PRIVACY-PRESERVING NONPARAMETRIC DECENTRALIZED DETECTION

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ABSTRACT

We consider the problem of decentralized detection of a hypothesis H using multiple sensors. The sensors also want to keep the fusion center from inferring about another hypothesis G. Each sensor makes an observation and summarizes the observation using a local decision rule. The sensor summaries are communicated to the fusion center to perform an overall decision making. As the underlying joint distribution of the hypotheses and sensor observations is unknown, we aim at finding sensor decision rules that minimize the regularized empirical risk of deciding H at the fusion center, while ensuring that the regularized risk of the fusion center deciding G correctly is more than a given threshold. We propose an optimization approach based on the Gauss-Seidel method, and show that it converges to a critical point.

Index Terms— Decentralized detection, kernel method, nonparametric, privacy-preserving, correlated source

1. INTRODUCTION

Sensor networks have seen widespread applications in industrial, military, and civilian monitoring applications like intrusion detection, target tracking, leakage detection and fall detection [1–7]. In the emerging Internet of Things (IoT) paradigm, large numbers of sensors are deployed to enable sense-making and intelligent analytics based on the sensors' observations. This can be modeled using the decentralized detection framework [8–12], where each sensor makes an observation, summarizes this observation using a local decision rule, and sends the summary to a fusion center. Based on the received sensor summaries, the fusion center then makes the final inference on a phenomenon of interest. It is intuitively clear, and has been shown in [13–15], that the error decay rate at the fusion center increases with the amount and quality of information that the sensors convey to it.

While the fusion center's role is to perform inference on a particular hypothesis of interest, there is nothing stopping it from using the received sensor information to infer another correlated hypothesis. An example is the deployment of home-monitoring video cameras in old folks' homes for fall detection. If the cameras transmit the raw video feed to a fusion center, the fusion center can not only use these video feeds for fall detection, but also has the potential to intrude on the privacy of the home inhabitants. The camera sensors therefore need to perform intelligent observation summary with a suitable sensor rule in order to limit the amount and quality of information they send to the fusion center. Another example is when an insurance company wishes to determine if a person has a particular pre-existing medical condition using medical records from hospitals the person has been treated at. However, these medical records may reveal more than the particular condition that the insurance company is investigating. The hospitals will need to decide what to send to the insurance company to avoid disclosing the person's other medical conditions. Although this latter example is not in the context of sensor networks, we can see that it nevertheless falls in the framework of how to preserve privacy in decentralized detection while still enabling the fusion center to make an inference on a particular hypothesis.

Several works have addressed the issue of privacy preservation in sensor networks from different perspectives. In [16], the author considered the problem of encoding a sequence of independent and identically distributed (i.i.d.) random variable pairs, so that the distortion rate of decoding the first source in the pair at a receiver is bounded by a predefined threshold but the equivocation rate of the second source is at least above another level. In [17], the authors proposed a general statistical inference framework to capture the privacy threat incurred by a user who releases data to a passive but curious adversary. In [18], the authors studied the bounds of how much utility is possible for a given level of privacy and vice-versa, using an information-theoretic framework. In these works, the focus is on preserving the privacy of a correlated source sequence. This is different from our problem of interest, which is to preserve the privacy of a correlated hypothesis state. In [19], preserving the privacy of a correlated hypothesis state was studied in the decentralized detection framework. The authors assumed that the underlying joint probability distribution of the hypotheses and the sensor observations are known a priori. They formulated a Bayesian detection problem in which optimal sensor rules are derived to minimize the Bayesian cost incurred at a fusion center for detecting the first hypothesis, while ensuring that the cost for detecting the second hypothesis is above a predefined threshold. The reference [20], considers decentralized detection in the presence of an eavesdropper. The goal here is to design suitable sensor rules that limits the capability of the eavesdropper from inferring the same hypothesis as the fusion center. Again, the joint probability distribution of the hypothesis and the sensor observations are known a priori.

Decentralized detection has been widely studied under the assumption that the joint probability distribution of the hypothesis and the sensor observations are known a priori, and that conditioned on the true hypothesis state, the sensor observations are i.i.d. [8, 9]. However, in many applications, distribution information may not be readily available or may be hard to estimate. Sensor observations are also often not i.i.d. A nonparametric approach to decentralized detection was introduced by [21], which proposes the use of kernel-based method to learn the optimal sensor decision rules from a given set of labeled training data. Subsequently, [22] extended this method using a weighted kernel to allow sensor selection in the decentralized detection procedure. These works however do not address the privacy issue described above.

In this paper, we develop a privacy-preserving nonparametric decentralized detection method. Similar to [21, 22], we assume that a set of labeled training data is available. We employ a kernel-based approach to learn the sensor rules so that the empirical regularized error of detecting one hypothesis is minimized, while the empirical regularized error of detecting another hypothesis, which we wish to keep private, is above a given threshold.

The rest of the paper is organized as follows. In Section 2, we present our system model and problem formulation. In Section 3, we propose a kernel-based algorithm that determines the optimal sensor rules and fusion center rules based on a set of training data, subject to a privacy constraint. We present simulation results in Section 4, and conclude in Section 5.

2. PROBLEM FORMULATION

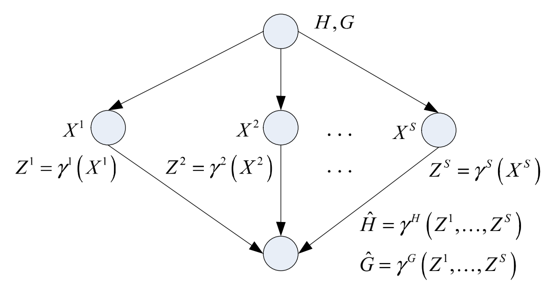

Fig. 1. Decentralized detection of H and G.

We consider the problem of designing local sensor decision rules in order for a fusion center to infer a hypothesis H, while preserving the privacy of a correlated hypothesis G. As depicted in Figure 1, suppose that the two hypotheses H and G take binary values $\{-1, +1\}$. Each sensor t, $t = 1, 2, \ldots, S$, makes a noisy observation $X^t \in \mathcal{X}$ of (H, G), summarizes its observation using a local decision rule $\gamma^t : \mathcal{X} \mapsto \mathcal{Z}$, and transmits $Z^t = \gamma^t(X^t)$ to a fusion center. We assume that both the observation space and the local decision space are discrete, i.e., $\mathcal{X} = \{1, 2, \ldots, M\}$, and $\mathcal{Z} = \{1, 2, \ldots, L\}$, where $M \gg L$. Let $\underline{X} = \{X^1, X^2, \ldots, X^S\}$ and $\underline{Z} = \{Z^1, Z^2, \ldots, Z^S\}$. Based on the received messages $\underline{Z}$, the fusion center makes a decision $\hat{H} = \gamma^H(\underline{Z}) \in \{-1, +1\}$ about the state of the hypothesis H, and a decision $\hat{G} = \gamma^G(\underline{Z}) \in \{-1, +1\}$ about the state of the hypothesis G.

We consider H to be the "public" hypothesis that the sensors want the fusion center to infer correctly. On the other hand, G is a "private" hypothesis that the sensors wish to hide from the fusion center. The fusion center, however, is curious, and after receiving the local decisions from the sensors, can implement the best rule to guess the private hypothesis G. Our goal is to find, for each sensor t, $t = 1, \ldots, S$, a local decision rule γ^t to minimize the Bayes risk $\mathbb{P}(H \neq \gamma^H(\underline{Z}))$, while keeping $\mathbb{P}(G \neq \gamma^G(\underline{Z}))$ sufficiently large for any fusion rule γ^G the fusion center may employ.

We allow each local sensor decision rule γ^t, $t = 1, \ldots, S$, to be randomized. Therefore, we can characterize it using a probability distribution $Q^t(Z^t \mid X^t)$. Since each Z^t can depend only on X^t, the conditional probability of $\underline{Z}$ given $\underline{X}$ is given by

$$Q(\underline{Z} \mid \underline{X}) = \prod_{t=1}^{S} Q^t(Z^t \mid X^t).$$

We assume that the joint probability distribution $\mathbb{P}(\underline{X}, H, G)$ is unknown, but we are given a set of n i.i.d. training data $(x_i, h_i, g_i)_{i=1}^n$ sampled from $\mathbb{P}(\underline{X}, H, G)$. Therefore, we adopt the framework of empirical risk minimization as in [21]. Let ϕ be a convex loss function, and we seek to minimize the empirical ϕ-risk of deciding H under l_2 regularization, while ensuring that the regularized empirical ϕ-risk of deciding G is higher than a given threshold T. Following [21], we restrict γ^H and γ^G to be from a reproducing kernel Hilbert space $\mathcal{H}$ associated with a kernel $K_z(\cdot, \cdot)$, i.e., γ^H and γ^G are of the form

$$\sum_{j=1}^{m} \alpha_j K_z(\cdot, \underline{z}_j),$$

for some $(\alpha_j)_{j=1}^m \in \mathbb{R}^m$, $(\underline{z}_j)_{j=1}^m \in (\mathcal{Z}^S)^m$, and $0 \leq m \leq \infty$. Let $\Phi(\underline{z}) = K_z(\cdot, \underline{z})$ be the feature map. Then, we can express the fusion center decision rules as [21]

$$\gamma^H(\underline{z}) = \left\langle w^H, \Phi(\underline{z}) \right\rangle,$$
$$\gamma^G(\underline{z}) = \left\langle w^G, \Phi(\underline{z}) \right\rangle,$$

where $w^H, w^G \in \mathcal{H}$, and $\langle \cdot, \cdot \rangle$ is the kernel inner product associated with $K_z(\cdot, \cdot)$. Let $\|\cdot\|$ denote the norm induced by the kernel inner product. Given the n i.i.d. training data points $(x_i, h_i, g_i)_{i=1}^n$, we seek to

$$\min_{\gamma^H \in \mathcal{H}, Q \in \mathcal{Q}} \sum_{\underline{z} \in \mathcal{Z}^S} \sum_{i=1}^{n} \phi(h_i \gamma^H(\underline{z})) Q(\underline{z} \mid \underline{x}_i) + \frac{\lambda}{2} \|w^H\|^2, \tag{1}$$

$$\text{s.t.} \sum_{\underline{z} \in \mathcal{Z}^S} \sum_{i=1}^{n} \phi(g_i \gamma_*^G(\underline{z})) Q(\underline{z} \mid \underline{x}_i) + \frac{\lambda}{2} \|w^G\|^2 \geq T, \tag{2}$$

$$\gamma_*^G = \arg\min_{\gamma^G \in \mathcal{H}} \sum_{\underline{z} \in \mathcal{Z}^S} \sum_{i=1}^{n} \phi(g_i \gamma^G(\underline{z})) Q(\underline{z} \mid \underline{x}_i) + \frac{\lambda}{2} \|w^G\|^2, \tag{3}$$

where $\lambda > 0$ is a regularization weight, and

$$\begin{aligned} \mathcal{Q} = \Big\{ & Q(\underline{z}|\underline{x}) = \prod_{t=1}^{S} Q^t(z^t|x^t) : \\ & \sum_{z \in \mathcal{Z}} Q^t(z \mid x^t) = 1,\ Q^t(z^t \mid x^t) \geq 0, \\ & \text{for all } x^t \in \mathcal{X}, z^t \in \mathcal{Z} \text{ and } t = 1, 2, \ldots, S \Big\}. \end{aligned}$$

Note that in (3), the fusion center attempts to find the best decision rule for deciding the private hypothesis G based on a regularized empirical risk minimization since without the regularization, it is known that the generalization error can become large [23]. Therefore, the optimal $\|w^G\|$ is relatively small. We have used the regularized empirical risk in the constraint (2) instead of just the empirical risk itself in order to simplify our algorithm design in the next section. In practical applications, a sufficiently large T can be chosen to account for the additional $\|w^G\|$ term.

3. ALGORITHM DESIGN

In this section, we first relax the optimization problem (1), propose an iterative solution method, and then show that our algorithm converges.

We employ the same lower bound relaxation as in (15) of [21], and define $\Phi'(\underline{x}) := \sum_{\underline{z}} Q(\underline{z}|\underline{x})\Phi(\underline{z})$. We consider the following optimization problem:

$$\min_{w^H\in\mathcal{H},Q\in\mathcal{Q}} \sum_{i=1}^{n} \phi\left(h_i\left\langle w^H, \Phi'(\underline{x}_i)\right\rangle\right) + \frac{\lambda}{2}\|w^H\|^2, \qquad (4)$$

$$\text{s.t.} \sum_{i=1}^{n} \phi\left(g_i\left\langle w_*^G, \Phi'(\underline{x}_i)\right\rangle\right) + \frac{\lambda}{2}\|w_*^G\|^2 \geq T,$$

$$w_*^G = \arg\min_{w^G\in\mathcal{H}} \sum_{i=1}^{n} \phi\left(g_i\left\langle w^G, \Phi'(\underline{x}_i)\right\rangle\right) + \frac{\lambda}{2}\|w^G\|^2.$$

From the Representer theorem [23], the optimal fusion rules have the form $w^H = \sum_{i=1}^n \alpha_i^H h_i \Phi'(\underline{x}_i)$ where $\underline{\alpha}^H = (\alpha_1^H, \ldots, \alpha_n^H) \in \mathbb{R}^n$, and $w^G = \sum_{i=1}^n \alpha_i^G g_i \Phi'(\underline{x}_i)$ where $\underline{\alpha}^G = (\alpha_1^G, \ldots, \alpha_n^G) \in \mathbb{R}^n$. Furthermore, let $K_Q(\underline{x}, \underline{x}') = \langle \Phi'(\underline{x}), \Phi'(\underline{x}')\rangle = \sum_{\underline{z}}\sum_{\underline{z}'} Q(\underline{z}|\underline{x})Q(\underline{z}'|\underline{x}')K_z(\underline{z}, \underline{z}')$. Then, (4) becomes

$$\min_{\underline{\alpha}^H\in\mathbb{R}^n,Q\in\mathcal{Q}} F^H(\underline{\alpha}^H, Q)$$
$$\text{s.t.} \quad F^G(\underline{\alpha}^G, Q) \geq T, \qquad (5)$$
$$\underline{\alpha}^G = \arg\min_{\underline{\alpha}\in\mathbb{R}^n} F^G(\underline{\alpha}, Q),$$

where

$$F^H(\underline{\alpha}^H, Q) = \sum_{i=1}^{n} \phi\left(h_i \sum_{j=1}^{n} \alpha_j^H h_j K_Q(\underline{x}_i, \underline{x}_j)\right) + \frac{\lambda}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i^H \alpha_j^H h_i h j K_Q(\underline{x}_i, \underline{x}_j),$$

and

$$F^G(\underline{\alpha}^G, Q) = \sum_{i=1}^{n} \phi\left(g_i \sum_{j=1}^{n} \alpha_j^G g_j K_Q(\underline{x}_i, \underline{x}_j)\right) + \frac{\lambda}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i^G \alpha_j^G g_i g_j K_Q(\underline{x}_i, \underline{x}_j).$$

By using the interior-point method with the logistic barrier, we obtain the following optimization problem

$$\min_{\underline{\alpha}^H\in\mathbb{R}^n,Q\in\mathcal{Q}} F^H(\underline{\alpha}^H, Q) - \frac{1}{\mu}\log\left(F^G(\underline{\alpha}^G, Q) - T\right), \qquad (6)$$
$$\text{s.t.} \quad \underline{\alpha}^G = \arg\min_{\underline{\alpha}\in\mathbb{R}^n} F^G(\underline{\alpha}, Q),$$

where $\mu > 0$ is the barrier parameter. From Proposition 2 in [21], for a fixed Q we have

$$\min_{\underline{\alpha}\in\mathbb{R}^n} F^G(\underline{\alpha}^G, Q) = \sup_{\underline{\alpha}^G\in\mathbb{R}^n}\left\{-\sum_{i=1}^{n}\phi^*(-\alpha_i) - \frac{1}{2\lambda}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i^G\alpha_j^G g_i g_j K_Q(\underline{x}_i, \underline{x}_j)\right\},$$

where ϕ^* is the conjugate dual of ϕ [24]. Then (6) becomes

$$\min_{\underline{\alpha}^H\in\mathbb{R}^n,\underline{\alpha}^G\in\mathbb{R}^n,Q\in\mathcal{Q}} F_0(\underline{\alpha}^H, \underline{\alpha}^G, Q),$$

where

$$F_0(\underline{\alpha}^H, \underline{\alpha}^G, Q) = F^H(\underline{\alpha}^H, Q) - \frac{1}{\mu}\log\Big(-\sum_{i=1}^{n}\phi^*(-\alpha_i^G) - \frac{1}{2\lambda}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i^G\alpha_j^G g_i g_j K_Q(\underline{x}_i, \underline{x}_j) - T\Big).$$

Algorithm 1 Gauss-Seidel Method

1: **Input:** $\{h_i, g_i, x_i^1, \ldots, x_i^S\}_{i=1}^n$
2: **Step 0:** Initialize $\underline{\alpha}^H[0] \in \mathbb{R}^n$, $\underline{\alpha}^G[0] \in \mathbb{R}^n$, $Q[0] \in \mathcal{Q}$, which satisfy the inequality constraint (5).
3: **Step $k \geq 1$:**

- Fix $\underline{\alpha}^G[k-1]$ and $Q[k-1]$, update

$$\underline{\alpha}^H[k] = \underline{\alpha}^H[k-1] - t_\alpha \nabla_{\underline{\alpha}^H} F_0(\underline{\alpha}^H[k-1], \underline{\alpha}^G[k-1], Q[k-1]),$$

where $t_\alpha \leq 2/L_0$, and L_0 is the Lipschitz constant of the objective function F_0.

- Fix $\underline{\alpha}^H[k]$ and $Q[k-1]$, update

$$\underline{\alpha}^G[k] = \underline{\alpha}^G[k-1] - t_\alpha \nabla_{\underline{\alpha}^G} F_0(\underline{\alpha}^H[k], \underline{\alpha}^G[k-1], Q[k-1]),$$

where $t_\alpha \leq 2/L_0$.

- Fix $\underline{\alpha}^H[k]$ and $\underline{\alpha}^G[k]$, update

$$Q[k] = \arg\min_{Q\in\mathcal{Q}} \left\| Q - Q[k-1] + t_Q \nabla_Q F_0(\underline{\alpha}^H[k], \underline{\alpha}^G[k], Q[k-1]) \right\|_{\ell_2},$$

where $t_Q \leq 1/L_0$.

Although $F_0(\underline{\alpha}^H, \underline{\alpha}^G, Q)$ is a non-convex function of $(\underline{\alpha}^H, \underline{\alpha}^G, Q)$, it can be shown that

- F_0 is convex in $\underline{\alpha}^H$, with both $\underline{\alpha}^G$ and Q fixed.
- F_0 is convex in $\underline{\alpha}^G$, with both $\underline{\alpha}^H$ and Q fixed.
- F_0 is convex in Q^t, with $\underline{\alpha}^G$, $\underline{\alpha}^H$ and all other $\{Q^r, r \neq t\}$ fixed.

We make use of the above properties in Algorithm 1 to minimize F_0 over $(\underline{\alpha}^H, \underline{\alpha}^G, Q)$ using a Gauss-Seidel method. At each step, each parameter is updated by the gradient projection method.

Since F_0 is not jointly convex over (α^H, α^G, Q), Algorithm 1 may not converge to a global optimal solution. Nevertheless, supposing that ϕ is a real analytic function, then since the composition of real analytic functions is real analytic, we conclude that $F_0(\underline{\alpha}^H, \underline{\alpha}^G, Q)$ is a real analytic function, which is bounded from below. Then, using similar arguments as that in Theorem 4 of [22], we have the following convergence result. The proof is omitted here due to space constraint.

Proposition 1. *If ϕ is a real analytic function, then Algorithm 1 converges to a critical point.*

4. SIMULATION RESULTS

In this section, we present simulation results to verify the performance of Algorithm 1. We consider the case where there are 20 sensors in the network, and 100 training samples and 1000 testing samples are generated. The sensor observation space is $\mathcal{X} = \{1, 2, \ldots, 11\}$, and the local decision space is $\mathcal{Z} = \{1, 2\}$. Each data point is randomly generated in $(H, G) \in \{-1, 1\}^2$ and is independent of the others. We evaluate our algorithm with different data models:

- I.I.D. model. For each $t = 1, \ldots, S$, we generate i.i.d. sensor observations by letting $X^t = x + N^t$, where N^t is generated uniformly at random from $\{-2, -1, 0, +1, +2\}$, and x is chosen according to the realization of (H, G) as in Table 1.
- Chain model. We set $X^1 = x + (N^1 + N^2)/2$, $X^5 = x+(N^4+N^5)/2$, and $X^t = x+(N^{t-1}+N^t+N^{t+1})/3$ for each sensor $t = 2, \ldots, S-1$, where x and N^t are generated in the same way as in i.i.d. model. This simulates a network in which the sensors are placed in a line, and neighboring sensors' observations are correlated.

(H, G)	x
$(-1, -1)$	-3
$(-1, 1)$	-1
$(1, -1)$	1
$(1, 1)$	3

Table 1. Sensor observations for different realizations of (H, G).

As shown in Fig 2 and Fig 3, we see that our algorithm yields a high error rate for the private hypothesis G, while keeping the error rate of deciding the public hypothesis H relatively low. And as expected, the error rates for deciding H and G increase with increasing threshold T in both models.

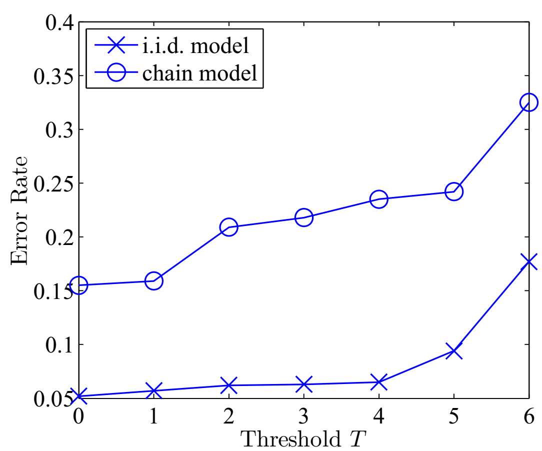

Fig. 2. Error rate of deciding public hypothesis H as T varies.

Next, we investigate how the error rates vary with the correlation between H and G. We set $T = 54$, and generate four different sets of data, where correlated random variables H and G have different correlation coefficient values $\rho_{H,G}$.

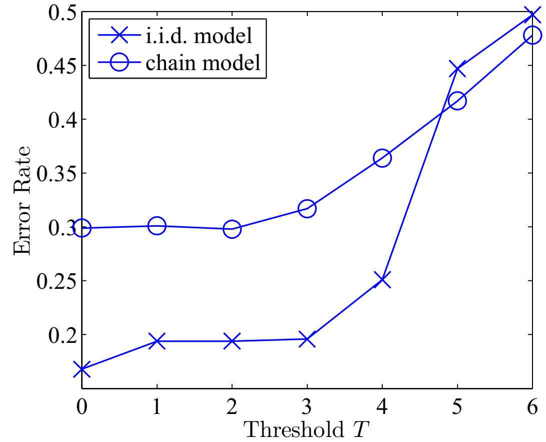

Fig. 3. Error rate of deciding public hypothesis G as T varies.

We show in Fig 4 the change of the error rates of H and G as the correlation coefficient of the joint hypothesis varies. We can find that the detection ability become more similar if H and G are more correlated.

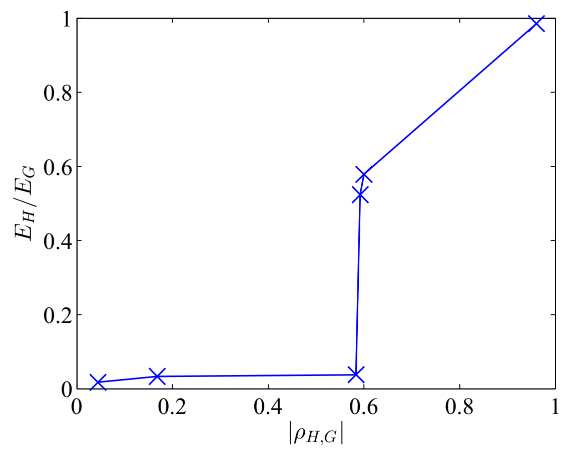

Fig. 4. The ratio between the error rates of H and G, as the correlation coefficient varies

5. CONCLUSION

In decentralized detection network, we studied the way to protect the private signal of correlated source from the curious fusion center. In this work, we proposed an algorithm to design the local decision rule and fusion center rule. And we ran several simulations to test our result.

6. ACKNOWLEDGEMENT

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