,0}^{(2)}$ for the known-CSI case is given by

$$P_{d,0}^{(2)} = \int_{0}^{\infty}\int_{-2\epsilon\ln\alpha}^{\infty}\frac{1}{\Lambda^{(2)}}f_{Y_0}(y;2,2\gamma)e^{-\frac{\gamma}{\Lambda^{(2)}}}dyd\gamma \doteq \alpha^{1/\Gamma_0^{(2)}} \quad (59)$$

where $\epsilon = (N_0 + \sum_{i=1}^{M}P_{f,i}\beta_i N_i)/(N_0 + \sum_{i=1}^{M}P_{d,i}\beta_i N_i)$, and $\Gamma_0^{(2)}$ can be derived by (58).

Theorem 4: For both AR and DR strategies, the values of $\Gamma_0^{(1)}$ and $\Gamma_0^{(2)}$ for the known-CSI case is greater than that of the unknown-CSI case, respectively.

Proof: See Appendix III. ∎

From *Theorem 4*, we can expect that the performance of the known-CSI case is better than that of the unknown-CSI case.

VI. Simulation Results

Simulation results are shown to evaluate the performance of our proposed cooperative spectrum sensing strategies in this section. The parameters used in AR strategy and DR strategy are listed as follows.

1) The power of signal x_s is normalized as a unit value or 0 dB expressed in units of decibel.
2) The maximum power constraint $\tilde{E}_i$ is equal to 0 dB.
3) The false alarm probability is set to $\alpha = 0.1$.
4) The variance of noise is equal to 0 dB.

Moreover, we assume that $\mathbb{U}_0$, $\mathbb{U}_i$'s, and $\mathbb{P}_t$ are co-linearly positioned, i.e., $\mathbb{U}_i$ is located on the line between $\mathbb{U}_0$ and $\mathbb{P}_t$ so as to achieve better detection performance than $\mathbb{U}_0$. Also, G_i can be modeled as $G_i = 1/|d_{pi} - d_{p0}|^3$.

A. Performance of Single-Relay Model

First, we consider the single-relay scenario. To compare the detection performances of non-cooperative (or non-relay) detection method, cooperative detection method in [15] and [16] and our proposed AR and DR strategies, we plot the curves of $P_{d,0}$ versus E_1 (or SNR) as E_0 is equal to 0 dB (Fig. 3), 4 dB (Fig. 4),

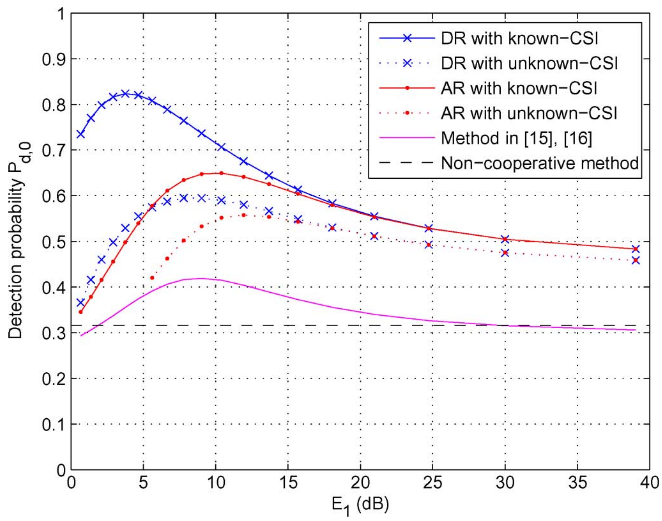


Fig. 3. Detection performances for single-relay model ($E_0 = 0$ dB).

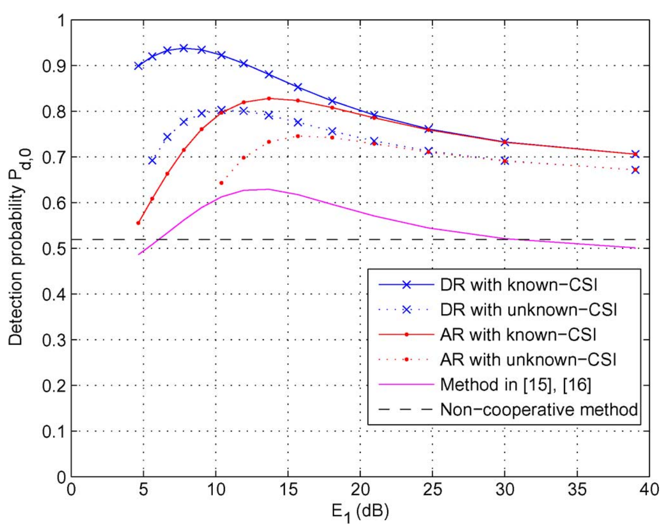


Fig. 4. Detection performances for single-relay model ($E_0 = 4$ dB).

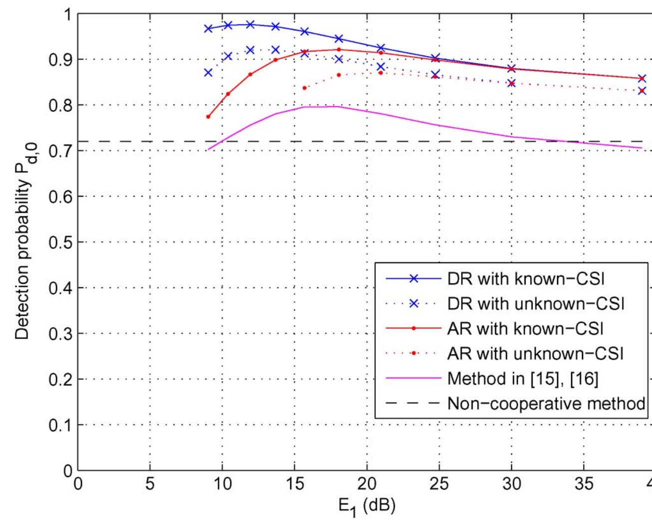


Fig. 5. Detection performances for single-relay model ($E_0 = 7.8$ dB).

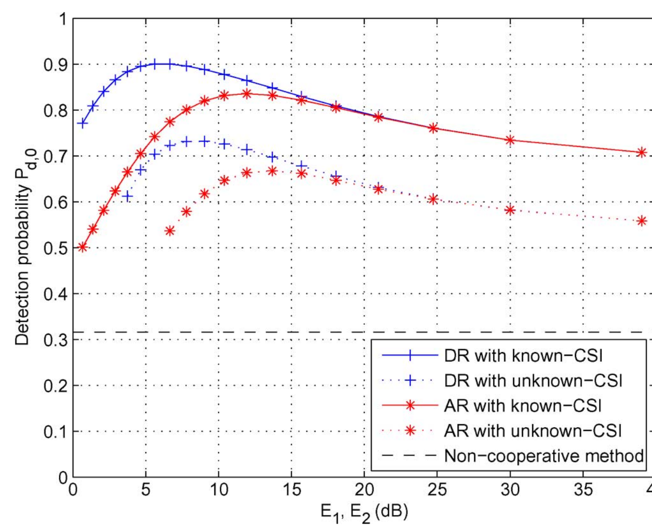


Fig. 6. Detection performances for multi-relay model ($E_0 = 0$ dB).

and 7.8 dB (Fig. 5). As seen in Figs. 3–5, both AR and DR strategies perform better than the non-cooperative (or non-relay) detection method and the method in [15], [16], which validates the conclusions obtained by *Theorem 1* and *Theorem 2*.

Moreover, in the region of lower E_1 (or SNR) received by the relay user $\mathbb{U}_1$, we observe that the DR strategy can dramatically improve the detection probability $P_{d,0}$, which shows the advantage of DR strategy that not only relays the signal, but also involves the relay SU's detection result, as compared to the AR strategy. However, as E_1 increases, two curves of DR and AR strategies almost coincide with each other, i.e., their performances become the same. This is because the relay $\mathbb{U}_1$ can always make a correct decision based on higher E_1 under both H_0 and H_1, but G_1becomes lower conversely so that the influence of noise cannot be ignored. Thus, it is not a surprise that $\mathbb{U}_0$ obtains the same performance of $P_{d,0}$ for both DR and AR. In addition, we see that both AR and DR strategies perform better than the non-cooperative detection method, which validates the conclusion that the relay $\mathbb{U}_1$ with higher received SNR from $\mathbb{P}_t$ and better channel gain to $\mathbb{U}_0$ are competent for helping $\mathbb{U}_0$ improve its $P_{d,0}$.

Finally, we consider the influence of $\mathbb{U}_1$'s position. As $\mathbb{U}_1$ moves from $\mathbb{U}_0$ to $\mathbb{P}_t$, the received signal power E_1 increases, but the channel gain G_1 decreases. Since $P_{d,0}$ is related to both E_1 and G_1, we note that the corresponding $P_{d,0}$ initially increases until to its maximum value, and then monotonically decreases, as E_1 varies from 0 to 40 dB. For this reason, the maximum $P_{d,0}$ occurs when both E_1 and G_1 are relatively large as seen in Figs. 3–5.

B. *Performance of Multi-Relay Model*

Next, we consider the multi-relay case. Assume that all the $\mathbb{U}_i$'s are located closely from each other, so that the values of E_i's or G_i's are equal for all the $\mathbb{U}_i$'s. Suppose that $M = 2$, we compare the performances of AR and DR strategies with that of the single-relay case.

As seen in Figs. 6–8, it is obviously seen that the performance of the multi-relay case is better than that of the single-relay case, and $P_{d,0}$ dramatically improves when E_0 is equal to $0, 4$, and 7.8 dB, respectively. This verifies the conclusion that as the number of the relay SUs with higher received SNR from $\mathbb{P}_t$ and better

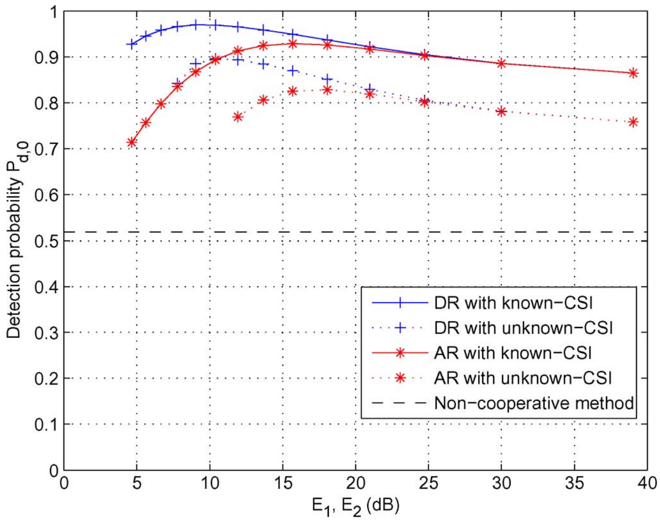


Fig. 7. Detection performances for multi-relay model ($E_0 = 4$ dB).

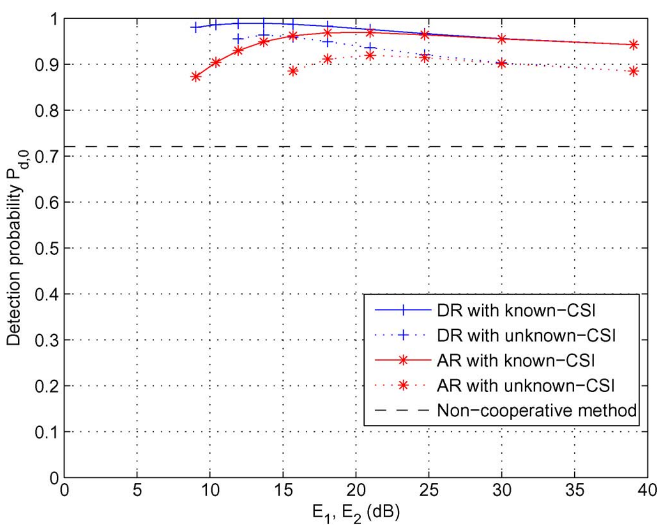


Fig. 8. Detection performances for multi-relay model ($E_0 = 7.8$ dB).

channel gain to $\mathbb{U}_0$ increases, the detection performance $P_{d,0}$ at $\mathbb{U}_0$ improves for both AR and DR strategies.

Moreover, as compared the performances between AR strategy and DR strategy for $M = 2$, we see that DR strategy can perform better than AR strategy. This can be explained by the parameter Γ_0. Considering the energy detection technique, the detection performance depends on the expected power ratio of the received signal under H_1 and that of value under H_0, which is due to the properties of exponential functions. Obviously, the received Γ_0 for DR strategy is greater than that of AR strategy, which has been theoretically proved in *Theorem 3*; thus, the better performance for DR strategy can be achieved. Similarly, the curvilinear trend of $P_{d,0}$ for the multi-relay case is the same with that of the single-relay case, which has been explained as before.

C. Effects of Known-CSI and Unknown-CSI Cases

In Section V, we have assumed that CSI can be known by $\mathbb{U}_i$'s, and also analyzed the corresponding performance for both AR strategy and DR strategy. Now, we validate the analytical results as follows. For both AR and the DR strategies, the curves in Figs. 3–8 clearly show that $P_{d,0}$ with known-CSI (solid line) is higher than that of unknown-CSI case (dotted line). Moreover, we see that DR strategy outperforms AR strategy for both known-CSI and unknown-CSI cases. Also, in the region of larger E_i's, they can almost achieve the same performances due to the higher value of $P_{d,i}$'s that we explained before. By *Theorem 4*, we know that the received Γ_0 for the known-CSI case is higher than that of the unknown-CSI case; therefore, the detection performance can be improved as CSI is known by SUs.

Finally, based on *Theorems 2–4*, the performance comparisons between single-relay and multi-relay models, DR and AR strategies, known-CSI and unknown-CSI cases, clearly validate the conclusion that the greater expected power ratio Γ_0, the better detection performance. Therefore, the performance of our proposed cooperative spectrum sensing strategies can be improved by two ways: increase the number of the eligible relay SUs or know the CSI.

VII. Conclusion

In this paper, we have proposed two cooperative spectrum sensing strategies called *amplify-and-relay* (AR) and *detect-and-relay* (DR) for a CR mesh networks. The frame structure has been suitably designed, arranging AR or DR to be executed in the spectrum sensing phase before the data transmission. For both single-relay and multi-relay models with known-CSI or unknown-CSI, we have derived the closed-form expressions of the false alarm probability and the detection probability, respectively. The simulation results show that our proposed strategies can achieve better performance as compared with the method proposed in [15] and [16] and the non-cooperative (or non-relay) spectrum sensing method. We also note that, given a target false alarm probability, the detection probability dramatically increases as the number of relay SUs increases, and the performance is better for the known-CSI case than that of the unknown-CSI case.

Appendix I
Proof of *Theorem 2*

For $a_i/b_i > a_0/b_0, i = 1, \cdots, M$, we have

$$\frac{a_0 + a_1 + \cdots + a_M}{b_0 + b_1 + \cdots + b_M} > \frac{a_0}{b_0}. \tag{60}$$

Since we have assumed that only $\mathbb{U}_i$ with the higher SNR is eligible to help $\mathbb{U}_0$, $E_i/N_i > E_0/N_0$ can be attained.

Now, we set that $a_0 = E_0 + N_0, b_0 = N_0\ a_i = \beta_i(E_i + N_i)g_i$, and $b_i = \beta_i N_i g_i$; thus, the left-hand side in (60) is the corresponding $\Gamma_0^{(1)}$ for AR strategy, and the right-hand side refers to the non-cooperative detection case. Therefore, *Theorem 2* is proved.

APPENDIX II
PROOF OF *Theorem 3*

Using (42), we have

$$\begin{aligned}\Gamma_0^{(2)} &= \frac{N_0 + E_0 + \sum_{i=1}^{M} \mathbf{E}\left\{\hat{\theta}_{i|H_1}\beta_i(N_i+E_i)g_i\right\}}{N_0 + \sum_{i=1}^{M} \mathbf{E}\left\{\hat{\theta}_{i|H_0}\beta_i N_i g_i\right\}} \\ &= \frac{N_0 + E_0 + \sum_{i=1}^{M} P_{d,i}\beta_i(N_i+E_i)}{N_0 + \sum_{i=1}^{M} P_{f,i}\beta_i N_i} \\ &> \frac{N_0 + E_0 + \sum_{i=1}^{M} \beta_i(N_i+E_i)}{N_0 + \sum_{i=1}^{M} \beta_i N_i} \\ &= \Gamma_0^{(1)} \end{aligned} \tag{61}$$

where $\theta_{i|H_j}$ denotes $\mathbb{U}_i$'s decision results under H_j, and $P_{f,i}$ and $P_{d,i}$ are given by (4) and (6), respectively. Moreover, the inequality in (61) holds due to $P_{d,i}/P_{f,i} > 1$. Thus, it follows that *Theorem 3* is proved.

APPENDIX III
PROOF OF *Theorem 4*

For AR strategy with known-CSI, $\Gamma_0^{(1)}$ is attained by (55)

$$\begin{aligned}\Gamma_0^{(1)} &= \frac{N_0 + \sum_{i=1}^{M}\beta_i N_i + E_0 + \left(\sum_{i=1}^{M}\sqrt{\beta_i/d_{pi}^3}\right)^2 E_s}{N_0 + \sum_{i=1}^{M}\beta_i N_i} \\ &> \frac{N_0 + \sum_{i=1}^{M}\beta_i N_i + E_0 + \sum_{i=1}^{M}\left(\sqrt{\beta_i/d_{pi}^3}\right)^2 E_s}{N_0 + \sum_{i=1}^{M}\beta_i N_i} \\ &= \frac{N_0 + E_0 + \sum_{i=1}^{M}\beta_i(N_i+E_i)}{N_0 + \sum_{i=1}^{M}\beta_i N_i}. \end{aligned} \tag{62}$$

Obviously, the last equation given in (62) refers to the value of $\Gamma_0^{(1)}$ for the unknown-CSI case.

In a similar way, using (58), $\Gamma_0^{(2)}$ for DR strategy with known-CSI is given by

$$\begin{aligned}\Gamma_0^{(2)} &= \frac{\mathbf{E}\left[\sum_{i=1}^{M}\hat{\theta}_{i|H_1}\beta_i N_i + \left(\sum_{i=1}^{M}\hat{\theta}_{i|H_1}\sqrt{\beta_i/d_{pi}^3}\right)^2 E_s\right]}{N_0 + \mathbf{E}\left[\sum_{i=1}^{M}\hat{\theta}_{i|H_0}\beta_i N_i\right]} \\ &\quad + \frac{N_0+E_0}{N_0 + \mathbf{E}\left[\sum_{i=1}^{M}\hat{\theta}_{i|H_0}\beta_i N_i\right]} \\ &> \frac{\mathbf{E}\left[\sum_{i=1}^{M}\hat{\theta}_{i|H_1}\beta_i N_i + \sum_{i=1}^{M}\hat{\theta}_{i|H_1}\left(\sqrt{\beta_i/d_{pi}^3}\right)^2 E_s\right]}{N_0 + \mathbf{E}\left\{\sum_{i=1}^{M}\hat{\theta}_{i|H_0}\beta_i N_i\right\}} \\ &\quad + \frac{N_0+E_0}{N_0 + \mathbf{E}\left[\sum_{i=1}^{M}\hat{\theta}_{i|H_0}\beta_i N_i\right]} \\ &= \frac{N_0 + E_0 + \sum_{i=1}^{M}\mathbf{E}\left[\hat{\theta}_{i|H_1}\beta_i(N_i+E_i)\right]}{N_0 + \sum_{i=1}^{M}\mathbf{E}\left[\hat{\theta}_{i|H_0}\beta_i N_i\right]} \end{aligned} \tag{63}$$

where the last equation denotes the value of $\Gamma_0^{(2)}$ for the unknown-CSI case in (61).

From the derivation process in (62) and (63), we see that *Theorem 4* is proved.

REFERENCES

[1] J. Mitola and G. Q. Maguire, "Cognitive radios: Making software radios more personal," *IEEE Personal Commun.*, vol. 6, no. 4, pp. 13–18, Aug. 1999.

[2] J. Mitola, "Cognitive radio: An integrated agent architecture for software defined radio," Ph.D. dissertation, Royal Inst. Technol. (KTH), Stockholm, Sweden, 2000.

[3] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[4] U.S. Federal Communications Commission, Spectrum Policy Task Force Rep. Nov. 2002 [Online]. Available: www.fcc.gov/sptf/reports.html

[5] M. H. Islam, C. L. Koh, S. W. Oh, X. Qing, Y. Y. Lai, C. Wang, Y.-C. Liang, B. E. Toh, F. Chin, G. L. Tan, and W. Toh, "Spectrum survey in Singapore: Occupancy measurements and analysis," in *Proc. IEEE CROWNCOM'08*, Singapore, May 2008, pp. 1–7.

[6] "Darpa: The Next Generation (XG) Program." [Online]. Available: http://www.darpa.mil/ato/programs/xg/index.htm

[7] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proc. IEEE*, vol. 55, no. 4, pp. 523–531, Apr. 1967.

[8] O. Younis and S. Fahmy, "Distributed clustering in ad hoc sensor networks: A hybrid energy-efficient approach," in *Proc. IEEE INFOCOM'04*, Hong Kong, China, Mar. 2004, pp. 629–640.

[9] B. Wild and K. Ramachandran, "Detecting primary receivers for cognitive radio applications," in *Proc. IEEE DySPAN'05*, Baltimore, MD, Nov. 2005, pp. 124–130.

[10] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in *Proc. IEEE ASILOMAR'04*, Pacific Grove, CA, Nov. 2004, pp. 772–776.

[11] A. Ghasemi and E. S. Sousa, "Collaborative spectrum sensing in cognitive radio networks," in *Proc. IEEE DySPAN'05*, Baltimore, MD, Nov. 2005, pp. 131–136.

[12] M. Gandetto and C. Regazzoni, "Spectrum sensing: A distributed approach for cognitive terminals," *IEEE J. Sel. Areas Commun.*, vol. 25, no. 3, pp. 546–557, Apr. 2007.

[13] Y.-C. Liang, Y. Zeng, E. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 7, no. 4, pp. 1326–1337, Mar. 2008.

[14] C. Sun, W. Zhang, and K. B. Letaief, "Cluster-based cooperative spectrum sensing in cognitive radio systems," in *Proc. IEEE ICC'07*, Glasgow, U.K., 2007, pp. 2511–2515.

[15] G. Ganesan and Y. G. Li, "Cooperative spectrum sensing in cognitive radio, part I: Two user networks," *IEEE Trans. Wireless Commun.*, vol. 6, no. 6, pp. 2204–2213, Jun. 2007.

[16] G. Ganesan and Y. G. Li, "Cooperative spectrum sensing in cognitive radio, part II: Multiuser networks," *IEEE Trans. Wireless Commun.*, vol. 6, no. 6, pp. 2214–2222, Jun. 2007.

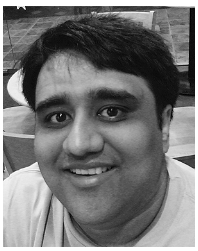
[17] *IEEE Standard for Local and Metropolitan Area Networks—Part 16: Air Interface for Fixed Broadband Wireless Access Systems*, IEEE Std. 802.16, 2004.

[18] *IEEE Standard for Local and Metropolitan Area Networks—Part 16: Air Interface for Fixed and Mobile Broadband Wireless Access Systems*, IEEE Std. 802.16e, 2005.

[19] Q. Chen, F. Gao, A. Nallanathan, and Y. Xin, "Improved cooperative spectrum sensing in cognitive radio," in *Proc. IEEE VTC-Spring'08*, Singapore, May 2008, pp. 1418–1422.

Qian Chen (S'09) received the B.Eng. and M.Eng. degrees in computer science and engineering from Xi'an Jiao Tong University, Xi'an, China, in 2003 and 2006, respectively. He is currently working toward the Ph.D. degree in the Electrical and Computer Engineering Department, National University of Singapore.

From 2006 to 2007, he was a Project Manager at the Huawei Technologies Co., Ltd., Shenzhen, China. His research interests include cognitive radio networks, mobile ad hoc and sensor networks, signal processing, and MAC layer issues.



Mehul Motani (M'10) received the Ph.D. degree from Cornell University, Ithaca, NY, focusing on information theory and coding for CDMA systems.

He is an Associate Professor in the Electrical and Computer Engineering Department, National University of Singapore. Previously, he was a Research Scientist at the Institute for Infocomm Research in Singapore for three years and a Systems Engineer at Lockheed Martin in Syracuse, NY, for over four years. Recently, he has been working on research problems which sit at the boundary of information theory, communications, and networking, including the design of wireless ad-hoc and sensor network systems.

Prof. Motani was awarded the Intel Foundation Fellowship for work related to his Ph.D. He has served on the organizing committees of ISIT, WiNC, and ICCS, and the technical program committees of MobiCom, Infocom, ICNP, SECON, and several other conferences. He participates actively in the IEEE and ACM and has served as the secretary of the IEEE Information Theory Society Board of Governors. He is currently an Associate Editor for the IEEE TRANSACTIONS ON INFORMATION THEORY and an Editor for the IEEE TRANSACTIONS ON COMMUNICATIONS.

Wai-Choong (Lawrence) Wong (M'77–SM'93) received the B.Sc. (first class honors) and Ph.D. degrees in electronic and electrical engineering from Loughborough University, Loughborough, U.K.

He is a Professor in the Department of Electrical and Computer Engineering, National University of Singapore (NUS). He is currently Deputy Director (Strategic Development) at the Interactive and Digital Media Institute (IDMI) in NUS. He was previously Executive Director of the Institute for Infocomm Research (I2R) from November 2002 to November 2006. Since joining NUS in 1983, he served in various positions in department, faculty and university levels, including Head of the Department of Electrical and Computer Engineering from January 2008 to October 2009, Director of the NUS Computer Centre from July 2000 to November 2002, and Director of the Centre for Instructional Technology from January 1998 to June 2000. Prior to joining NUS in 1983, he was a Member of Technical Staff at AT&T Bell Laboratories, Crawford Hill Lab, from 1980 to 1983. His research interests include wireless networks and systems, multimedia networks, and source-matched transmission techniques with over 200 publications and four patents in these areas. He is coauthor of the book *Source-Matched Mobile Communication* (IEEE Press, 1995).

Prof. Wong received the IEEE Marconi Premium Award in 1989, the NUS Teaching Award in 1989, the IEEE Millennium Award in 2000, the e-nnovator Awards in 2000, and the Open Category, and Best Paper Award at the IEEE International Conference on Multimedia and Expo (ICME) in 2006.

Arumugam Nallanathan (S'97–M'00–SM'05) is a Senior Lecturer in the Department of Electronic Engineering at King's College London, London, U.K. He was an Assistant Professor in the Department of Electrical and Computer Engineering, National University of Singapore, from August 2000 to December 2007. His research interests include cognitive radio, relay networks, MIMO-OFDM systems, ultra-wide bandwidth (UWB) communication and localization. In these areas, he has published over 160 journal and conference papers. He is a co-recipient of the Best Paper Award presented at 2007 IEEE International Conference on Ultra-Wideband (ICUWB'2007).

Dr. Nallanathan currently serves on the Editorial Board of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, and IEEE SIGNAL PROCESSING LETTERS as an Associate Editor. He served as a Guest Editor for *EURASIP Journal of Wireless Communications and Networking*: Special issue on UWB Communication Systems-Technology and Applications. He served as the General Track Chair for the IEEE VTC'2008-Spring, Co-Chair for the IEEE GLOBECOM'2008 Signal Processing for Communications Symposium and IEEE ICC'2009 Wireless Communications Symposium. He currently serves as Co-Chair for the IEEE GLOBECOM'2011 Signal Processing for Communications Symposium and Technical program Co-Chair for IEEE International Conference on Ultra-Wideband'2011 (IEEE ICUWB'2011). He also currently serves as the Secretary for the Signal Processing and Communications Technical Committee of the IEEE Communications Society.