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On Low Complexity Cooperative Spectrum Sensing for Cognitive Networks

(Invited Paper)

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***Abstract*—This paper presents a practical system design approach for cooperative spectrum sensing in cognitive sensor networks. An optimization problem is formulated, where the objective is to choose appropriate number of samples used in local energy calculation and linear combination weights for a global fusion center that together maximize global spectrum detection probability. Depending on the local information available to the fusion center and secondary users, practical system design is proposed in high fusion signal to noise ratio (SNR) regime, which has minimal implementation complexity and negligible performance loss, thus provides an efficient system design alternative in practice. Simulation results are presented to verify the analytical results.**

I. Introduction

Cognitive radio [1] is a key technology to exploit underutilized spectrum and enhance spectrum efficiency. In cognitive sensor networks, secondary (*unlicensed*) users monitor local communication conditions and opportunistically access unoccupied spectrum when/where the primary (*licensed*) user is inactive. To enable this dynamic spectrum access, the secondary user needs to continuously monitor local spectrum and detect spectrum holes [1]. This technique, called *spectrum sensing*, requires that the secondary user reliably detect weak signals from primary users in order to avoid harmful interference. However, due to the nature of the wireless channel (e.g., fading), a secondary user may not be able to reliably differentiate between a spectrum hole and a weak primary signal if it conducts spectrum sensing on its own. To improve detection reliability, multiple users can engage in cooperative spectrum sensing and thus take advantage of spatial diversity [2].

In [2], cooperative spectrum sensing was studied based on linear combination rule where the received signals at the fusion center are assigned different weights for global fusion and convex optimization is formulated to solve the linear weights. The optimization problem presented in [2] needs several iterations to converge to the solution. Moreover, the number of samples used for local energy calculation was considered the same for all secondary users, which does not fully exploit the diversity. In this paper, we take a more practical system design approach towards cooperative spectrum sensing in high fusion signal to noise ratio (SNR) regime. In particular, we aim to achieve a desirable global detection performance by choosing the appropriate number of samples used for local energy calculation and linear weights for global fusion. We show that our design solutions have minimal implementation complexity and negligible performance loss compared to the optimal design, thus provide an efficient system design alternative.

This paper is outlined as follows: Section II describes the system model. Section III presents the performance evaluation and problem formulation. Section IV discusses the high fusion SNR analysis. Simulation results are presented in Section V and we conclude our discussion in Section VI.

II. System Model

A. Local Energy Statistic

For secondary user i, $(1 \leq i \leq \mathrm{N})$, the hypothesis test for the energy of a received signal in a given band is

$$\begin{cases} \mathcal{H}_0: & x_i = (1/\kappa_i)\sum_{k=1}^{\kappa_i}|n_i(k)|^2 \\ \mathcal{H}_1: & x_i = (1/\kappa_i)\sum_{k=1}^{\kappa_i}|h_i s(k) + n_i(k)|^2, \end{cases} \tag{1}$$

where κ_i is the number of samples, $s(k)$ is the transmitted signal from the primary user and $n_i(k)$ is the noise received by secondary user i. We assume $s(k)$ is complex PSK modulated and independent and identically distributed (i.i.d.) with mean zero and variance σ_s^2; h_i is the channel gain, which is assumed to be constant during the cooperative spectrum sensing period; and $n_i(k)$ is i.i.d. as a circular, symmetric, complex Gaussian random variable with mean zero and variance σ_n^2, i.e., $n_i(k) \sim \mathcal{CN}(0, \sigma_n^2)$ and is independent of $s(k)$. We define the local received SNR at the secondary user as $\gamma_i = \sigma_s^2|h_i|^2/\sigma_n^2$.

When κ_i is large, the local energy statistic x_i can be approximated as Gaussian random variable [2][3], i.e.,

$$\begin{cases} \mathcal{H}_0: & x_i \sim \mathcal{N}(\sigma_n^2,\ \sigma_n^4/\kappa_i) \\ \mathcal{H}_1: & x_i \sim \mathcal{N}((1+\gamma_i)\sigma_n^2,\ (1+2\gamma_i)\sigma_n^4/\kappa_i). \end{cases} \tag{2}$$

In this paper, we assume the local received SNR γ_i is known at the secondary user i. This value could be estimated from experimental measurements when the primary system is turned on and off [2]. Additionally, we assume that the total number of samples in local energy calculation is equal to a predefined value. This indicates that $\mathbf{1}^{\mathrm{T}}\boldsymbol{\kappa} = \kappa_{\mathrm{tot}}$, where $\mathbf{1} = [1, 1, \cdots, 1]^{\mathrm{T}}$ and $\boldsymbol{\kappa} = [\kappa_1, \kappa_2, \cdots, \kappa_{\mathrm{N}}]^{\mathrm{T}}$.

B. AF Transmission and Linear Global Fusion

During the cooperation period, the secondary user transmits its local energy statistic to the fusion center using amplify-and-forward (AF) on parallel access channels (PAC) [4]. The received signal at the fusion center is shown in Fig. 1, i.e.,

$$y_i = g_i x_i + v_i, \tag{3}$$

where g_i is the amplifier gain for the secondary user i and v_i is i.i.d. Gaussian noise, i.e., $v_i \sim \mathcal{N}(0, \sigma_v^2)$ and is independent of x_i.

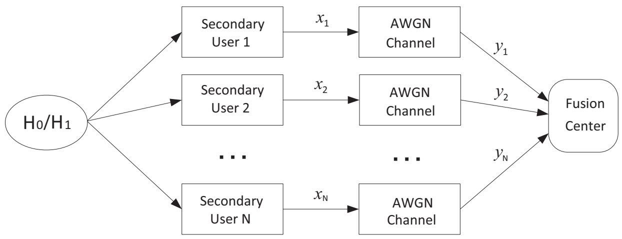

Fig. 1. Cooperative spectrum sensing in cognitive sensor networks.

Once the fusion center receives the signals from the secondary users, it combines the received signals and makes a global decision as follows [2][5]:

$$\Lambda = \sum_{i=1}^{\mathrm{N}} \omega_i y_i \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \tau_g, \tag{4}$$

where τ_g is the global decision threshold. We assume the weights $\|\boldsymbol{\omega}\| = 1$, where $\boldsymbol{\omega} = [\omega_1, \omega_2, \cdots, \omega_{\mathrm{N}}]^{\mathrm{T}}$ and $\|\cdot\|$ denotes the ℓ_2 norm of a vector.

III. Performance Evaluation and Optimization Problem Formulation

A. Performance Evaluation: NP Detection

At the fusion center, the combined signal Λ has Gaussian distribution under hypothesis $\mathcal{H}_0$ and $\mathcal{H}_1$, i.e.,

$$\begin{cases} \mathbb{E}\{\Lambda|\mathcal{H}_0\} = \sum_{i=1}^{\mathrm{N}} \omega_i g_i \sigma_n^2 \\ \mathbb{E}\{\Lambda|\mathcal{H}_1\} = \sum_{i=1}^{\mathrm{N}} \omega_i g_i (1+\gamma_i) \sigma_n^2, \end{cases}$$

and

$$\begin{cases} \mathrm{Var}\{\Lambda|\mathcal{H}_0\} = \sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2 \sigma_n^4/\kappa_i + \sigma_v^2 \\ \mathrm{Var}\{\Lambda|\mathcal{H}_1\} = \sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2 (1+2\gamma_i) \sigma_n^4/\kappa_i + \sigma_v^2. \end{cases}$$

For Neyman-Pearson (NP) detection with false alarm probability $\mathrm{P}_f = \alpha$, the global decision threshold is

$$\tau_g = \sum_{i=1}^{\mathrm{N}} \omega_i g_i \sigma_n^2 + Q^{-1}(\alpha) \left(\sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2 \sigma_n^4/\kappa_i + \sigma_v^2 \right)^{1/2},$$

where $Q(x)$ is the complementary distribution function of the standard Gaussian, i.e., $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp(-t^2/2)\mathrm{d}t$. The global detection probability is then

$$\mathrm{P}_d = Q\left(\frac{Q^{-1}(\alpha)\sqrt{\sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2/\kappa_i + \tilde{\sigma}_v^2} - \sum_{i=1}^{\mathrm{N}} \omega_i g_i \gamma_i}{\sqrt{\sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2 (1+2\gamma_i)/\kappa_i + \tilde{\sigma}_v^2}} \right),$$

where $\tilde{\sigma}_v^2 = \sigma_v^2/\sigma_n^4$. In the cognitive sensor networks, the received primary user power measured by the secondary user can be very small [6], i.e., $\gamma_i \ll 1$. Additionally, the number of samples can be large, i.e., $\kappa_i \gg 1$. Thus, $\gamma_i/\kappa_i \approx 0$. Then, for NP detection with false alarm probability $\mathrm{P}_f = \alpha$, the global detection probability can be approximated as

$$\mathrm{P}_d = Q\left(Q^{-1}(\alpha) - \frac{\sum_{i=1}^{\mathrm{N}} \omega_i g_i \gamma_i}{\sqrt{\sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2/\kappa_i + \tilde{\sigma}_v^2}} \right). \tag{5}$$

B. Optimization Problem Formulation

Our objective is to find the number of samples $\boldsymbol{\kappa}$ and the linear combining weights $\boldsymbol{\omega}$ to maximize the global detection performance. This is in contrast to [2], where only $\boldsymbol{\omega}$ is considered to be optimized for cooperative spectrum sensing. The optimization problem can be formulated as[1]

$$\begin{aligned} \max_{\boldsymbol{\kappa},\boldsymbol{\omega}} \quad & \mathrm{P}_d(\boldsymbol{\kappa},\boldsymbol{\omega}) \\ \text{s.t.} \quad & \|\boldsymbol{\omega}\| = 1,\ \boldsymbol{\omega} \succeq \mathbf{0} \\ & \mathbf{1}^{\mathrm{T}}\boldsymbol{\kappa} = \kappa_{\mathrm{tot}},\ \boldsymbol{\kappa} \succeq \mathbf{0}. \end{aligned} \tag{6}$$

This is equivalent to

$$\begin{aligned} \max_{\boldsymbol{\kappa},\boldsymbol{\omega}} \quad & \frac{\sum_{i=1}^{\mathrm{N}} \omega_i g_i \gamma_i}{\sqrt{\sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2/\kappa_i + \tilde{\sigma}_v^2}} \\ \text{s.t.} \quad & \|\boldsymbol{\omega}\| = 1,\ \boldsymbol{\omega} \succeq \mathbf{0} \\ & \mathbf{1}^{\mathrm{T}}\boldsymbol{\kappa} = \kappa_{\mathrm{tot}},\ \boldsymbol{\kappa} \succeq \mathbf{0}. \end{aligned} \tag{7}$$

Let us denote the solution as $\left(\boldsymbol{\kappa}^{(\mathrm{opt})}, \boldsymbol{\omega}^{(\mathrm{opt})}\right)$ and the maximum global detection probability as $\mathrm{P}_d^{(\mathrm{opt})}$. In the sequel, we will focus on the high fusion SNR regime for cooperative spectrum sensing. As shown below, the practical system design has minimal implementation complexity and negligible performance loss, thus provides an efficient system design alternative.

IV. High Fusion SNR Analysis

In this section, we investigate the practical system design for cooperative spectrum sensing in the high fusion SNR regime. This indicates that $\tilde{\sigma}_v^2$ is small compared to the first term in the denominator in (5). Hence, the global detection probability can be further approximated as

$$\mathrm{P}_d = Q\left(Q^{-1}(\alpha) - \frac{\sum_{i=1}^{\mathrm{N}} \omega_i g_i \gamma_i}{\sqrt{\sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2/\kappa_i}} \right). \tag{8}$$

As discussed below, the design criteria depend on whether the fusion center or the secondary users has full or partial knowledge of local information, i.e., the local received SNR $\boldsymbol{\gamma}$ and the amplifier gains $\boldsymbol{g}$, where $\boldsymbol{\gamma} = [\gamma_1, \gamma_2, \cdots, \gamma_{\mathrm{N}}]^{\mathrm{T}}$ and $\boldsymbol{g} = [g_1, g_2, \cdots, g_{\mathrm{N}}]^{\mathrm{T}}$. In particular, we consider four scenarios: 1) the fusion center has full knowledge of $(\boldsymbol{\gamma}, \boldsymbol{g})$ and the secondary users know the norm square of the local received SNR; 2) the fusion center has full knowledge of $(\boldsymbol{\gamma}, \boldsymbol{g})$ while the secondary users are blind; 3) the fusion center is blind while the secondary users know the total amplifier

[1] If $\kappa_i = 0$, we simply assume that the secondary user i does not perform the local energy calculation and does not transmit the local information to the fusion center.

gain; 4) the fusion center and secondary users are both blind. Let us define the system solutions for these four scenarios as $\left(\boldsymbol{\kappa}^{(i)}, \boldsymbol{\omega}^{(i)}\right)$, $i = 1, \cdots, 4$, and the global detection probabilities as $\mathrm{P}_d^{(i)}$, $i = 1, \cdots, 4$, respectively.

A. Case I

Here, we assume that the fusion center knows the local information $(\boldsymbol{\gamma}, \boldsymbol{g})$ and the secondary users know $\|\boldsymbol{\gamma}\|^2$. In practice, this can be realized for the secondary users to report the local information to the fusion center and for the fusion center to broadcast $\|\boldsymbol{\gamma}\|^2$ to the secondary users[2]. In this scenario, we consider a two-stage optimization strategy to maximize the global detection performance. Specifically, we first optimize the linear weights based on the number of samples, then we optimize the number of samples accordingly.

1) First Stage: Optimization of Linear Weights: We first assume that $\boldsymbol{\kappa}$ is known to the fusion center, then we see that the objective of the optimization problem is equivalent to maximizing the following function.

$$f(\boldsymbol{\omega}) = \frac{\left(\sum_{i=1}^{\mathrm{N}} \omega_i g_i \gamma_i\right)^2}{\sum_{i=1}^{\mathrm{N}} \omega_i^2 g_i^2 / \kappa_i} = \frac{(\boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{a})^2}{\boldsymbol{\omega}^{\mathrm{T}} A \boldsymbol{\omega}},$$

where $A = \operatorname{diag}\left\{g_1^2/\kappa_1, g_2^2/\kappa_2, \cdots, g_{\mathrm{N}}^2/\kappa_{\mathrm{N}}\right\}$ and $\boldsymbol{a} = [g_1\gamma_1, g_2\gamma_2, \cdots, g_{\mathrm{N}}\gamma_{\mathrm{N}}]^{\mathrm{T}}$. Using the Cauchy-Schwarz inequality, we see that

$$f(\boldsymbol{\omega}) = \frac{(\boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{a})^2}{\|A^{1/2}\boldsymbol{\omega}\|^2} = \frac{\left(\tilde{\boldsymbol{\omega}}^{\mathrm{T}} A^{-1/2} \boldsymbol{a}\right)^2}{\|\tilde{\boldsymbol{\omega}}\|^2} \leq \|A^{-1/2}\boldsymbol{a}\|^2$$

and equality holds only when $\tilde{\boldsymbol{\omega}} = \zeta A^{-1/2}\boldsymbol{a}$, or equivalently, $\boldsymbol{\omega} = \zeta A^{-1}\boldsymbol{a}$, where ζ is a constant. Since $\|\boldsymbol{\omega}\| = 1$, the optimal linear weights are given as

$$\omega_i = \frac{\kappa_i \gamma_i / g_i}{\sqrt{\sum_{i=1}^{\mathrm{N}} \kappa_i^2 \gamma_i^2 / g_i^2}}. \tag{9}$$

2) Second Stage: Optimization of Number of Samples: Plugging (9) into (8), the global detection probability reduces to $\mathrm{P}_d = Q\left(Q^{-1}(\alpha) - \left(\sum_{i=1}^{\mathrm{N}} \gamma_i^2 \kappa_i\right)^{1/2}\right)$. Based on the Cauchy-Schwarz inequality and recall that $\mathbf{1}^{\mathrm{T}}\boldsymbol{\kappa} = \kappa_{\text{tot}}$, it is easy to show that the optimal number of samples is given as $\kappa_i^{(1)} = \left[\frac{\gamma_i^2}{\|\boldsymbol{\gamma}\|^2}\kappa_{\text{tot}}\right]^{\dagger}$, where $[\cdot]^{\dagger}$ denotes the integer operation. It is worth noting that this operation should guarantee $\mathbf{1}^{\mathrm{T}}\boldsymbol{\kappa} = \kappa_{\text{tot}}$. A simple strategy for the integer operation can be given as

$$[x_i]^{\dagger} = \begin{cases} \lceil x_i \rceil, & \text{when } \gamma_i \in \mathcal{S}^+ \\ \lfloor x_i \rfloor, & \text{when } \gamma_i \in \mathcal{S}^-, \end{cases}$$

where $\lceil\cdot\rceil$ and $\lfloor\cdot\rfloor$ denote the ceiling and floor operations, respectively, $\mathcal{S}^+ = \left\{\gamma_{[\mathrm{N}_{\text{mid}}+1]}, \gamma_{[\mathrm{N}_{\text{mid}}+2]}, \cdots, \gamma_{[\mathrm{N}]}\right\}$ and $\mathcal{S}^- = \left\{\gamma_{[1]}, \gamma_{[2]}, \cdots, \gamma_{[\mathrm{N}_{\text{mid}}]}\right\}$. Here $\mathrm{N}_{\text{mid}} = \lfloor \mathrm{N}/2 \rfloor$ and $\gamma_{[i]}$ denotes the i-th smallest component of $\boldsymbol{\gamma}$, i.e., $\gamma_{[1]} \leq \gamma_{[2]} \leq \cdots \leq \gamma_{[\mathrm{N}]}$.

[2]We assume that local information remains unchanged during cooperative spectrum sensing.

For simplicity, we neglect the rounding effect of $\boldsymbol{\kappa}$ in the following analysis. It is interesting to note that $\boldsymbol{\kappa}^{(1)}$ follows from the maximal ratio combining strategy, i.e., when the local received SNR of one secondary user is larger, this secondary user is assigned more number of samples to achieve better global detection performance.

Then, plugging $\boldsymbol{\kappa}^{(1)}$ into (9), the optimal linear weights can be given as $\omega_i^{(1)} = \frac{\gamma_i^3/g_i}{\sqrt{\sum_{i=1}^{\mathrm{N}} \gamma_i^6/g_i^2}}$. Furthermore, the global detection probability can be calculated as

$$\mathrm{P}_d^{(1)} = Q\left(Q^{-1}(\alpha) - \frac{\sqrt{\sum_{i=1}^{\mathrm{N}} \gamma_i^4}}{\|\boldsymbol{\gamma}\|} (\kappa_{\text{tot}})^{1/2}\right). \tag{10}$$

B. Case II

In this case, we consider a simple strategy for local energy calculation where the number of samples for all secondary users is same, i.e., $\kappa_i^{(2)} = [\kappa_{\text{tot}}/\mathrm{N}]^{\dagger}$. Then, we see that the optimal linear weights can be computed as $\omega_i^{(2)} = \frac{\gamma_i/g_i}{\sqrt{\sum_{i=1}^{\mathrm{N}} \gamma_i^2/g_i^2}}$. Moreover, the global detection probability is given as

$$\mathrm{P}_d^{(2)} = Q\left(Q^{-1}(\alpha) - \|\boldsymbol{\gamma}\| \left(\frac{\kappa_{\text{tot}}}{\mathrm{N}}\right)^{1/2}\right).$$

It is interesting to note that the soft combining scheme in [5] can be viewed as a special case of this scenario when $g_i = g$.

C. Case III

Since the fusion center has no knowledge of the local information, an equal gain combining scheme is utilized to make a global decision, i.e., $\omega_i^{(3)} = 1/\sqrt{\mathrm{N}}$. Then, the global detection probability is given as $\mathrm{P}_d = Q\left(Q^{-1}(\alpha) - \frac{\boldsymbol{\gamma}^{\mathrm{T}}\boldsymbol{g}}{\sqrt{\sum_{i=1}^{\mathrm{N}} g_i^2/\kappa_i}}\right)$.

To maximize this global detection performance, we formulate the following convex optimization problem by choosing appropriate number of samples.

$$\begin{aligned} \min \quad & \sum_{i=1}^{\mathrm{N}} g_i^2/\kappa_i \\ \text{s.t.} \quad & \mathbf{1}^{\mathrm{T}}\boldsymbol{\kappa} = \kappa_{\text{tot}},\ \boldsymbol{\kappa} \succeq \mathbf{0}. \end{aligned} \tag{11}$$

The Lagrangian dual problem can be formulated as

$$\begin{aligned} \max \quad & -\kappa_{\text{tot}}\nu + 2\sum_{i=1}^{\mathrm{N}} g_i\sqrt{\nu - \lambda_i} \\ \text{s.t.} \quad & \lambda_i \geq 0. \end{aligned} \tag{12}$$

It is easy to see that $\lambda_i^* = 0$ and $\nu^* = (\mathbf{1}^{\mathrm{T}}\boldsymbol{g})^2/\kappa_{\text{tot}}^2$. Then, the optimal number of samples can be calculated as $\kappa_i^{(3)} = \left[\frac{g_i}{\mathbf{1}^{\mathrm{T}}\boldsymbol{g}}\kappa_{\text{tot}}\right]^{\dagger}$. Hence, the global detection probability is given as

$$\mathrm{P}_d^{(3)} = Q\left(Q^{-1}(\alpha) - \frac{\boldsymbol{\gamma}^{\mathrm{T}}\boldsymbol{g}}{\mathbf{1}^{\mathrm{T}}\boldsymbol{g}} (\kappa_{\text{tot}})^{1/2}\right).$$

D. Case IV

In this case, since the fusion center and secondary users have no knowledge of the local information, we use a simple strategy: equal number of samples and equal gain combining, i.e., $\left(\kappa_i^{(4)}, \omega_i^{(4)}\right) = \left([\kappa_{\text{tot}}/\mathrm{N}]^{\dagger}, 1/\sqrt{\mathrm{N}}\right)$. Hence, the global detection probability is given as

$$\mathrm{P}_d^{(4)} = Q\left(Q^{-1}(\alpha) - \frac{\boldsymbol{\gamma}^{\mathrm{T}}\boldsymbol{g}}{\|\boldsymbol{g}\|}\left(\frac{\kappa_{\text{tot}}}{\mathrm{N}}\right)^{1/2}\right).$$

E. Performance Comparison

Here, we compare the global detection performance of practical system design in the high fusion SNR regime. Interestingly, we see that the global detection probabilities for all four scenarios are increasing functions of κ_{tot}, i.e., when the total number of samples increases, the global detection performance improves. Furthermore, we note that

$$\mathrm{P}_d^{(1)} \geq \mathrm{P}_d^{(2)} \geq \mathrm{P}_d^{(4)} \text{ and } \mathrm{P}_d^{(3)} \geq \mathrm{P}_d^{(4)}. \tag{13}$$

The above can be readily derived based on Cauchy-Schwarz inequality and thus omitted from the paper. We see that the design solution $\left(\boldsymbol{\kappa}^{(4)}, \boldsymbol{\omega}^{(4)}\right)$ has the worst global detection performance. This is not surprising since it does not require *a prior* information for system design. Moreover, it is worth noting that we can not guarantee $\mathrm{P}_d^{(1)} \geq \mathrm{P}_d^{(3)}$, but though extensive simulations, we find that it is true in most cases.

V. Simulation Results

In our simulations, we assume $\mathrm{N} = 4$, $\tilde{\sigma}_v^2 = 1$, $\kappa_{\text{tot}} = 200$, $\boldsymbol{\gamma} = [-10, -13, -16, -19]^{\mathrm{T}}(\text{dB})$ and $\boldsymbol{g} = [23.03, 25.42, 20.51, 26.98]^{\mathrm{T}}(\text{dB})$ for the high SNR regime.

Fig. 2 shows the receiver operating characteristic (ROC) performance in the high fusion SNR regime by choosing different system design solutions. From the plot, we see that the design solution $\left(\boldsymbol{\kappa}^{(1)}, \boldsymbol{\omega}^{(1)}\right)$ has negligible performance degradation compared to the optimal solution $\left(\boldsymbol{\kappa}^{(\text{opt})}, \boldsymbol{\omega}^{(\text{opt})}\right)$, but with minimal implementation complexity, thus provides an efficient system design alternative. Additionally, we see that the design solution $\left(\boldsymbol{\kappa}^{(4)}, \boldsymbol{\omega}^{(4)}\right)$ has the worst global detection performance as mentioned in Section IV-E.

Fig. 3 shows the global detection performance as a function of κ_{tot} in the high fusion SNR regime when choosing $\left(\boldsymbol{\kappa}^{(1)}, \boldsymbol{\omega}^{(1)}\right)$. As expected, we see that the global detection performance improves when the total number of samples increases as discussed in Section IV-E.

VI. Conclusions

In this paper, we have considered the practical system design approach for cooperative spectrum sensing in the cognitive sensor networks with centeralized fusion center. In particular, we investigate practical system design to achieve a desirable global detection performance in the high fusion SNR regime by choosing appropriate number of samples and linear weights. We show that our design solutions have minimal implementation complexity and negligible performance loss, thus provide an efficient system design alternative.

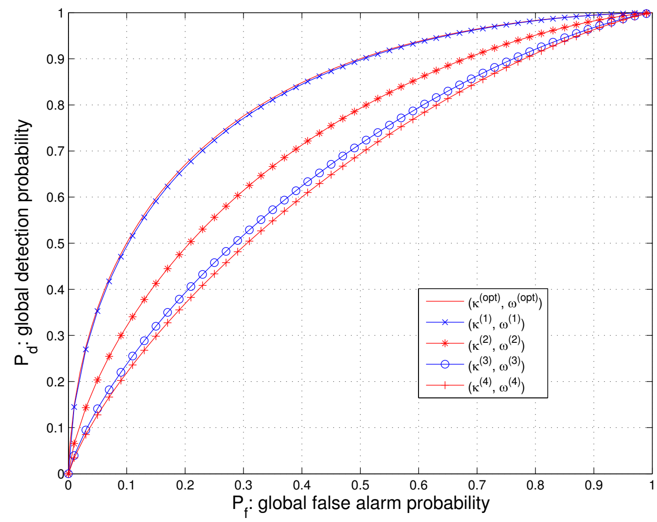

Fig. 2. Performance comparison by choosing different system design solutions in the high fusion SNR regime.

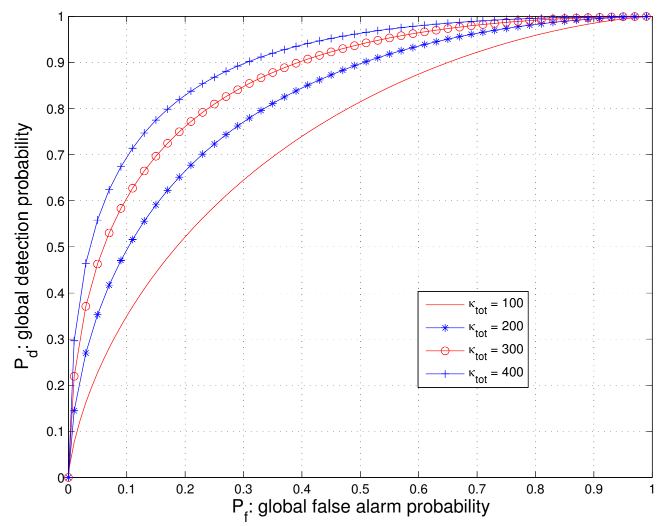

Fig. 3. Global detection performance as a function of κ_{tot} in the high fusion SNR regime.

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