

A Novel CoMAC-based Cooperative Spectrum Sensing Scheme in Cognitive Radio Networks

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Abstract—Conventional cooperative spectrum sensing (CSS) schemes in cognitive radio networks (CRNs) require that the secondary users (SUs) report their sensing data sequentially to the fusion center, which yields long reporting delay especially in the case of large number of cooperative SUs. By exploiting the computation over multiple-access channel (CoMAC) method, this paper proposes a novel CoMAC-based CSS scheme that allows the cooperative SUs to encode their local statistics in transmit power and to transmit simultaneously the modulated symbols sequence carrying transmit power information to the fusion center. The fusion center then makes the final decision on the presence of primary users by recovering the overall test statistic of energy detection from the energy of the received signal. Performance metrics of the CoMAC-based CSS scheme, i.e., detection probability and false alarm probability, are further derived based on the central limit theorem. Finally, based on the derived detection and false alarm probabilities, both energy detection threshold and spectrum sensing time are optimized to improve the average throughput of the CRN.

I. INTRODUCTION

With the proliferation of wireless technologies, spectrum scarcity problem hinders the further development of nowadays wireless communication systems. For this, an emerging technology-cognitive radio (CR), in which the secondary users (SUs) are able to detect the spectrum opportunity and access the vacant spectrum of primary users (PUs), has received much attention recently [1]. Spectrum sensing is the most fundamental function of cognitive radio [2]. Due to the presence of noise and fading of wireless channels, hidden terminals, and obstacles, etc., spectrum sensing of individual nodes cannot achieve high detection accuracy. In contrast, cooperative spectrum sensing (CSS) exploits a parallel fusion sensing architecture in which independent SUs transmit their sensing data to a fusion center. The fusion center then makes a final soft or hard decision regarding the presence or absence of PUs. The cooperative gain in spectrum sensing performance has been extensively demonstrated in existing works [3]-[8].

In conventional CSS schemes, the local statistic of each SU has to be sent to the fusion center in consecutive time slots based on a time division multiple access (TDMA) scheme, due to the extremely limited bandwidth of the common control channel. Correspondingly, the fusion center decodes each received local statistic sequentially and finally computes the overall test statistic which in this paper turns out the arithmetic

mean of the collected local statistics. The drawback of conventional CSS schemes is the large reporting delay, especially when the CRN scales. Code division multiple access (CDMA) and orthogonal frequency division multiple access (OFDMA) can allow SUs to transmit concurrently in the same time slot their local statistics to the fusion center. However, either CDMA or OFDMA requires a reporting control channel with large bandwidth, which is impractical in the CRN scenario.

Motivated by the recent robust analog function computation scheme—computation over multiple-access channel (CoMAC) [9][10], this paper proposes a novel CoMAC-based CSS scheme, in which each SU first transmits a distinct complex-valued sequence at a transmit power depending on the SU reading and consequently the received energy at the fusion center equals the sum of all transmit energies corrupted by background noise. The fusion center then takes advantage of the collected energy information to estimate the desired arithmetic mean of the local statistics from SUs, based on which the spectrum availability is determined. This paper then establishes an analytical framework on the performance of the proposed CoMAC-based CSS scheme. The major contributions of this paper are summarized as follows:

- We develop a CoMAC-based CSS scheme for accelerating the spectrum sensing in CRNs with guaranteed sensing accuracy. In contrast to conventional CSS schemes, the proposed CSS scheme needs only one reporting time unit to collect all of the local statistics.
- We derive the detection probability and the false alarm probability, two primary performance metrics of the proposed CSS approach and show their asymptotic trends.
- We further optimize the throughput performance of the CoMAC-based CSS by formulating an optimal sensing problem and demonstrate its convexity.

II. TECHNICAL BACKGROUND ON COOPERATIVE SPECTRUM SENSING

Consider a single-hop infrastructure CRN with M SUs, one fusion center, one control channel and one licensed channel with bandwidth W . We assume that all nodes are synchronized and the time is divided into frames. Each frame is designed with the periodic spectrum sensing for the CRN. The frame structure consists of three phases: a sensing phase, a reporting

phase and a transmission phase. In the sensing phase, all cooperative SUs perform spectrum sensing by energy detection locally. In the reporting phase, the local sensing data at each SU is sequentially reported to the fusion center. Then, the fusion center makes the global decision with respect to received local sensing results according to one given fusion rule and broadcasts the global decision over the control channel at the end of the reporting phase. The time for decision fusion and broadcast at the fusion center is fixed and we set the time as one reporting mini-slot for simplicity in the following analysis. In the transmission phase, the transmissions of SUs are scheduled by a TDMA MAC protocol if the PU is detected absent by the end of the reporting phase. Let τ_s and τ_t denote the length of the sensing phase and the transmission phase, respectively, and let τ denote one mini-slot length in the reporting phase. Then one frame length is given by $T = \tau_s + (M + 1)\tau + \tau_t$. The state of PU, i.e., absent or present, does not change within one frame. For notational convenience, we drop the time index and consider an arbitrary frame.

The local spectrum sensing problem at each SU, say i ($1 \leq i \leq M$), can be formulated as a binary hypothesis between the following two hypothesis:

$$\begin{cases} \mathcal{H}_0 : y_i(n) = u_i(n), & n = 1, 2, \dots, N_i \\ \mathcal{H}_1 : y_i(n) = h_i(n)s(n) + u_i(n), & n = 1, 2, \dots, N_i \end{cases} \quad (1)$$

where \mathcal{H}_0 and \mathcal{H}_1 denote the PU is absent and present on the licensed channel, respectively. $N_i = \tau_s f_i^s$ denotes the number of samples, where $f_i^s (f_i^s \geq 2W)$ represents the sampling frequency of SU i . $y_i(n)$ represents the received signal at the SU i . $u_i(n)$ represents the circular symmetric complex Gaussian noise with mean 0 and variance σ_u^2 . The primary signal $s(n)$ is a random process with mean 0 and variance σ_s^2 . Similar to [3], the channel gain $|h_i(n)|$ is assumed Rayleigh-distributed with the same variance σ_h^2 . $s(n)$, $u_i(n)$, and $h_i(n)$ are independent of each other, and the average received SNR at each sensor is given as $\gamma = \frac{\sigma_h^2 \sigma_s^2}{\sigma_u^2}$. For spectrum sensing, SU i uses the average of energy content in received samples as the test statistic for energy detector

$$T_i(y) = \frac{1}{N_i} \sum_{n=1}^{N_i} |y_i(n)|^2, \quad (2)$$

and then $T_i(y)$ is reported to the fusion center.

At the fusion center, the overall test statistic for spectrum sensing is calculated as

$$T_s^{all}(y) = \frac{1}{M} \sum_{i=1}^M T_i(y). \quad (3)$$

To make the final decision, the fusion center compares $T_s^{all}(y)$ with a threshold ε_s . The PU is estimated to be absent if $T_s^{all}(y) < \varepsilon_s$, or present otherwise. This process is referred to as the soft decision-based CSS.

Different from soft decision, in hard decision the SUs feed back only their binary decision results to the fusion center. The local binary decision μ_i for SU i is made as follows:

$$\mu_i = \begin{cases} 1, & T_i(y) \geq \varepsilon_i \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

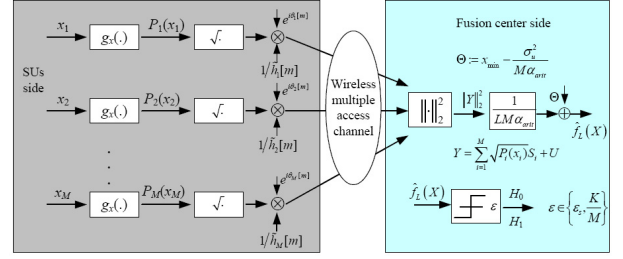


Fig. 1. Block diagram of the CoMAC-based CSS scheme

where ε_i denotes the local detection threshold of SU i . At the fusion center, the overall test statistic for spectrum sensing with the hard decision rule is calculated as

$$T_h^{all}(y) = \frac{1}{M} \sum_{i=1}^M \mu_i. \quad (5)$$

The fusion rule adopted by fusion center is commonly termed as the K -out-of- M rule, where the final decision $\mu = 1$ if $T_h^{all}(y) \geq \frac{K}{M}$.

III. COMAC-BASED COOPERATIVE SPECTRUM SENSING

From Section II, we observe that in order to compute the overall test statistic (no matter $T_s^{all}(y)$ in (3) or $T_h^{all}(y)$ in (5)), the fusion center has to collect the reports from SUs successively. This paper combines the CoMAC method [10] with CSS schemes to reduce the reporting delay in the reporting phase, which finally enhances the average throughput of the CRN.

Fig. 1 illustrates the working principle of the novel CoMAC-based CSS scheme. We use $x_i \in \{T_i(y), \mu_i\}$ to represent the local statistic of SU i . M SUs jointly detect the presence of PU resulting in local statistics $x_i \in \mathbb{X} \subset \mathbb{R}$, $i = 1, \dots, M$, and send local statistics to the fusion center, where $\mathbb{X} := [x_{min} \ x_{max}]$ denotes the hardware-dependent sensing range. The fusion center then computes an arithmetic mean of the received data.

At each SU, the local statistic is encoded in transmit power. For this, we introduce a bijective continuous mapping $g_x : \mathbb{X} \rightarrow [0, P_{max}]$ from the set of all local statistics onto the set of all feasible transmit powers, where P_{max} represents the transmit power constraint on each SU. The employed mapping function is $g_x(x) = \alpha_{arit}(x - x_{min})$, where $\alpha_{arit} = \frac{P_{max}}{x_{max} - x_{min}}$. The quantity $P_i(x_i) = g_x(x_i)$ is called the transmit power of SU i . Let $S_i := (S_i[1], S_i[2], \dots, S_i[L])^T \in \mathbb{C}^L$ denote a sequence of random transmit symbols independently generated by SU i and let L denote the length of the symbol sequence. The symbols of the sequence are assumed to be of the form $S_i[m] = e^{j\theta_i[m]}$, $m = 1, \dots, L$, where \mathbf{i} denotes the imaginary unit, and $\{\theta_i[m]\}_{i,m}$ are continuous random phases that are independent identically and uniformly distributed on $[0, 2\pi)$. Then the m th transmit symbol of SU i takes the form

$$W_i[m] = \frac{\sqrt{P_i(x_i)}}{\tilde{h}_i[m]} S_i[m], \quad (6)$$

where $\tilde{h}_i[m]$ denotes an independent complex-valued flat fading process between SU i and the fusion center. It is reported in [9] that the channel magnitude $|\tilde{h}_i[m]|$ at the transmitter is sufficient to achieve the same performance as with full channel state information. In practical systems $|\tilde{h}_i[m]|$ can be estimated from the Received Signal Strength Indication (RSSI) of the broadcast global decision by the fusion center during the last time frame.

Concurrent transmission of SUs yields the output at the fusion center

$$Y = \sum_{i=1}^M \sqrt{P_i(x_i)} S_i + U, \quad (7)$$

where $Y := (Y[1], Y[2], \dots, Y[L])^T \in \mathbb{C}^L$, and $U := (U[1], U[2], \dots, U[L])^T \in \mathbb{C}^L$ represents an independent stationary complex Gaussian noise, that is $U \sim \text{CN}(\mathbf{0}, \sigma_u^2 \mathbf{I}_L)$. For simplicity, let $X = [x_1, x_2, \dots, x_M] \in \mathbb{R}^M$ denote the local statistic vector.

Remark 1: Extension of the model (7) to capture wireless fast fading will be considered in our future works. Relevant results published in recent works such as those in [9] will be useful for these further studies.

Lemma 1: [10] Let $f: \mathbb{R}^M \rightarrow \mathbb{R}$ be the desired function arithmetic mean, i.e., $f(X) = \frac{\sum_{i=1}^M x_i}{M}$. Then, given $L \in \mathbb{N}$, the unbiased and consistent estimate $\hat{f}_L(X)$ of $f(X)$ is defined to be

$$\hat{f}_L(X) := \frac{1}{M\alpha_{arit}} \left(\frac{\|Y\|_2^2}{L} - \sigma_u^2 \right) + x_{min}. \quad (8)$$

It is reasonable to assume that all CSS parameters in (8) including α_{arit} , L , x_{min} and σ_u^2 are known to fusion center, where α_{arit} , L , and x_{min} are reported by the SUs to fusion center and σ_u^2 can be estimated according to the long-term historical observation at the fusion center.

With Lemma 1, the fusion center achieves the estimate of $T_s^{all}(y)$ in (3) (or $T_h^{all}(y)$ in (5)), denoted by $\hat{f}_L(T(y))$, where $T(y) = [T_1(y), T_2(y), \dots, T_M(y)] \in \mathbb{R}^M$. Instead of $T_s^{all}(y)$ (or $T_h^{all}(y)$), $\hat{f}_L(T(y))$ is then exploited by the fusion center to perform energy detection. In the rest of this paper, we will only focus on the sensing performance analysis for the CoMAC-based CSS scheme with soft decision. As the analyzing method is also applicable to its hard decision counterpart (simply replace $T_i(y)$ ($i = 1, 2, \dots, M$) and ε_s with μ_i and $\frac{K}{M}$), we omit the analysis for hard decision for brevity.

IV. SENSING PERFORMANCE ANALYSIS

Detection probability and false alarm probability are two main performance metrics measuring the sensing performance of spectrum sensing in CRNs. Detection probability, P_d , is the probability that if there are PU activities, the SUs can detect them successfully. While false alarm probability, P_f , is the probability that if there are no PU activities, the SUs falsely estimate that the PUs are present. Therefore, P_d and P_f of the proposed CoMAC-based CSS scheme are given by

$$P_d = \Pr(\hat{f}_L(T(y)) \geq \varepsilon_s | \mathcal{H}_1) \quad (9)$$

and

$$P_f = \Pr(\hat{f}_L(T(y)) \geq \varepsilon_s | \mathcal{H}_0). \quad (10)$$

According to Lemma 1, the detection condition in (9) and (10) can be reformulated as follows

$$\hat{f}_L(T(y)) \geq \varepsilon_s \Leftrightarrow \|Y\|_2^2 \geq \eta(\varepsilon_s; L, M), \quad (11)$$

where $\eta(\varepsilon_s; L, M) = LM\alpha_{arit}(\varepsilon_s - x_{min}) + L\sigma_u^2$.

A. Approximation of Sensing Performances

From Lemma 1, we know that the sum-energy of vector Y (i.e., $\|Y\|_2^2$) is critical for the calculation of $\hat{f}_L(T(y))$. Thus we first give out the expression of $\|Y\|_2^2$

$$\|Y\|_2^2 = \Delta_1 + \Delta_2, \quad (12)$$

where $\Delta_1 = L \sum_{i=1}^M P_i(T_i(y))$ and $\Delta_2 = U^H U + \sum_{i=1}^M \sum_{j=1, j \neq i}^M \sqrt{P_i(T_i(y)) P_j(T_j(y))} S_i^H S_j + 2 \sum_{i=1}^M \sqrt{P_i(T_i(y))} \text{Re}\{S_i^H U\}$.

Apparently, Δ_1 is a linear combination of all $T_i(y)$, $i = 1, 2, \dots, M$. According to (2), the mean and the variance of $T_i(y)$ are given by

$$\mathbb{E}\{T_i(y)\} = \begin{cases} \sigma_u^2, & \mathcal{H}_0 \\ (\gamma+1)\sigma_u^2, & \mathcal{H}_1 \end{cases} \quad (13)$$

$$\text{Var}\{T_i(y)\} = \begin{cases} \frac{\sigma_u^4}{N_i}, & \mathcal{H}_0 \\ \frac{(2\gamma+1)}{N_i} \sigma_u^4, & \mathcal{H}_1 \end{cases} \quad (14)$$

For convenience, we assume $N_i = N = 2\tau_s W$ (i.e., $f_i^s = 2W$).

As the local statistics $T_i(y)$ at different SUs are independent, the mean and the variance of Δ_1 can be trivially calculated as follows

$$\mathbb{E}\{\Delta_1\} = L \sum_{i=1}^M \mathbb{E}\{P_i(T_i(y))\} = \begin{cases} L\Omega_0, & \mathcal{H}_0 \\ L\Omega_1, & \mathcal{H}_1 \end{cases} \quad (15)$$

$$\begin{aligned} \text{Var}\{\Delta_1\} &= L^2 \sum_{i=1}^M \text{Var}\{P_i(T_i(y))\} \\ &= \begin{cases} \frac{L^2 M \alpha_{arit}^2 \sigma_u^4}{N}, & \mathcal{H}_0 \\ \frac{L^2 M \alpha_{arit}^2 \sigma_u^4 (2\gamma+1)}{N}, & \mathcal{H}_1 \end{cases} \end{aligned} \quad (16)$$

where for brevity we define $\Omega_0 := M\alpha_{arit}(\sigma_u^2 - x_{min})$ and $\Omega_1 := M\alpha_{arit}((\gamma+1)\sigma_u^2 - x_{min})$.

Similar to [10], we can also calculate the mean and variance of Δ_2 as follows

$$\mathbb{E}\{\Delta_2\} = L\sigma_u^2 \quad (17)$$

$$\text{Var}\{\Delta_2\} = \begin{cases} L\Omega_0(M-1+2\sigma_u^2), & \mathcal{H}_0 \\ L\Omega_1(M-1+2\sigma_u^2) + L\sigma_u^4, & \mathcal{H}_1 \end{cases} \quad (18)$$

Due to the fact that the local statistics $T(y)$, the modulated symbols sequence S_i , $i = 1, \dots, M$, and the noise U are mutually independent, and it is trivial to verify

$$\mathbb{E}\{\Delta_1 \Delta_2\} = \mathbb{E}\{\Delta_1\} \mathbb{E}\{\Delta_2\}. \quad (19)$$

With (15)-(19) in hand, we can easily calculate the mean and variance of $\|Y\|_2^2$

$$\mathbb{E}\{\|Y\|_2^2\} = \begin{cases} L(\Omega_0 + \sigma_u^2), & \mathcal{H}_0 \\ L(\Omega_1 + \sigma_u^2), & \mathcal{H}_1 \end{cases} \quad (20)$$

$$\text{Var}\{\|Y\|_2^2\} = \begin{cases} L\Omega_0(M-1+2\sigma_u^2) + \frac{L^2M\alpha_{\text{arit}}^2\sigma_u^4}{N}, & \mathcal{H}_0 \\ L\Omega_1(M-1+2\sigma_u^2) + L\sigma_u^4 + \frac{L^2M\alpha_{\text{arit}}^2\sigma_u^4(2\gamma+1)}{N}, & \mathcal{H}_1 \end{cases} \quad (21)$$

With the help of the central limit theorem we can approximate the distribution of $\|Y\|_2^2$ by Gaussian distribution.

Theorem 1: For any fixed M , $P_{\max} < \infty$ and a compact set \mathbb{X} , we have

$$\forall T(y) \in \mathbb{X}^M : \frac{\|Y\|_2^2 - \mathbb{E}\{\|Y\|_2^2\}}{\sqrt{\text{Var}\{\|Y\|_2^2\}}} \xrightarrow{d} \mathbf{N}(0,1), \quad (22)$$

as $L \rightarrow \infty$, where \xrightarrow{d} denotes the convergence in distribution.

Considering (10) and Theorem 1, we know that for a sufficiently large L , P_f finds a well-qualified approximation \tilde{P}_f as follows

$$P_f = \Pr(\|Y\|_2^2 \geq \eta(\varepsilon_s; L, M) | \mathcal{H}_0) \\ \approx \tilde{P}_f := Q\left(\frac{LM\alpha_{\text{arit}}(\varepsilon_s - \sigma_u^2)}{\sqrt{L\Omega_0(M-1+2\sigma_u^2) + \frac{L^2M\alpha_{\text{arit}}^2\sigma_u^4}{N}}}\right) \quad (23)$$

where “ \approx ” straightforwardly follows from Theorem 1, and $Q(x)$ is the complementary distribution of the standard Gaussian, i.e., $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp(-\frac{t^2}{2}) dt$.

Similarly, the approximation of P_d for sufficiently large L , \tilde{P}_d , is given by

$$\tilde{P}_d = Q\left(\frac{LM\alpha_{\text{arit}}(\varepsilon_s - (1+\gamma)\sigma_u^2)}{\sqrt{L\Omega_1(M-1+2\sigma_u^2) + \frac{L\sigma_u^4N + L^2M\alpha_{\text{arit}}^2\sigma_u^4(2\gamma+1)}{N}}}\right). \quad (24)$$

From (23) and (24), we have to constrain ε_s to the domain $\sigma_u^2 < \varepsilon_s < (1+\gamma)\sigma_u^2$ in order to make $\tilde{P}_d > 0.5$ and $\tilde{P}_f < 0.5$, which should be the case for most CR scenarios.

B. Analysis of Approximation Error

From the definition of $T_s^{\text{all}}(y)$ in (3), we know that $T_s^{\text{all}}(y)$ is simply the average of the squares sum of MN Gaussian variables, each Gaussian variable with mean 0 and variance σ_u^2 . Hence, normalized with σ_u^2 (or $\sigma_u^2(1+\gamma)$), $T_s^{\text{all}}(y)$ has a central Chi-square distribution with MN degrees of freedom. Then the detection probability and false alarm probability of conventional CSS schemes are given by

$$\check{P}_d = \Pr\left(T_s^{\text{all}}(y) \geq \varepsilon_s | \mathcal{H}_1\right) = \frac{\Gamma\left(\frac{MN}{2}, \frac{MN\varepsilon_s}{2\sigma_u^2(1+\gamma)}\right)}{\Gamma\left(\frac{MN}{2}\right)} \quad (25)$$

and

$$\check{P}_f = \Pr\left(T_s^{\text{all}}(y) \geq \varepsilon_s | \mathcal{H}_0\right) = \frac{\Gamma\left(\frac{MN}{2}, \frac{MN\varepsilon_s}{2\sigma_u^2}\right)}{\Gamma\left(\frac{MN}{2}\right)}, \quad (26)$$

where $\Gamma(x) = \int_0^\infty t^{x-1} \exp(-t) dt$ and $\Gamma(x, a) = \int_a^\infty t^{x-1} \exp(-t) dt$.

Let e_d ($e_d = \check{P}_d - \tilde{P}_d$) and e_f ($e_f = \check{P}_f - \tilde{P}_f$) represent the approximation errors of the detection probability and false alarm probability of the proposed CoMAC-based CSS scheme, respectively. We will defer the demonstration of the approximation efficiency to Section VI, and in Section V we respectively use \tilde{P}_d and \tilde{P}_f instead of \check{P}_d and \check{P}_f to perform the spectrum sensing optimization.

V. SPECTRUM SENSING OPTIMIZATION

The objective of the spectrum sensing optimization problem is to identify the optimal detection threshold and spectrum sensing time such that the achievable throughput of the CRN is maximized while the PU is sufficiently protected. Given a sufficiently large L , the optimization problem can be formulated as follows

$$\max_{\{\varepsilon_s, \tau_s\} \geq 0} F(\varepsilon_s, \tau_s) \quad (27a)$$

$$s.t. \tilde{P}_d(\varepsilon_s, \tau_s) \geq \omega, \quad (27b)$$

$$\tau_s \leq T - 2\tau, \quad (27c)$$

where $F(\varepsilon_s, \tau_s) = \frac{T-2\tau-\tau_s}{T} (1 - \tilde{P}_f(\varepsilon_s, \tau_s)) C_0 \Pr(\mathcal{H}_0)$ represents the average throughput of the CRN. C_0 denotes the throughput of SUs if they are allowed to continuously operate in the case of \mathcal{H}_0 , and $\Pr(\mathcal{H}_0)$ denotes the probability of \mathcal{H}_0 . When the PU is active, the throughput of SUs will be close to zero and thus neglected in the definition of $F(\varepsilon_s, \tau_s)$. ω is a pre-specified threshold that is close to but less than 1.

The maximum of problem (27) must be achieved with the equality constraint in (27b), i.e., $\tilde{P}_d(\varepsilon_s^*, \tau_s^*) = \omega$, where $\{\varepsilon_s^*, \tau_s^*\}$ represents an optimal solution of problem (27). At this time, we have

$$\eta(\varepsilon_s^*) = \sqrt{\text{Var}(\|Y\|_2^2 | \mathcal{H}_1)} Q^{-1}(\omega) + \mathbb{E}(\|Y\|_2^2 | \mathcal{H}_1) \quad (28)$$

and further

$$\varepsilon_s^* = \frac{\sqrt{\text{Var}(\|Y\|_2^2 | \mathcal{H}_1)} Q^{-1}(\omega) + L\Omega_1}{LM\alpha_{\text{arit}}} + x_{\min}. \quad (29)$$

Plugging (29) into problem (27), we then achieve its equivalent form

$$\max_{0 \leq \tau_s \leq T-2\tau} \hat{F}(\tau_s) \quad (30)$$

where $\hat{F}(\tau_s) = \frac{T-2\tau-\tau_s}{T} (1 - \tilde{P}_f(\tau_s; \varepsilon_s^*)) C_0 \Pr(\mathcal{H}_0)$.

Theorem 2: When $\varepsilon_s^* \geq \sigma_u^2$ (i.e., $\tilde{P}_f \leq 0.5$), problem (30) is convex and its optimal solution τ_s^* is unique.

The detailed proof of Theorem 1 and Theorem 2 will be found in the journal version of this paper.

VI. SIMULATION

This section performs simulations to verify the effectiveness of the proposed CoMAC-based CSS scheme. Similar to [2], [3], the simulation setup is given as follows: $\Pr(\mathcal{H}_0) = 0.8$, $\omega = 0.9$, $W = 6\text{MHz}$, $C_0 = 6.6582$, $\gamma = -10\text{dB}$, $M \in \{5, 6, \dots, 25\}$, $L \in [50, 500]$, $T = 300\text{ms}$, $\tau = 10\text{ms}$, $\alpha_{\text{arit}} = 10$, $\sigma_u^2 = 1$. The simulation code is developed by Matlab.

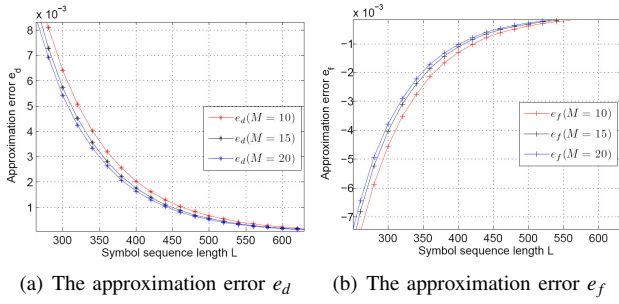


Fig. 2. Approximation error analysis

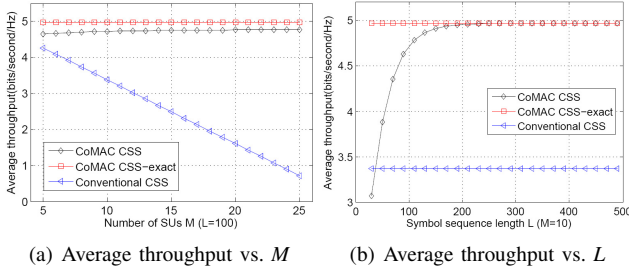


Fig. 3. Throughput comparison between different CSS schemes

A. Approximation Error Analysis

For an arbitrarily chosen $\varepsilon_s \in (\sigma_u^2, (1 + \gamma)\sigma_u^2)$ and $\tau_s \in (0, T - (M + 1)\tau)$, say $\varepsilon_s = 1.05$ and $\tau_s = 10\text{ms}$, Fig. 2 demonstrates the approximation accuracy of the CoMAC-based CSS scheme with respect to L and M . We observe that both e_d and e_f monotonically converge to zero as L increases to infinity, and decreases as the number of SUs M increases. This stems from the fact that larger L and M imply more summation terms in (12), which in turn improves the approximation accuracy because of the central limit theorem.

In order to keep a low approximation error (e.g., $|e_d|, |e_f| < 10^{-3}$), we should adopt a large enough L (e.g., $L \in [470, +\infty)$) from Fig. 2. Note that L cannot be arbitrarily large in one reporting mini-slot. Taking IEEE 802.11 physical layer whose one symbol time is $t_s = 4\mu\text{s}$ as an example, we calculate the maximum number of symbols during one reporting mini-slot by $\frac{\tau}{t_s} = 2500 (> 470)$, which proves that the proposed scheme is indeed feasible.

B. Performance Comparison

Fig. 3 presents the throughput comparison of different CSS schemes. For convenience, we denote the CoMAC-based scheme with \tilde{P}_d and \tilde{P}_f as “CoMAC CSS”, the CoMAC-based scheme with \check{P}_d and \check{P}_f as “CoMAC CSS-exact”, and the conventional CSS schemes with the Gaussian distribution of \tilde{P}_d and \tilde{P}_f [2] [3] as “Conventional CSS”. Fig. 3(a) and Fig. 3(b) display how the optimal throughput evolves with parameters M and L , respectively, where M varies from 5 to 25 with fixed L ($L = 100$) and L varies from 30 to 500 with fixed M ($M = 10$).

As shown in Fig. 3(a), “Conventional CSS” degrades as M increases, which means that the cost of large reporting time dominates the performance gain owing to cooperation

diversity. Conversely, both “CoMAC CSS” and “CoMAC CSS-exact” could benefit from the cooperation diversity without sacrificing a large portion of time on reporting local statistics, and thus outweigh “Conventional CSS”.

From Fig. 3(b), we know that by using a sufficiently large L (e.g., $L > 50$), “CoMAC CSS” dominates “Conventional CSS” even if the number of SUs is not very large ($M = 10$). The network throughput under the “conventional CSS”, 3.3717, can be boosted up to 4.9696 in the case of $L = 250$, in which the throughput gain of “CoMAC CSS” is roughly calculated $\frac{4.9696 - 3.3717}{3.3717} \approx 47.39\%$. Finally, because of the negligible approximation errors e_d and e_f , we observe that “CoMAC CSS” matches “CoMAC CSS-exact” very well when $L > 250$.

VII. CONCLUSION

This paper proposes a novel CoMAC-based CSS scheme that noticeably reduces the reporting delay of local statistics. Then, the detection and the false alarm probabilities of the proposed CSS scheme are approximated and analyzed. Finally, we obtain the optimal energy detection threshold and spectrum sensing time yielding the maximal average throughput. Extensive simulations have demonstrated the efficiency of this work.

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