Cooperative Spectrum Sensing in Heterogeneous Cognitive Radio Networks Based on Normalized Energy Detection

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***Abstract*—Spectrum sensing is an essential technology to detect the presence of primary users' (PUs) signals in cognitive radio (CR) networks. To achieve desirable performances under shadowing and fading environments, cooperative spectrum sensing has been proposed as a promising scheme, which takes advantage of spatial and multiuser diversity gain. In this paper, we investigate cooperative sensing (CS) in a heterogeneous CR network scenario, where each secondary user (SU) may be equipped with different numbers of receive antennas and may have different signal processing capabilities, e.g., sampling rates. By considering the discrepancy in sensing reliability of different SUs, we propose an optimal normalized energy detection-based CS (NED-CS) scheme by virtue of the principle of log-likelihood ratio test (LRT). This LRT-based NED-CS scheme also takes into account the reporting errors at a fusion center (FC), which may receive erroneous results from some SUs due to channel fading and quantization errors. Our derivation shows that the detection statistic of our proposed LRT-based NED-CS scheme is the linear combination of modified local detection statistics, and the optimal combining coefficient can be shown to be a function of the numbers of antennas, the received signal samples, the received signal-to-noise ratios (SNRs), and the variances of reporting errors at each SU. Meanwhile, to drop the prerequisite on *a priori* information on the received SNRs of all SUs and the variances of reporting errors and to simplify the decision making and threshold setting, a simplified LRT (SLRT)-based NED-CS scheme is proposed as well. Furthermore, we analyze and compare the performance of our proposed LRT-based NED-CS scheme with existing NED-CS schemes, including the equal gain combination (EGC) method and the maximum normalized energy (MNE) detector, with reporting errors under both additive white Gaussian noise (AWGN) and Rayleigh fading channels in a heterogeneous CR network. We derive the probability density function (PDF) of received SNR at each SU and obtain the series expansions and closed-form approximate expressions of detection and false alarm probabilities of our proposed LRT-based NED-CS scheme. Our analytical results match simulation results well, and both of them show that the proposed LRT- and SLRT-based NED-CS schemes perform significantly better than the existing EGC and MNE methods.**

***Index Terms*—Cognitive radio (CR), cooperative spectrum sensing, heterogeneous networks, normalized energy detection (ED), reporting errors.**

I. Introduction

In a cognitive radio (CR) network, secondary (unlicensed) users (SUs) need to reliably sense the primary (licensed) channel first before they can access the primary channel opportunistically without causing harmful interferences to primary users (PUs) [1]–[3]. Spectrum sensing is therefore a key task for CR networks. Obviously, the most challenging task of spectrum sensing is to detect a weak PU signal with very low signal-to-noise ratio (SNR).

A. Prior Works

Cooperative sensing (CS) with soft combination, i.e., multiple SUs sense the common signal in a coordinated mode, has been proven to be more reliable than single SU sensing [4]–[13] under a practical fading environment. For its low implementation complexity, energy detection (ED)-based cooperative spectrum sensing has been widely investigated in recent years. In particular, the maximum ratio combining (MRC) and the square-law combining (SLC) have been studied in [9] and [12]. However, the MRC scheme needs the channel state information (CSI) from the PU to the SUs and from each SU to the fusion center (FC). If the SLC scheme is applied with a variable amplification factor at each SU, the CSI from the PU to the SUs and from the SUs to the FC are also needed. As a result, both MRC and SLC schemes have substantially high complexity. In contrast, cooperative ED with equal gain combination (EGC) is often considered in practical implementation due to its low complexity [9], [13]. Meanwhile, by considering

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different received SNRs of SUs, in [8], a CS method was proposed based on normalized ED when SUs are equipped with a single receive antenna. The maximum normalized energy (MNE) scheme is also presented in [13]. In some practical application environments, each SU in a CR network may have not only diverse received SNRs but different hardware configurations as well, such as their numbers of antennas and the precision of analog-to-digital converter (ADC). These different hardware configurations lead to different sensing reliability values for each SU. For such a heterogeneous CR network composed of SUs with different sensing capabilities and reliability values, an efficient scheme has yet to be proposed, to the best of our knowledge, to address the CS of SUs with diverse capabilities.

In general, SUs need to quantize their local sensing data before sending them to the FC due to the limitation of bandwidth. Quantization schemes for CR spectrum sensing systems have been considered in [14]–[17]. Inevitably, the local sensing data are always contaminated with quantization noise of ADC and interferences of reporting channels when they are reported by each SU to the FC. In [8], the reporting error is modeled as a Gaussian random variable (RV), based on which the impact of the reporting errors on the sensing performances has been analyzed for the case of ED-based linear combining cooperative spectrum sensing. Moreover, the performance limits of cooperative spectrum sensing based on hard decision have been presented in [18]. Space–time coding has been also proposed to mitigate the impact of reporting errors of cooperative spectrum sensing in [18].

B. Contributions

In this paper, we address the issue of cooperative spectrum sensing in a heterogeneous CR network, in which each SU may be equipped with different numbers of antennas and sampling rates. In addition, each SU may experience distinct channel fading and suffer from different noise levels due to their respective locations and device performances, such as amplifier and ADC. As a result, each SU may have different sensing capabilities and reliability values. This is a universal and fundamental characteristic of a heterogeneous CR network, which has not been taken into account in any previously proposed cooperative spectrum sensing schemes. To address this underlying issue, we herein derive an optimal normalized ED-based CS (NED-CS) scheme by virtue of the principle of log-likelihood ratio test (LRT), in which each SU acquires time-independent signal samples of PU. Compared with existing works on the same topic, our contributions and novelties are listed as follows.

- First, our proposed LRT-based NED-CS scheme takes into account the diverse sensing capability and reliability of SUs with reporting errors in a heterogeneous CR network. In this proposed scheme, each SU sends its local test statistic and the corresponding sensing parameters to the FC. In the FC, the global test statistic is obtained based on the modified local test statistics, which are computed based on each SU's local test statistic and the corresponding sensing parameters. Our analysis has established that the global test statistics are linear combination of those modified local test statistics. We have also proven that the optimal combining coefficient is a function of the numbers of receive antennas, the received signal samples, the received SNRs, and the variances of reporting errors of SUs.
- Second, a simplified LRT (SLRT)-based NED-CS scheme is proposed, which drops the prerequisite on *a priori* information on both received SNRs and the variances of reporting errors of SUs. Therefore, this SLRT-based NED-CS scheme can be easily implemented in practice.
- Third, we analyze and compare the performances of our proposed LRT-based NED-CS scheme with the well-known existing NED-CS schemes, including EGC and MNE methods with reporting errors under both additive white Gaussian noise (AWGN) and Rayleigh fading channels in a heterogeneous CR network. We obtain the series expansions and closed-form approximate expressions of detection and false alarm probabilities of our proposed LRT-based NED-CS scheme and derive the probability density function (PDF) of SUs' received SNRs. Then, the detection threshold can be analytically obtained to meet any specific requirements on false alarm probability.

Extensive numerical simulations have been carried out on our new schemes, whose results match the analytical results well. Both simulation and analytical results have validated the performance gain of our proposed spectrum sensing scheme relative to existing methods. The results have also shown that the more diverse the SUs' sensing reliability values, the more pronounced the gain from our new scheme will be, which makes our new scheme ideal for a CR network that is heterogeneous in nature.

The remainder of this paper is organized as follows. The system model is described in Section II. In Section III, the proposed LRT- and SLRT-based NED-CS schemes are derived in a heterogeneous CR network. For the sake of completeness, the well-known NED-CS schemes, including the EGC and MNE methods, are also briefly described in this section. In Section IV, the performances of these NED-CS schemes are analyzed under both AWGN and Rayleigh fading channels in a heterogeneous CR network. Extensive simulation results and corresponding discussions are presented in Section V. Finally, conclusions are drawn in Section VI, and some proofs are presented in the Appendixes.

Notations: $E\{\cdot\}$ denotes expectation; $\|\cdot\|$ represents the standard vector norm; $\det(\cdot)$ stands for the determinant of a matrix; superscripts $(\cdot)^T$ and $(\cdot)'$ stand for the transpose and derivative of the variable within the bracket, respectively; $\text{diag}[a_1,\ldots,a_K]^T$ is a diagonal matrix with elements $a_k, k = 1,\ldots,K$ on the main diagonal; $\max_{1\leq i\leq K}(a_k)$ is the maximum value over a_k; $p_v(\cdot)$ and $P_v(\cdot)$ stand for the PDF and cumulative distribution function (CDF) of variable v, respectively; $\mathcal{N}(\cdot)$ represents the Gaussian distribution; and $Q(t) = 1/\sqrt{2\pi}\int_t^\infty e^{-u^2/2}\text{du}$ denotes the tail probability of standard Gaussian distribution.

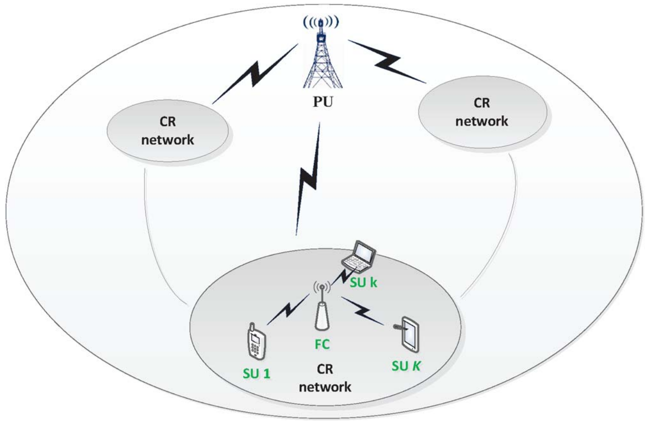

Fig. 1. Cooperative spectrum sensing scenario in a heterogeneous CR network.

II. System Model

As shown in Fig. 1, we investigate the cooperative spectrum sensing in a centralized heterogeneous CR network with an FC[1] and $K \geq 1$ SUs, which share the same spectrum resource with a PU network. In this paper, we consider the CR network to be a heterogeneous network, for which each SU may have different received SNRs and signal sampling rates and may be equipped with different numbers of receive antennas. We assume that the PU transmitter has one transmit antenna and the kth SU has M_k receive antennas, for which $N_k, k = 1, \ldots, K$ samples can be obtained from each receive antenna. The spectrum sensing problem for a single SU can be formulated as the following binary hypothesis test [19], [20]:

$$\begin{aligned} \mathcal{H}_0 &: \mathbf{y}_k(n) = \mathbf{w}_k(n), n = 1, \ldots, N_k \\ \mathcal{H}_1 &: \mathbf{y}_k(n) = \mathbf{h}_k s(n) + \mathbf{w}_k(n), n = 1, \ldots, N_k \end{aligned} \quad (1)$$

where $\mathbf{y}_k(n)$ denotes the $M_k \times 1$ equivalent baseband representation of the nth sample vector of the received signal, and $\mathbf{h}_k = [h_{k,1}, \ldots, h_{k,M_k}]^T$ is the $M_k \times 1$ channel fading coefficients' vector of the kth SU's receive antennas, which is assumed to be quasi-static during each sensing period. In this paper, we assume that $h_{k,m}, m = 1, \ldots, M_k$ are independently and identically distributed (i.i.d.) with average power $E\{|h_{k,m}|^2\} = 1$ and $h_{k,m}, k = 1, \ldots, K$ are independent of each other. $s(n)$ is the nth sample of the PU signal with average power $E\{|s(n)|^2\} = P_s$; $\mathbf{w}_k(n) = [w_{k,1}(n), \ldots, w_{k,M_k}(n)]^T$ is the complex Gaussian noise vector that is independent of $\mathbf{h}_k$ and $s(n)$, and $w_{k,m}(n), k = 1, \ldots, K, m = 1, \ldots, M_k, n = 1, \ldots, N_k$ are i.i.d. with zero mean and variance $\sigma_{w,k}^2$.

ED [21] is a well-established method for spectrum sensing due to its low complexity. In [20] and [22], ED has been extended to the case of multiple receive antennas. To quantize the local sensing data more accurately and to mitigate the impact of diverse noise variance at each SU, the energy of the received signals is usually normalized [8]. Therefore, the test statistic of the kth SU can be given as

$$T_k = \frac{1}{M_k N_k \sigma_{w,k}^2} \sum_{n=1}^{N_k} \|\mathbf{y}_k(n)\|^2. \quad (2)$$

By using the signal model S3 in [23], the received SNR γ_k of the kth SU can be given as follows:

$$\gamma_k = \frac{1}{M_k} \sum_{m=1}^{M_k} \frac{|h_{k,m}|^2 P_s}{\sigma_{w,k}^2}. \quad (3)$$

In a NED-CS scheme, each SU reports its local test statistical T_k to the FC.[2] In any practical scenario, errors will be inevitably introduced onto the data reported by SUs due to ADC quantization and wireless channel impairment. Then, the received data from the kth SU at the FC can be modeled as

$$\varsigma_k = T_k + n_k, k = 1, \ldots, K \quad (4)$$

where n_k denotes the reporting error.

Based on the central limit theorem, when $M_k N_k$ is a large number,[3] T_k can be approximated to have the following Gaussian distribution [20]:

$$T_k \sim \begin{cases} \mathcal{N}\left(1, \frac{1}{M_k N_k}\right), & \mathcal{H}_0 \\ \mathcal{N}\left(\gamma_k + 1, \frac{1+2\gamma_k}{M_k N_k}\right), & \mathcal{H}_1. \end{cases} \quad (5)$$

In general, n_k can be modeled as a Gaussian RV with zero mean [8], i.e.,

$$n_k \sim \mathcal{N}\left(0, \sigma_{n_k}^2\right) \quad (6)$$

where $\sigma_{n_k}^2$ represents the variance of the reporting errors introduced by both quantization errors and channel fading.[4] For the convenience of analysis, we assume that the reporting errors under $\mathcal{H}_0$ and $\mathcal{H}_1$ have the same distribution. As T_k and n_k both follow Gaussian distribution and they are independent of each other, ς_k therefore follows a Gaussian distribution as well, i.e.,

$$\varsigma_k \sim \begin{cases} \mathcal{N}\left(1, \frac{1}{M_k N_k} + \sigma_{n_k}^2\right), & \mathcal{H}_0 \\ \mathcal{N}\left(\gamma_k + 1, \frac{1+2\gamma_k}{M_k N_k} + \sigma_{n_k}^2\right), & \mathcal{H}_1. \end{cases} \quad (7)$$

III. Normalized Energy-Detection-Based-Comparative Sensing Schemes With Reporting Errors in a Heterogeneous Cognitive Radio Network

In NED-CS schemes, the reporting local test statistics $\varsigma_k, k = 1, \ldots, K$ are combined in the FC. Here, we first derive an optimal NED-CS scheme based on the LRT. Then, we present an SLRT-based NED-CS scheme that drops the prerequisite on *a priori* information on both received SNRs and the variances of reporting errors. For the sake of performance comparison, two well-known NED-CS schemes, including EGC and MNE, are also briefly described.

[1] In a centralized CR network, the function of FC is commonly performed by the CR base station.

[2] Note that we assume that all the SUs simultaneously send their respective local test statistics to the FC. In addition, the reporting delay is ignored so that the following analysis can be tractable. We recognize that the influence of reporting delay on the sensing performance is an interesting issue in CS. However, the analysis on this issue is out of the scope of this paper.

[3] The simulation results in [20] show that $M_k N_k = 16$ is large enough.

[4] Note that the quantization error for a single sample is commonly considered to be uniformly distributed in practice [24]. However, as the test statistic is the sum of $M_k N_k$ independent quantized samples, it is reasonable to assume that the contamination of signal due to quantization errors is also Gaussian distributed.

A. LRT-Based NED-CS Scheme

By considering the discrepancy of different SUs' sensing capability and reliability in a heterogeneous CR network, we can propose an optimal NED-CS scheme with reporting errors based on the LRT. The detection statistic of this LRT-based NED-CS scheme can be given as the following proposition.

Proposition 1: The detection statistics of the LRT-based NED-CS scheme is

$$T_{\mathrm{LRT}} = \sum_{k=1}^{K} \frac{M_k N_k \gamma_k \left[\varsigma_k^2 - \left(1 - M_k N_k \sigma_{n_k}^2\right)\varsigma_k\right]}{\left(1 + M_k N_k \sigma_{n_k}^2\right)\left(1 + 2\gamma_k + M_k N_k \sigma_{n_k}^2\right)}. \quad (8)$$

Proof: See Appendix A. ■

We further define the modified data of the kth SU at the FC as a variable υ_k, which is given by

$$\upsilon_k = \varsigma_k^2 - \left(1 - M_k N_k \sigma_{n_k}^2\right)\varsigma_k \quad (9)$$

and the combining coefficient corresponding to the kth SU's modified data υ_k is

$$w_k = \frac{M_k N_k \gamma_k}{\left(1 + M_k N_k \sigma_{n_k}^2\right)\left(1 + 2\gamma_k + M_k N_k \sigma_{n_k}^2\right)}. \quad (10)$$

Then, the detection statistic of the LRT-based NED-CS scheme can be written as

$$T_{\mathrm{LRT}} = \sum_{k=1}^{K} w_k \upsilon_k. \quad (11)$$

Hence, the detection statistic of the LRT-based NED-CS scheme is shown to be the linear combination of the modified data of SUs defined in (9). In addition, the combining coefficient calculated by (10) is a simple function of the received SNR γ_k, the number of antennas M_k, the number of received signal samples N_k, and the variance of the reporting errors $\sigma_{n_k}^2$ at each SU.

B. SLRT-Based NED-CS Scheme

The most challenging task in implementing the LRT scheme in (8) is that the FC needs the information on the received SNR γ_k and the variance of the reporting errors $\sigma_{n_k}^2$ at each SU. Similar to [8], we can estimate the SNR based on the received real-time signals. As shown in (7), ς_k under $\mathcal{H}_1$ is centered at $\gamma_k + 1$ with variance $(1 + 2\gamma_k)/(M_k N_k) + \sigma_{n_k}^2$. When $M_k N_k$ is large enough and $\sigma_{n_k}^2$ is small, the probability that ς_k approaches $\gamma_k + 1$ is almost 1. We can therefore have the approximation $\varsigma_k \approx \gamma_k + 1$. Thus, SNR can be then estimated as $\hat{\gamma}_k = \varsigma_k - 1$. However, as SUs can only obtain finite signal samples, ς_k may be nonpositive with the probability of nonzero. Moreover, $\hat{\gamma}_k = \varsigma_k - 1$ under $\mathcal{H}_0$ will be centered at zero. The LRT scheme may therefore not work reliably if SUs adopt the SNR estimator of $\hat{\gamma}_k = \varsigma_k - 1$.

To achieve more reliable detection at SNR level θ, a better estimation of SNR at the kth SU can be given as

$$\hat{\gamma}_k = \max(\varsigma_k - 1, \theta). \quad (12)$$

Meanwhile, it is also challenging to accurately estimate the variance of reporting errors $\sigma_{n_k}^2$ in practice. For a relatively less noisy CR network, we can approximate the $\sigma_{n_k}^2$ to zero. By inserting (12) and $\sigma_{n_k}^2 = 0$ into (8), an SLRT-based NED-CS scheme in a heterogeneous CR network can be shown to have its global test statistic as

$$T_{\mathrm{SLRT}} = \sum_{k=1}^{K} \frac{M_k N_k \hat{\gamma}_k}{1 + 2\hat{\gamma}_k}\left(\varsigma_k^2 - \varsigma_k\right). \quad (13)$$

Note that other methods of SNR estimation can of course be adopted in the LRT-based NED-CS scheme, which will result in different flavors of the LRT-based NED-CS scheme.

The procedure of the proposed SLRT-based NED-CS scheme is summarized in Algorithm 1 SLRT.

Algorithm 1 SLRT

SU:

1: The kth SU computes its normalized energy T_k and SNR $\hat{\gamma}_k$ according to (2) and (12), respectively.

2: Each SU reports its normalized energy T_k, the number of antennas and samples (M_k and N_k), and the estimated SNR $\hat{\gamma}_k$ to the FC.

FC:

3: The FC softly combines the data obtained by step 2 and obtains the global test statistic T_{SLRT} according to (13).

4: Decision: if $T_{\mathrm{SLRT}} \geq \tau$, the PU signal is deemed to be present (yes); otherwise, the PU signal is deemed to be absent (no).

C. Existing NED-CS Schemes

When there is no *a priori* information available at the FC on the SUs that participate in CS, a relatively simple sensing method is to calculate the arithmetic mean of the received local test statistics of SUs [9], [13]. This method is referred to as EGC. The global test statistic of the EGC scheme is given by

$$T_{\mathrm{EGC}} = \frac{1}{K}\sum_{k=1}^{K} \varsigma_k. \quad (14)$$

When the normalized signal energy of SUs has substantially large dynamic range, a natural way of detection for the FC is to choose the strongest local normalized energy that is reported by SUs [8]. This scheme is called MNE-based CS. Its global test statistic can be given by

$$T_{\mathrm{MNE}} = \max_{1 \leq k \leq K} (\varsigma_k). \quad (15)$$

Note that this scheme is different from the method that selects the known SU with the largest normalized signal energy for sensing. The largest normalized energy may not always be at the same SU due to the time-varying nature of wireless channels. The MNE scheme is equivalent to the "OR decision rule" for local test statistics of SUs.

IV. Performance Analysis of Normalized Energy-Detection-Based-Comparative Sensing Schemes

Here, the performances of our proposed LRT-based NED-CS scheme and existing EGC and MNE methods are analytically derived with reporting errors under both AWGN and Rayleigh fading channels in a heterogeneous CR network.

A. Performance Analysis Under the AWGN Channel

1) LRT-Based NED-CS Scheme: Based on (11), the detection statistic T_{LRT} can be decomposed into an RV ψ_{LC} and a constant C, i.e.,

$$T_{\mathrm{LRT}} = \psi_{LC} - C \tag{16}$$

where constant C is

$$C = \sum_{k=1}^{K} w_k \left(\frac{1 - M_k N_k \sigma_{n_k}^2}{2} \right)^2 \tag{17}$$

and the RV ψ_{LC} is

$$\psi_{LC} = \sum_{k=1}^{K} \sigma_{\zeta_k}^2 \left(\frac{\zeta_k}{\sigma_{\zeta_k}} \right)^2. \tag{18}$$

Note that $\zeta_k = \sqrt{w_k}(\varsigma_k - (1 - M_k N_k \sigma_{n_k}^2)/2)$ is a Gaussian RV with variance $\sigma_{\zeta_k}^2 = w_k \sigma_{\varsigma_k}^2$ and mean $\mu_{\zeta_k} = \sqrt{w_k}(\mu_{\varsigma_k} - (1 - M_k N_k \sigma_{n_k}^2)/2)$, where $\sigma_{\varsigma_k}^2$ and μ_{ς_k} are the variance and the mean of ς_k based on (7), respectively. Then, $(\zeta_k/\sigma_{\zeta_k})^2$ follows the noncentral chi-squared distribution with a degree of freedom 1 and a noncentrality parameter $(\mu_{\zeta_k}/\sigma_{\zeta_k})^2$ [26]. As a result, ψ_{LC} is a linear combination of K independent noncentral chi-squared RVs with combination coefficients $\sigma_{\zeta_k}^2, k = 1, \ldots, K$.

To present the closed-form expressions of the detection and false alarm probabilities of the LRT-based NED-CS scheme, it is necessary to obtain the distribution function of ψ_{LC}. Unfortunately, as a linear combination of noncentral chi-squared RVs, the closed-form distribution function of ψ_{LC} is not yet known [27]. Therefore, it is very difficult to directly obtain the closed-form expressions of the detection and false alarm probabilities of the LRT-based NED-CS scheme. In statistics theory, series expansions and moment-based approximation are commonly used to calculate the distribution function of the linear combination of noncentral chi-squared RVs [28]–[31]. Therefore, we also resort to a series expansion to approach the exact detection and false alarm probabilities of the LRT-based NED-CS scheme at first. Then, moment-based closed-form expressions are further derived to get their approximations to facilitate numerical computations.

For the detection and false alarm probabilities of LRT-based NED, let τ denote the detection threshold. Furthermore, under hypothesis $\mathcal{H}_1$, let the mean and variance of ζ_k be $\mu_{\zeta_k|\mathcal{H}_1}$ and $\sigma_{\zeta_k|\mathcal{H}_1}^2$, respectively. Similarly, $\mu_{\zeta_k|\mathcal{H}_0}$ and $\sigma_{\zeta_k|\mathcal{H}_0}^2$ denote the mean and variance of ζ_k under hypothesis $\mathcal{H}_0$, respectively. Then, we have the following proposition.

Proposition 2: The series expansions of detection probability of the LRT-based NED-CS scheme $P_{d,\mathrm{LRT}}(\tau)$ can be given by

$$P_{d,\mathrm{LRT}}(\tau) = 1 - \sum_{i=0}^{\infty} a_{\mathcal{H}_1}, i \left[\frac{\Gamma\left(l_{\mathcal{H}_1,i}/2, C/\left(2\beta_{\mathcal{H}_1}\right)\right)}{\Gamma\left(l_{\mathcal{H}_1,i}/2\right)} - \frac{\Gamma\left(l_{\mathcal{H}_1,i}/2, (\tau + C)/\left(2\beta_{\mathcal{H}_1}\right)\right)}{\Gamma\left(l_{\mathcal{H}_1,i}/2\right)} \right] \tag{19}$$

where parameter $l_{\mathcal{H}_1,i}$, parameter $\beta_{\mathcal{H}_1}$, and series coefficient $a_{\mathcal{H}_1,i}$ are presented in (43), (46), and (44) in Appendix B, respectively. $\Gamma(s)$ and $\Gamma(s,x)$ are the complete and upper incomplete gamma functions defined in [26], respectively.

Similarly, under hypothesis $\mathcal{H}_0$, the series expansions of false alarm probability of the LRT-based NED-CS scheme $P_{\mathrm{fa,LRT}}(\tau)$ can be given by

$$P_{d,\mathrm{LRT}}(\tau) = 1 - \sum_{i=0}^{\infty} a_{\mathcal{H}_0,i} \left[\frac{\Gamma\left(l_{\mathcal{H}_0,i}/2, C/\left(2\beta_{\mathcal{H}_0}\right)\right)}{\Gamma\left(l_{\mathcal{H}_0,i}/2\right)} - \frac{\Gamma\left(l_{\mathcal{H}_0,i}/2, (\tau + C)/\left(2\beta_{\mathcal{H}_0}\right)\right)}{\Gamma\left(l_{\mathcal{H}_0,i}/2\right)} \right] \tag{20}$$

where parameter $l_{\mathcal{H}_0,i}$, parameter $\beta_{\mathcal{H}_0}$, and series coefficient $a_{\mathcal{H}_0,i}$ can be obtained by substituting $\mu_{\zeta_k|\mathcal{H}_0}$ and $\sigma_{\zeta_k|\mathcal{H}_0}^2$ for $\mu_{\zeta_k|\mathcal{H}_1}$ and $\sigma_{\zeta_k|\mathcal{H}_1}^2$ in (43), (46), and (44) in Appendix B, respectively.

Proof: See Appendix B. ■

Proposition 3: The closed-form approximation of detection probability of the LRT-based NED-CS scheme can be given as

$$P_{d,\mathrm{LRT}}(\tau) \approx 1 - \frac{\Gamma\left(l_{\mathcal{H}_1}/2, \tau_{\mathcal{H}_1,C}^*/2\right) - \Gamma\left(l_{\mathcal{H}_1}/2, \tau_{\mathcal{H}_1,\tau+C}^*/2\right)}{\Gamma\left(l_{\mathcal{H}_1}/2\right)} \tag{21}$$

where parameter $l_{\mathcal{H}_1}$ is presented in (54) in Appendix C. $\tau_{\mathcal{H}_1,C}^*$ and $\tau_{\mathcal{H}_1,\tau+C}^*$ are the modified detection thresholds, which are presented in (56) and (57) in Appendix C, respectively.

Similarly, the closed-form approximation of false alarm probability of the LRT-based NED-CS scheme can be given as

$$P_{\mathrm{fa,LRT}}(\tau) \approx 1 - \frac{\Gamma\left(l_{\mathcal{H}_0}/2, \tau_{\mathcal{H}_0,C^*}/2\right) - \Gamma\left(l_{\mathcal{H}_0}/2, \tau_{\mathcal{H}_0,\tau+C}^*/2\right)}{\Gamma\left(l_{\mathcal{H}_0}/2\right)} \tag{22}$$

where parameter $l_{\mathcal{H}_0}$ can be calculated by substituting $\mu_{\zeta_k|\mathcal{H}_0}$ and $\sigma_{\zeta_k|\mathcal{H}_0}^2$ for $\mu_{\zeta_k|\mathcal{H}_1}$ and $\sigma_{\zeta_k|\mathcal{H}_1}^2$ in (54) in Appendix C. In addition, the modified detection thresholds $\tau_{\mathcal{H}_0,C}^*$ and $\tau_{\mathcal{H}_0,\tau+C}^*$ can be derived by the same substitution in (56) and (57) in Appendix C, respectively.

Proof: See Appendix C. ■

As the series expansions of detection and false alarm probabilities can be accurate enough, we can evaluate the performances of the aforementioned closed-form approximations by comparing (21) and (22) with (19) and (20), respectively. We assume that there is $K = 4$ SUs distributing in a CR network, which are equipped with $M_1 = 8$, $M_2 = 6$, $M_3 = 4$, and $M_4 = 2$ receive antennas and have $N_1 = 250$, $N_2 = 200$, $N_3 = 150$, and $N_4 = 100$ signal samples, respectively. Their received SNRs are $\gamma_1 = -13$ dB, $\gamma_2 = -16$ dB, $\gamma_3 = -19$ dB, and $\gamma_4 = -22$ dB, respectively. The reporting errors are set to be $\sigma_{n_k}^2 = 0.1/(M_k N_k), k = 1, \ldots, K$. The exact and approximate results provided by series expansions and closed-form approximations are presented in Table I, respectively. In Table I, the truncation errors of series expansions presented in (50) and (51) in Appendix B are less than 10^{-6}. We can find that the closed-form approximate expressions provide good results for both detection and false alarm probabilities.

2) EGC and MNE Schemes: Based on the distribution of ς_k presented in (7), the distribution of the global test statistics

TABLE I
PERFORMANCES OF CLOSED-FORM APPROXIMATION OF DETECTION AND FALSE ALARM PROBABILITIES

	τ	EXACT VALUE	APPROXIMATE VALUE	DIFFERENCE
$P_{d,LRT}$	10	0.994653	0.994645	0.000008
	16	0.479107	0.479106	0.000001
	22	0.007357	0.007364	−0.000007
$P_{fa,LRT}$	6	0.989602	0.989592	0.000010
	11	0.449792	0.449786	0.000006
	16	0.008949	0.008956	−0.000007

T_{EGC} of the EGC scheme can be given by

$$T_{\mathrm{EGC}} \sim \begin{cases} \mathcal{N}\left(1, \frac{1}{K^2}\sum\limits_{k=1}^{K}\left(\frac{1}{M_kN_k}+\sigma_{n_k}^2\right)\right), & \mathcal{H}_0 \\ \mathcal{N}\left(\sum\limits_{k=1}^{K}\frac{1+\gamma_k}{K}, \sum\limits_{k=1}^{K}\frac{(1+2\gamma_k)/(M_kN_k)+\sigma_{n_k}^2}{K^2}\right), & \mathcal{H}_1. \end{cases} \tag{23}$$

Therefore, the performance of the EGC scheme with reporting errors can be given as

$$P_{\mathrm{fa,EGC}}(\tau) = Q\left(\frac{\tau-1}{\sqrt{\frac{1}{K^2}\sum\limits_{k=1}^{K}\left(\frac{1}{M_kN_k}+\sigma_{n_k}^2\right)}}\right) \tag{24}$$

$$P_{d,\mathrm{EGC}}(\tau) = Q\left(\frac{\tau-\frac{1}{K}\sum\limits_{k=1}^{K}(1+\gamma_k)}{\sqrt{\frac{1}{K^2}\sum\limits_{k=1}^{K}\left(\frac{1+2\gamma_k}{M_kN_k}+\sigma_{n_k}^2\right)}}\right). \tag{25}$$

Meanwhile, as the MNE method simply picks the largest value among the received local test statistics with reporting errors ς_k, the performance of the MNE method can be expressed as

$$\begin{aligned} P_{\mathrm{fa,MNE}}(\tau) &= 1 - P\left(\max_{1\le k\le K}(\varsigma_k) < \tau|\mathcal{H}_0\right) \\ &= 1 - \prod_{k=1}^{K}\left(1 - Q\left(\frac{\tau-1}{\sqrt{\frac{1}{M_kN_k}+\sigma_{n_k}^2}}\right)\right) \end{aligned} \tag{26}$$

$$\begin{aligned} P_{d,\mathrm{MNE}}(\tau) &= 1 - P\left(\max_{1\le k\le K}(\varsigma_k) < \tau|\mathcal{H}_1\right) \\ &= 1 - \prod_{k=1}^{K}\left(1 - Q\left(\frac{\tau-1-\gamma_k}{\sqrt{\frac{1+2\gamma_k}{M_kN_k}+\sigma_{n_k}^2}}\right)\right). \end{aligned} \tag{27}$$

B. Performance Analysis Under Rayleigh Fading Channels

1) Probability Distribution of Received SNR: To facilitate the performance analysis under fading channels, we first derive the PDF of the received SNR at each SU.

It follows from (3) that the received SNR γ_k of the kth SU can be expressed as

$$\gamma_k = \frac{1}{M_k}\sum_{m=1}^{M_k}\gamma_{k,m} \tag{28}$$

where $\gamma_{k,m} = |h_{k,m}|^2 P_s/\sigma_{w,k}^2$ denotes the received SNR at the mth receive antenna. Under Rayleigh fading channels, the received SNR $\gamma_{k,m}$ follows gamma distribution [25], i.e.,

$$\gamma_{k,m} \sim \Gamma(1, \bar{\gamma}_{k,m}) \tag{29}$$

where $\bar{\gamma}_{k,m} = E\{|h_{k,m}|^2\}P_s/\sigma_{w,k}^2 = P_s/\sigma_{w,k}^2$ is the mean of $\gamma_{k,m}$, and $\bar{\gamma}_{k,m}, m = 1,\ldots,M_k$ are identical. Note that $\gamma_{k,m}$, $m = 1,\ldots,M_k$ are i.i.d. Then, as an equally weighted sum of $\gamma_{k,m}$, γ_k follows gamma distribution as well, i.e.,

$$\gamma_k \sim \Gamma\left(M_k \frac{\bar{\gamma}_k}{M_k}\right) \tag{30}$$

where $\bar{\gamma}_k = P_s/\sigma_{w,k}^2$ is the mean of γ_k based on (28). Therefore, the PDF of γ_k can be given as

$$p_{\gamma_k}(\gamma_k) = \frac{\left(\frac{\bar{\gamma}_k}{M_k}\right)^{-M_k}}{(M_k-1)!}\gamma_k^{M_k-1}e^{-\frac{\gamma_k}{\bar{\gamma}_k}M_k}. \tag{31}$$

2) False Alarm and Average Detection Probabilities: For the LRT-based NED-CS scheme, both false alarm and detection probabilities are instantaneous and are dependent on channel fading. The instantaneous false alarm probability can be expressed as (22), where the received SNRs follow the distribution presented in (31). The average detection probability can be calculated by averaging instantaneous detection probability over the distributions of received SNRs. By using the closed-form approximation of the instantaneous detection probability presented in (21), the average detection probability can be given as follows[5]:

$$\begin{aligned} &P_{d,\mathrm{av,LRT}}(\tau) \\ &= \int_0^\infty \cdots \int_0^\infty P_{d,\mathrm{LRT}}(\tau)p_{\gamma_1}(\gamma_1)\ldots p_{\gamma_K}(\gamma_K)d\gamma_1\ldots d\gamma_K \\ &= 1 - \int_0^\infty \cdots \int_0^\infty \frac{\Gamma\left(l_{\mathcal{H}_1}/2, \tau^*_{\mathcal{H}_1\cdot C}/2\right) - \Gamma\left(l_{\mathcal{H}_1}/2, \tau^*_{\mathcal{H}_1\cdot\tau+C}/2\right)}{\Gamma\left(\frac{l_{\mathcal{H}_1}}{2}\right)} \\ &\quad \times p_{\gamma_1}(\gamma_1)\ldots p_{\gamma_K}(\gamma_K)d\gamma_1\ldots d\gamma_K. \end{aligned} \tag{32}$$

[5]Generally, we hope that the SNRs $\gamma_1,\ldots,\gamma_K$ can be combined into a single SNR expression so that this multiple integral can be simplified to a single integral [23]. Unfortunately, this simplification is hard achieve as $P_{d,\mathrm{LRT}}(\tau)$ is very complicated for our problem.

The last step is resulted from the fact that $\gamma_1, \ldots, \gamma_K$ are independent of each other.

For the EGC and MNE schemes, as the false alarm probabilities are not depended on channel fading, they are not instantaneous and can be expressed as (24) and (26), respectively. However, the detection probabilities are instantaneous and related to channel fading; thus, the average detection probabilities have to be calculated as follows:

$$\begin{aligned} &P_{d,\mathrm{av,EGC}}(\tau) \\ &= \int_0^\infty \cdots \int_0^\infty P_{d,\mathrm{EGC}}(\tau) p_{\gamma_1}(\gamma_1) \ldots p_{\gamma_K}(\gamma_K) d\gamma_1 \ldots d\gamma_K \\ &= \int_0^\infty \cdots \int_0^\infty Q\left(\frac{\tau - \frac{1}{K}\sum_{k=1}^{K}(1+\gamma_k)}{\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\frac{1+2\gamma_k}{M_k N_k} + \sigma_{n_k}^2\right)}}\right) \\ &\qquad \times p_{\gamma_1}(\gamma_1) \ldots p_{\gamma_K}(\gamma_K)\, d\gamma_1 \ldots d\gamma_K \end{aligned} \tag{33}$$

$$\begin{aligned} &P_{d,\mathrm{av,MNE}}(\tau) \\ &= \int_0^\infty \cdots \int_0^\infty P_{d,\mathrm{MNE}}(\tau)\, p_{\gamma_1}(\gamma_1) \ldots p_{\gamma_K}(\gamma_K)\, d\gamma_1 \ldots d\gamma_K \\ &= 1 - \prod_{k=1}^{K}\left(1 - \int_0^\infty Q\left(\frac{\tau - 1 - \gamma_k}{\sqrt{(1+2\gamma_k)/(M_k N_k) + \sigma_{n_k}^2}}\right) p_{\gamma_k}(\gamma_k) d\gamma_k\right). \end{aligned} \tag{34}$$

Note that these integrations over $\gamma_1, \ldots, \gamma_K$ can be numerically computed [32].

V. Simulation Results

Here, we present simulation results to evaluate the performances of our proposed LRT- and SLRT-based NED-CS schemes. For the sake of comparison, the performances of the EGC and MNE schemes are also presented. We assume that the PU sends independent binary phase-shift keying signals at 20-Mb/s bit rate in our simulations. The sensing time duration is set to be 1 ms. We also set the SUs to have different sampling rates and different numbers of antennas in the simulated heterogeneous CR network, in which SUs obtain different numbers of signal samples on the target spectrum. The carrier frequency is set to be 900 MHz.[6] We also assume that the receive antennas of each SU are spatially independent.

A. Performance Comparison Under the AWGN Channel

We assume that there are four SUs, i.e., $K = 4$ in a heterogeneous CR network. These SUs have eight, six, four, and two receive antennas, respectively. The numbers of signal samples used for sensing at the four SUs are 250, 200, 150, and 100.

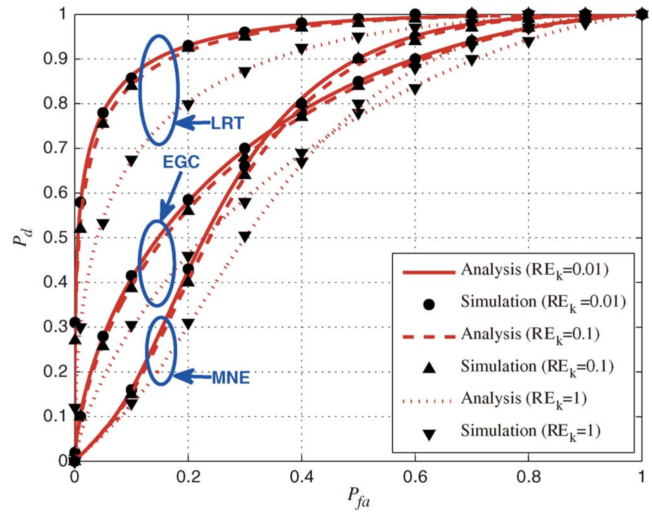

Fig. 2. ROC with reporting errors in a heterogeneous CR network under the AWGN channel.

Their received SNRs are −13 dB, −16 dB, −19 dB, and −22 dB. To have a manifesting comparison between the variance of reporting errors and that of T_k under $\mathcal{H}_0$, we define herein a normalization factor $RE_k = \sigma_{n_k}^2 M_k N_k$. Fig. 2 shows the receiver operating characteristics (ROCs) of the LRT-based NED-CS scheme, the EGC method, and the MNE detector with $RE_k = 0.01$, $RE_k = 0.1$, and $RE_k = 1$, respectively. It has been shown with the simulation results that the ROC degrades as RE_k increases when the reporting errors become larger. It is also evident that our proposed LRT-based NED-CS scheme achieves substantially better ROC than both EGC and MNE methods. Meanwhile, our simulation results match the theoretical performances elegantly.

B. Performance Comparison Under the Fading Channel

The flat Rayleigh fading channel with maximum Doppler shift $f_d = 100$ Hz is assumed. We set the normalization factor of reporting errors $RE_k = 0.1$ and $\theta = 0.001$. The average detection probability is our metric for performance comparison. In addition, to compare their performances on a fair ground, we set the probabilities of false alarm to be $P_{\mathrm{fa}} = 0.01$ for all methods. We investigate the average detection probabilities of these methods in several heterogeneous scenarios.

1) SUs experience distinct shadowing.[7]
2) SUs are equipped with different numbers of receive antennas.
3) SUs have different sampling rates.
4) SUs are equipped with different numbers of receive antennas, have different sampling rates, and experience distinct shadowing.

In the simulations, we define the average received SNR of all SUs as $\mathrm{SNR}_{\mathrm{av}} = \sum_k \bar{\gamma}_k / K$, where $\bar{\gamma}_k$ is the average received SNR of the kth SU. Furthermore, we set $\bar{\gamma}_k = \mathrm{SNR}_{\mathrm{av}} + g_k$,

[6]For other system parameters, the similar performance comparison results to what were presented in this paper can be also observed.

[7]In practical environments, several SUs may experience similar shadowing. For this case, we assume that only one of them reports its test statistic to the FC by a clustering mechanism [33].

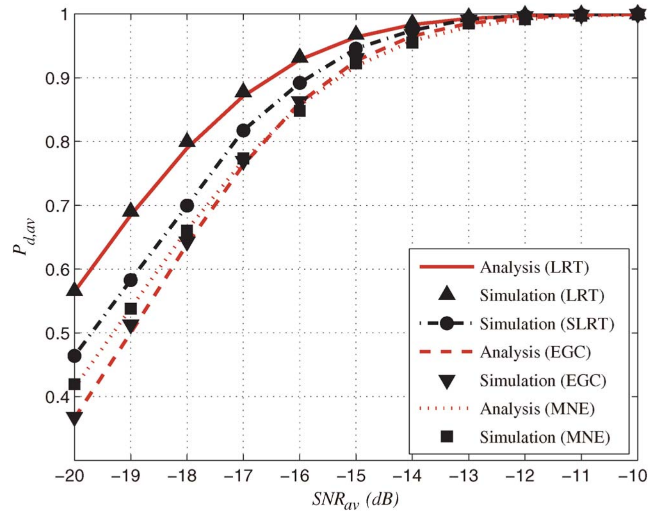

Fig. 3. Average probability of detection in a heterogeneous CR network (each SU experiences distinct shadowing).

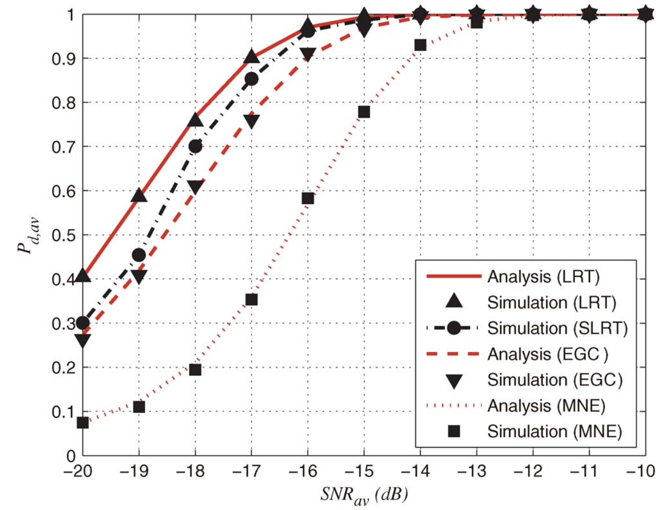

Fig. 4. Average probability of detection in a heterogeneous CR network (each SU has different numbers of antennas).

where g_k stands for the difference of the average received SNR among SUs.[8] We further define the difference vector $\mathbf{g} = [g_1, \ldots, g_K]^T$.

First, we investigate the impact of different received signal qualities on the average detection probability $P_{d,\text{av}}$ at each SU. When the difference vector is $\mathbf{g} = [6\text{ dB}, 2\text{ dB}, -2\text{ dB}, -6\text{ dB}]^T$, the number of each SU's antennas is 2, and the number of the samples of each SU is 2000; the detection performances of the proposed LRT- and SLRT-based NED-CS schemes, the EGC method, and the MNE detector are shown in Fig. 3. It is shown that the simulation results and analytical results match very well. Meanwhile, these results indicate that the LRT-based NED-CS scheme achieves the best performance among all, whereas the SLRT-based NED-CS scheme can also achieve better performance than the EGC method and the MNE detector. The performance gain manifests the advantage of our proposed LRT-based NED-CS scheme, which takes into account the different sensing reliability values of SUs in terms of their SNRs. Although it is not as advantageous as the LRT-based NED-CS method performance-wise, our SLRT-based NED-CS also has performance gain over EGC and MNE methods because it exploits the different estimated SNRs of SUs, whereas EGC and MNE ignore the differences.

Second, Fig. 4 compares the average detection probabilities $P_{d,\text{av}}$ for different numbers of SU receive antennas, which are eight, six, four, and two, respectively. We assume that the number of samples at each SU is 2000 and each SU has the same SNR, i.e., $\mathbf{g} = [0, 0, 0, 0]^T$. It is also shown that analytical results match simulation results well. Furthermore, the proposed LRT-based NED-CS scheme achieves the best detection performance because it exploits the different sensing reliability values of SUs resulted from their different numbers of receive antennas. Similarly, the proposed SLRT-based NED-CS scheme also performs better than the EGC method and the MNE detector.

[8]We assume that the SUs have the information on the noise variance based on some estimation methods [34]. Moreover, perfect information on the noise variance gives the performance bound.

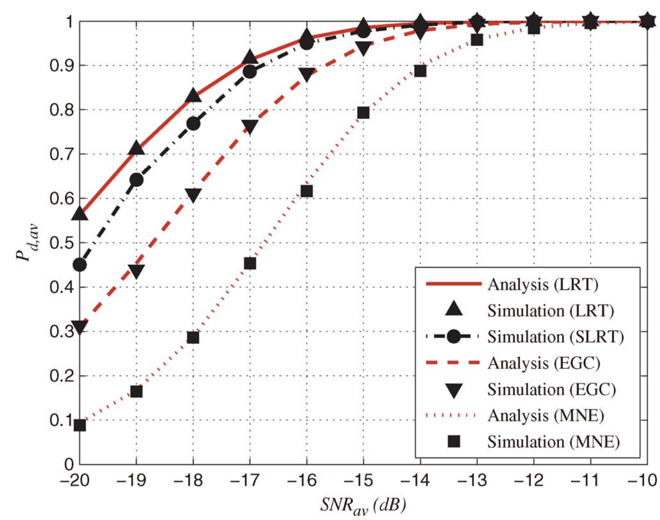

Fig. 5. Average probability of detection in a heterogeneous CR network (each SU has different sampling rates).

Subsequently, Fig. 5 shows the impact of the SU's sampling rate on the detection performances of cooperative spectrum sensing when the numbers of samples of the SUs are 16 000, 8000, 4000, and 2000, respectively. The number of each SU's antennas is two, and all SUs have the same SNR. Similarly, the analytical results match the simulation results elegantly. The LRT-based NED-CS scheme obtains the best performance, and the SLRT-based NED-CS scheme can also achieve better performance than the EGC method and the MNE detector. The underlying reason is that the proposed LRT- and SLRT-based NED-CS schemes take into consideration the difference of each SU's local sensing reliability caused by the different numbers of received signal samples.

Finally, Fig. 6 compares the detection performances in a specific heterogeneous network, in which the antenna numbers of four SUs are eight, six, four, and two, and the sample numbers

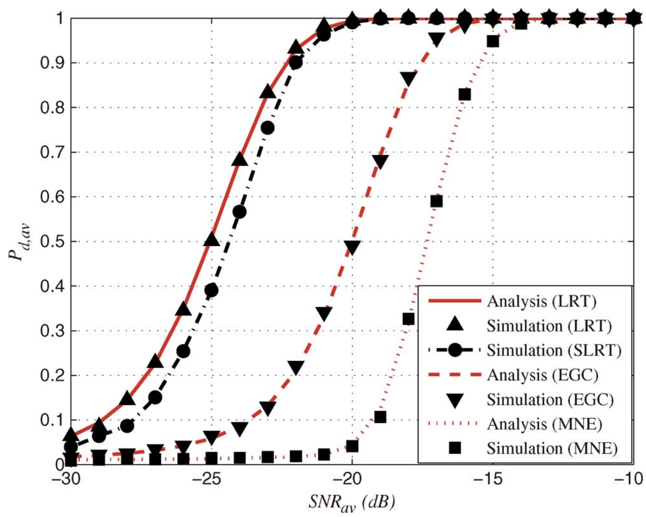

Fig. 6. Average probability of detection in a heterogeneous CR network (the sampling rate and the number of antennas of each SU are all different, and each SU experiences distinct shadowing).

are 16 000, 8000, 4000, and 2000, respectively. The SNR difference vector is $\mathbf{g} = [3 \text{ dB}, 1 \text{ dB}, -1 \text{ dB}, -3 \text{ dB}]^T$. It is also shown that the simulation results and the analytical results match well. Meanwhile, the proposed LRT-based NED-CS scheme shows the best detection performance. We can also observe that the proposed SLRT-based NED-CS scheme achieves much better detection performance than the EGC method and the MNE detector. For instance, when $P_d = 0.9$, the detection performance gains of the LRT- and SLRT-based NED-CS schemes are about 4–5 dB over EGC and 6–7 dB over MNE. The main reason of the gain is that our proposed LRT- and SLRT-based NED-CS schemes consider all influencing factors, which result in different local sensing reliability values in the heterogeneous CR network to improve its performance of spectrum sensing.

VI. Conclusion

In this paper, we have proposed an optimal NED-CS scheme with reporting errors by virtue of the principle of LRT in a heterogeneous CR network. The proposed LRT-based NED-CS scheme is the linear combination of the modified local test statistic defined in (9). The combining coefficient is a simple function of the numbers of antennas and samples, the received SNRs, and the variance of the reporting errors at each SU. Furthermore, an SLRT-based NED-CS scheme has been further proposed so that the prerequisite of prior information on SNR and the variance of reporting errors can be dropped. The performances of the proposed LRT-based NED-CS scheme, the well-known EGC method, and the MNE detector with reporting errors have been analyzed under both AWGN and Rayleigh fading channels. Extensive simulations and numerical computations have been performed to evaluate the performances of our proposed LRT- and SLRT-based NED-CS schemes. The results show that the analysis matches the simulations well, and both of them verify that our proposed LRT- and SLRT-based NED-CS schemes can improve the sensing performance by taking the difference of each SU's sensing reliability into account. Specifically, the LRT- and SLRT-based NED-CS schemes can achieve substantially better sensing performance than the EGC method and the MNE detector in heterogeneous CR networks, where the differences of SU's sensing reliability are relatively large.

Appendix A
Proof of Proposition 1

Based on the Neyman–Pearson theorem [35], for a given probability of false alarm P_{fa}, the test statistic, which maximizes the probability of detection P_d, is the LRT. Therefore, the LRT-based NED-CS scheme has the following test statistic:

$$T_{\text{LRT}}(\mathbf{x}) = \frac{p(\mathbf{x}|\mathcal{H}_1)}{p(\mathbf{x}|\mathcal{H}_0)} \tag{35}$$

where vector $\mathbf{x}$ denotes the accumulation of the received local test statistic of all K SUs in the considered heterogeneous CR network. $\mathbf{x}$ is defined as

$$\mathbf{x} = [\varsigma_1, \ldots, \varsigma_K]^T. \tag{36}$$

Hence, based on the distribution of T_k shown in (5), the likelihood function under $\mathcal{H}_0$ is

$$p(\mathbf{x}|\mathcal{H}_0) = \frac{1}{\prod_{k=1}^{K}\sqrt{2\pi\left(\frac{1}{M_kN_k}+\sigma_{n_k}^2\right)}} \times \exp\left\{-\sum_{k=1}^{K}\frac{(\varsigma_k-1)^2}{2\left(\frac{1}{M_kN_k}+\sigma_{n_k}^2\right)}\right\}. \tag{37}$$

On the other hand, the likelihood function under $\mathcal{H}_1$ is given by

$$p(\mathbf{x}|\mathcal{H}_1) = \frac{1}{(2\pi)^{K/2}\det^{1/2}(\mathbf{C})} \times \exp\left\{-\frac{(\mathbf{x}-\mathbf{u})^T\mathbf{C}^{-1}(\mathbf{x}-\mathbf{u})}{2}\right\} \tag{38}$$

where $\mathbf{u}$ denotes the mean vector of $\mathbf{x}$ under $\mathcal{H}_1$, i.e.,

$$\mathbf{u} = [\gamma_1+1, \ldots, \gamma_K+1]^T \tag{39}$$

and $\mathbf{C}$ represents the covariance matrix of $\mathbf{x}$ under $\mathcal{H}_1$. If SUs are randomly distributed and far apart from each other, it can be verified that their received signals are spatially independent. Hence, covariance matrix $\mathbf{C}$ is a diagonal matrix given by

$$\mathbf{C} = \operatorname{diag}\left[\frac{1+2\gamma_1}{M_1N_1}+\sigma_{n_1}^2, \ldots, \frac{1+2\gamma_K}{M_KN_K}+\sigma_{n_K}^2\right]. \tag{40}$$

By omitting constant items, the LRT can be written as

$$\ln p(\mathbf{x}|\mathcal{H}_1) - \ln p(\mathbf{x}|\mathcal{H}_0) \Longleftrightarrow \sum_{k=1}^{K}\frac{(T_k-1)^2}{2/M_kN_k} - \frac{(\mathbf{x}-\mathbf{u})^T\mathbf{C}^{-1}(\mathbf{x}-\mathbf{u})}{2}. \tag{41}$$

By inserting (39) and (40) into (41), we can obtain the test statistic of the LRT-based NED-CS scheme as Proposition 1.

APPENDIX B
PROOF OF PROPOSITION 2

Under hypothesis $\mathcal{H}_1$, as ψ_{LC} is the linear combination of noncentral chi-squared RVs, the resulting CDF $P_{\psi_{LC}|\mathcal{H}_1}(\tau)$ based on series expansions can be given by [29]

$$P_{\psi_{LC}|\mathcal{H}_1}(\tau) = \sum_{i=0}^{\infty} a_{\mathcal{H}_1,i} P_{\chi^2_{l_{\mathcal{H}_1,i}}}\left(\frac{\tau}{\beta_{\mathcal{H}_1}}\right) \tag{42}$$

where the degree of freedom $l_{\mathcal{H}_1,i}$ of the ith central chi-squared distribution is

$$l_{\mathcal{H}_1,i} = 2i + K. \tag{43}$$

In addition, the ith series coefficient $a_{\mathcal{H}_1,i}$ can be given as follows [29]:

$$a_{\mathcal{H}_1,0} = \prod_{k=1}^{K}\left(\frac{\beta_{\mathcal{H}_1}}{\sigma_{\zeta_k|\mathcal{H}_1}}^2\right)^{1/2} \exp\left(-\frac{1}{2}\sum_{k=1}^{K}\frac{\mu^2_{\zeta_k|\mathcal{H}_1}}{\sigma^2_{\zeta_k|\mathcal{H}_1}}\right) \tag{44}$$

$$\begin{aligned} a_{\mathcal{H}_1,i} &= \frac{1}{i}\sum_{j=0}^{i-1} g_{\mathcal{H}_1,i-j} a_{\mathcal{H}_1,j}, i \geq 1 \\ g_{\mathcal{H}_1,j} &= \frac{1}{2}\sum_{k=1}^{K}\left(\frac{\sigma^2_{\zeta_k|\mathcal{H}_1} - \beta_{\mathcal{H}_1}}{\sigma^2_{\zeta_k|\mathcal{H}_1}}\right)^j \\ &\quad + \frac{j}{2}\sum_{k=1}^{K}\frac{\beta_{\mathcal{H}_1}\mu^2_{\zeta_k|\mathcal{H}_1}}{\sigma^4_{\zeta_k|\mathcal{H}_1}}\left(\frac{\sigma^2_{\zeta_k|\mathcal{H}_1} - \beta_{\mathcal{H}_1}}{\sigma^2_{\zeta_k|\mathcal{H}_1}}\right)^{j-1}, j \geq 1 \end{aligned} \tag{45}$$

$$\beta_{\mathcal{H}_1} = \min\left(\sigma^2_{\zeta_1|\mathcal{H}_1}, \ldots, \sigma^2_{\zeta_K|\mathcal{H}_1}\right). \tag{46}$$

Meanwhile, the truncation error $\varepsilon_{\psi_{LC}|\mathcal{H}_1}(\tau, I)$ corresponding to the first I terms of the series expansions of $P_{\psi_{LC}|\mathcal{H}_1}$ can be given by

$$\varepsilon_{\psi_{LC}|\mathcal{H}_1}(\tau, I) \leq 1 - \sum_{i=0}^{I-1} a_{\mathcal{H}_1,i}. \tag{47}$$

Based on (16), the detection probability $P_{d,\mathrm{LRT}}(\tau)$ of the LRT-based NED-CS scheme can be expressed as

$$\begin{aligned} P_{d,\mathrm{LRT}}(\tau) &= 1 - \int_0^{\tau} p_{T_{\mathrm{LRT}}|\mathcal{H}_1}(t)dt \\ &= 1 - \int_0^{\tau} p_{\varphi_{LC}|\mathcal{H}_1}(t + C)\, dt \\ &= 1 - \left[P_{\varphi_{LC}|\mathcal{H}_1}(\tau + C) - P_{\varphi_{LC}|\mathcal{H}_1}(C)\right] \end{aligned} \tag{48}$$

where $p_{T_{\mathrm{LRT}}|\mathcal{H}_1}(t)$ and $p_{\varphi_{LC}|\mathcal{H}_1}(t)$ are the PDFs of T_{LRT} and φ_{LC}, respectively. The CDF of a central chi-squared RV χ^2_l can be formulated as [26]

$$P_{\chi^2_l}(\tau) = 1 - \frac{\Gamma(l/2, \tau/2)}{\Gamma(l/2)} \tag{49}$$

where $\Gamma(s)$ and $\Gamma(s, x)$ are the complete and upper incomplete gamma functions based on [26], respectively. Then, by inserting (42) and (49) into (48), the series expansions of $P_{d,\mathrm{LRT}}(\tau)$ can be given by (19) in Proposition 2. Furthermore, the truncation error $\varepsilon_d(\tau, I)$ corresponding to the first I terms satisfies the following relationship, i.e.,

$$\begin{aligned} |\varepsilon_d(\tau, I)| &= \left|\varepsilon_{\psi_{LC}|\mathcal{H}_1}(C, I) - \varepsilon_{\psi_{LC}|\mathcal{H}_1}(\tau + C, I)\right| \\ &\leq \max\left\{\varepsilon_{\psi_{LC}|\mathcal{H}_1}(C, I), \varepsilon_{\psi_{LC}|\mathcal{H}_1}(\tau + C, I)\right\} \\ &\leq 1 - \sum_{i=0}^{I-1} a_{\mathcal{H}_1,i}. \end{aligned} \tag{50}$$

Similarly, under hypothesis $\mathcal{H}_0$, we can also obtain the series expansions of false alarm probability of the LRT-based NED-CS scheme $P_{\mathrm{fa,LRT}}(\tau)$, which is presented in (20) in Proposition 2. The truncation error corresponding to the first I terms can be given by

$$|\varepsilon_{\mathrm{fa}}(\tau, I)| \leq 1 - \sum_{i=0}^{I-1} a_{\mathcal{H}_0,i} \tag{51}$$

where the ith series coefficient $a_{\mathcal{H}_0,i}$ of the series expansions of $P_{\mathrm{fa,LRT}}(\tau)$ under hypothesis $\mathcal{H}_0$ can be computed by substituting $\mu_{\zeta_k|\mathcal{H}_0}$ and $\sigma^2_{\zeta_k|\mathcal{H}_0}$ for $\mu_{\zeta_k|\mathcal{H}_1}$ and $\sigma^2_{\zeta_k|\mathcal{H}_1}$ in (44), respectively.

APPENDIX C
PROOF OF PROPOSITION 3

Under hypothesis $\mathcal{H}_1$, as a linear combination of noncentral chi-squared RVs, the rth cumulant of ψ_{LC} can be expressed as [30]

$$c_{\mathcal{H}_1,r} = 2^{r-1}(r-1)!\left(\sum_{k=1}^{K}\sigma^{2r}_{\zeta_k|\mathcal{H}_1} + r\sum_{k=1}^{K}\sigma^{2r-2}_{\zeta_k|\mathcal{H}_1}\mu^2_{\zeta_k|\mathcal{H}_1}\right). \tag{52}$$

Usually, we can use a central chi-squared distribution to approximate the distribution of the linear combination of noncentral squared RVs [31], i.e.,

$$\Pr\left(\frac{\varphi_{LC} - \mu_{\varphi_{LC}|\mathcal{H}_1}}{\sigma_{\varphi_{LC}|\mathcal{H}_1}} \leq \tau^*\right) \approx \Pr\left(\frac{\chi^2_{l_{\mathcal{H}_1}} - \mu_{\chi^2|\mathcal{H}_1}}{\sigma_{\chi^2|\mathcal{H}_1}} \leq \tau^*\right) \tag{53}$$

where the mean and standard deviation of ψ_{LC} are $\mu_{\varphi_{LC}|\mathcal{H}_1} = c_{\mathcal{H}_1,1}$ and $\sigma_{\varphi_{LC}|\mathcal{H}_1} = \sqrt{c_{\mathcal{H}_1,2}}$. Meanwhile, the mean and standard deviation of the central chi-squared RV $\chi^2_{l_{\mathcal{H}_1}}$ are $\mu_{\chi^2|\mathcal{H}_1} = l_{\mathcal{H}_1}$ and $\sigma_{\chi^2|\mathcal{H}_1} = \sqrt{2l_{\mathcal{H}_1}}$, respectively. Based on the match of three-order moments, parameter $l_{\mathcal{H}_1}$ can be determined by assuming that $\chi^2_{l_{\mathcal{H}_1}}$ and ψ_{LC} have identical skewness [31]. As a result

$$l_{\mathcal{H}_1} = \frac{8c^3_{\mathcal{H}_1,2}}{c^2_{\mathcal{H}_1,3}}. \tag{54}$$

Based on the CDF expression of the central chi-squared RV $\chi^2_{l_{H_1}}$ presented in (49), we can formulate the CDF of ψ_{LC} as follows:

$$P_{\varphi_{LC}|\mathcal{H}_1}(\tau) \approx 1 - \frac{\Gamma\left(l_{H_1}/2, \tau^*_{\mathcal{H}_1\cdot\tau}/2\right)}{\Gamma\left(l_{\mathcal{H}_1}/2\right)} \tag{55}$$

where $\tau^*_{\mathcal{H}_1,\tau} = (\tau - \mu_{\varphi_{LC}|\mathcal{H}_1})\sigma_{\chi^2|\mathcal{H}_1}/\sigma_{\varphi_{LC}|\mathcal{H}_1} + \mu_{\chi^2|\mathcal{H}_1}$ is the modified detection threshold corresponding to τ. Then, let the modified detection thresholds $\tau^*_{\mathcal{H}_1,C}$ corresponding to C and $\tau^*_{\mathcal{H}_1,\tau+C}$ corresponding to $\tau + C$ be

$$\tau^*_{\mathcal{H}_1,C} = \frac{C - \mu_{\varphi_{LC}|\mathcal{H}_1}}{\sigma_{\varphi_{LC}|\mathcal{H}_1}} \sigma_{\chi^2|\mathcal{H}_1} + \mu_{\chi^2|\mathcal{H}_1} \tag{56}$$

$$\tau^*_{\mathcal{H}_1,\tau+C} = \frac{\tau + C - \mu_{\varphi_{LC}|\mathcal{H}_1}}{\sigma_{\varphi_{LC}|\mathcal{H}_1}} \sigma_{\chi^2|\mathcal{H}_1} + \mu_{\chi^2|\mathcal{H}_1} \tag{57}$$

respectively. Based on (48) in Appendix B, the detection probability $P_{d,\mathrm{LRT}}(\tau)$ of the LRT-based NED-CS scheme can be approximated as (21) in Proposition 3.

Similarly, under hypothesis $\mathcal{H}_0$, we can obtain the closed-form approximation of false alarm probability of the LRT-based NED-CS scheme, which is presented in (22) in Proposition 3.

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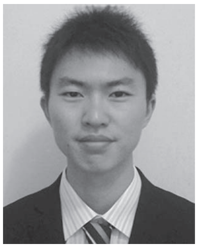

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