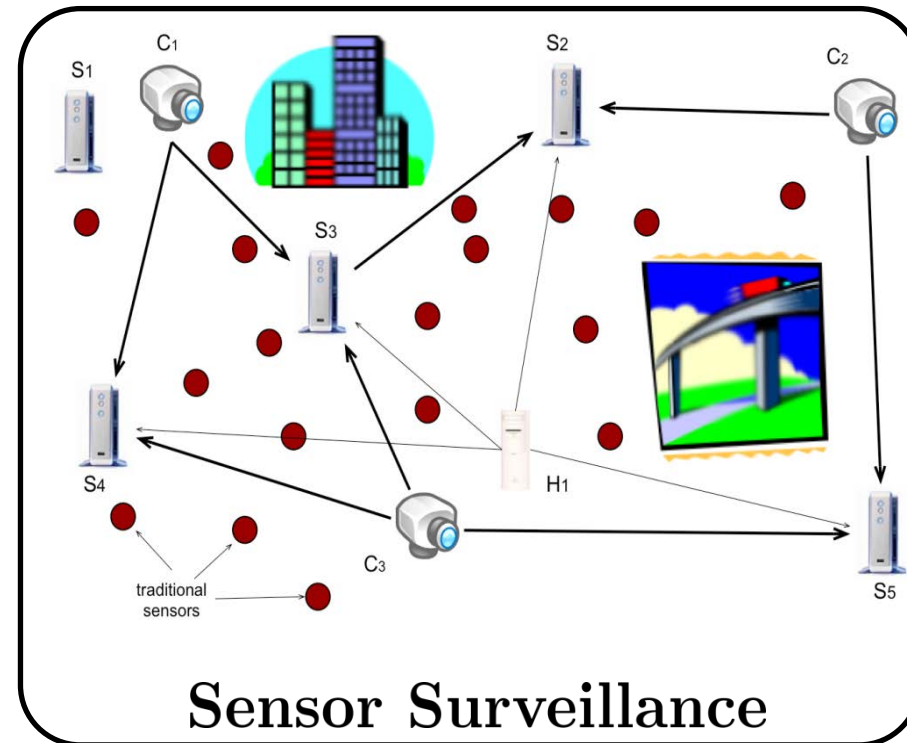
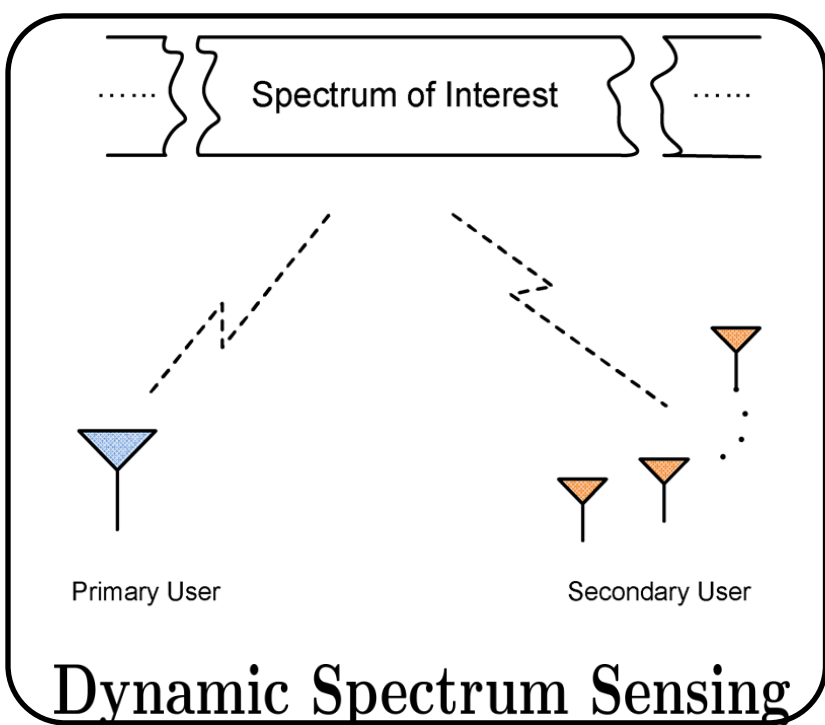


Motivation and Setup

Motivation



- Composite Hypothesis

$$\mathcal{H}_1 : \theta^* \neq 0$$

$$\mathcal{H}_0 : \theta^* = 0$$

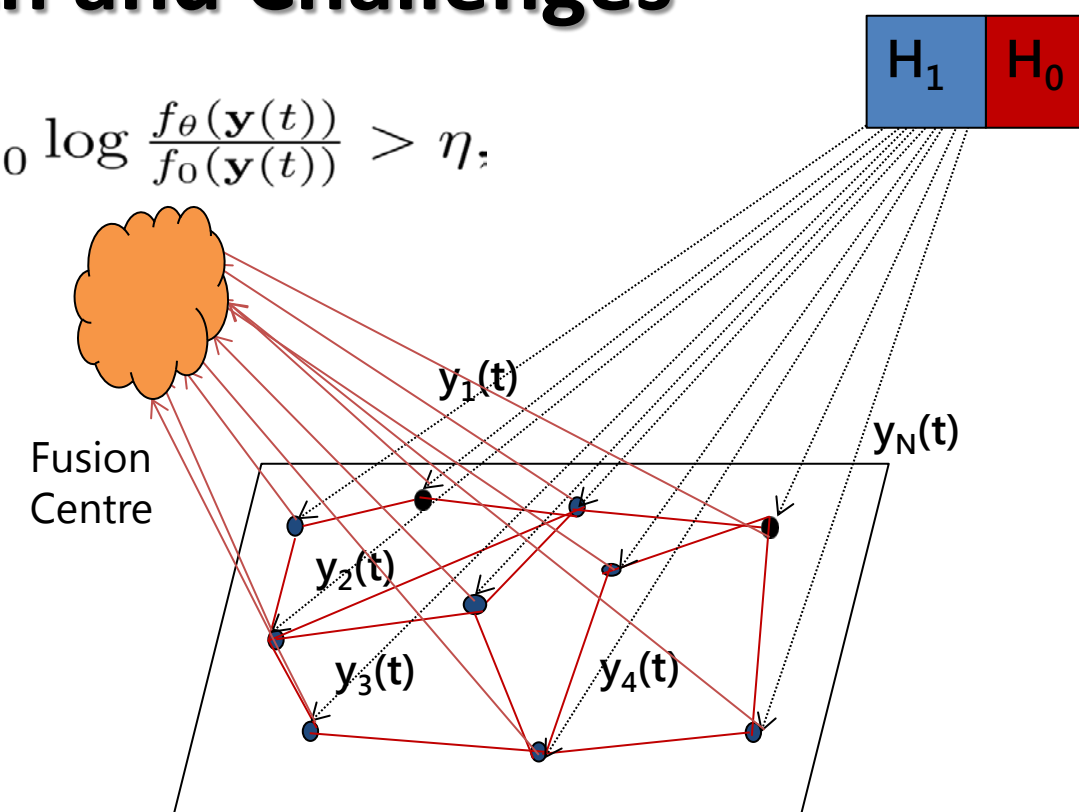
- θ^* : M -dimensional parameter, deterministic but unknown
- Network of N agents. Observation sequence at each agent

$$\mathbf{y}_n(t) = \mathbf{h}_n(\theta^*) + \gamma_n(t),$$

where $\mathbf{h}_n(\cdot)$ is a non-linear function, $\mathbf{h}_n(0) = 0$, $\mathbf{h}_n(\cdot) : \mathbf{R}^M \rightarrow \mathbf{R}^{M_n}$, $M_n \ll M$, $\gamma_n(t) \sim N(0, \Sigma_n)$

Centralized Approach and Challenges

$$\mathcal{H} = \begin{cases} \mathcal{H}_1, & \text{if } \max_{\theta} \sum_{t=0}^T \log \frac{f_{\theta}(\mathbf{y}(t))}{f_0(\mathbf{y}(t))} > \eta, \\ \mathcal{H}_0, & \text{otherwise,} \end{cases}$$



$f_0(\mathbf{y}(t)) = f_0^1(\mathbf{y}_1(t)) \cdots f_0^N(\mathbf{y}_N(t))$: likelihood of $\mathbf{y}(t)$ under \mathcal{H}_0
 $f_{\theta}(\mathbf{y}(t)) = f_{\theta}^1(\mathbf{y}_1(t)) \cdots f_{\theta}^N(\mathbf{y}_N(t))$: likelihood of $\mathbf{y}(t)$ under \mathcal{H}_1, θ

- Key bottleneck

$$\max_{\theta} \sum_{t=0}^T \log \frac{f_{\theta}(\mathbf{y}(t))}{f_0(\mathbf{y}(t))} = \max_{\theta} \sum_{t=0}^T \sum_{n=1}^N \log \frac{f_{\theta}^n(\mathbf{y}_n(t))}{f_0^n(\mathbf{y}_n(t))}$$

- Depends on the entire sensed data.

- High-dimensional data exchange at all times.

- Involves batch processing: Detection cannot start until the maximizer is obtained

Distributed Approach

Assumptions

(A.1)-Global Observability The sensing model is globally observable, i.e., any two distinct values of θ and θ^* in the parameter space satisfy

$$\sum_{n=1}^N \|\mathbf{h}_n(\theta) - \mathbf{h}_n(\theta^*)\|^2 = 0$$

if and only if $\theta = \theta^*$.

(A.2)-Network Connectivity The inter-agent communication graph is connected, i.e., $\lambda_2(\mathbf{L}) > 0$, where \mathbf{L} denotes the associated graph Laplacian matrix.

(A.3)-Smoothness For each agent n , $\forall \theta \neq \theta_1$, the sensing functions \mathbf{h}_n are continuously differentiable and Lipschitz continuous with constants $k_n > 0$, i.e.,

$$\|\mathbf{h}_n(\theta) - \mathbf{h}_n(\theta_1)\| \leq k_n \|\theta - \theta_1\|.$$

(A.4)-Monotonicity For each pair of θ and $\hat{\theta}$ with $\theta \neq \hat{\theta}$, there exists a constant $c^* > 0$ such that the following aggregate strict monotonicity condition holds

$$\sum_{n=1}^N (\theta - \hat{\theta})^{\top} (\nabla \mathbf{h}_n(\theta)) \Sigma_n^{-1} (\mathbf{h}_n(\theta) - \mathbf{h}_n(\hat{\theta})) \geq c^* \|\theta - \hat{\theta}\|^2.$$

CIGLRT: Consensus+Innovations GLRT Algorithm

Parameter Estimation Update

$$\theta_n(t+1) = \theta_n(t) - \beta_t \underbrace{\sum_{l \in \Omega_n} (\theta_n(t) - \theta_l(t))}_{\text{neighborhood consensus}} + \underbrace{\alpha_t \nabla \mathbf{h}_n(\theta_n(t)) \Sigma_n^{-1} (\mathbf{y}_n(t) - \mathbf{h}_n(\theta_n(t)))}_{\text{local innovation}}$$

The weight sequences $\{\alpha_t\}_{t \geq 0}$ and $\{\beta_t\}_{t \geq 0}$ are given by

$$\alpha_t = \frac{1}{(t+1)} \quad \beta_t = \frac{b}{(t+1)^{\tau_2}},$$

Decision Statistic Update

$$z_n(t+1) = \frac{t}{t+1} \left(z_n(t) - \underbrace{\delta \sum_{l \in \Omega_n} (z_n(t) - z_l(t))}_{\text{neighborhood consensus}} \right) + \underbrace{\frac{1}{t+1} \log \frac{f_{\theta_n(t)}(\mathbf{y}_n(t))}{f_0(\mathbf{y}_n(t))}}_{\text{local innovation}}$$

$$\delta \in \left(0, \frac{2}{\lambda_N(\mathbf{L})} \right),$$

$$\text{Decision Rule} \quad \mathcal{H}_n(t) = \begin{cases} \mathcal{H}_0 & z_n(t) \leq \eta \\ \mathcal{H}_1 & z_n(t) > \eta, \end{cases}$$

Probability of Errors

$$P_{M, \theta^*}(t) = P_{1, \theta^*}(z_n(t) \leq \eta)$$

$$P_{FA}(t) = P_0(z_n(t) > \eta),$$

Main Results

Asymptotic Normality and Error Analysis

Theorem 1: Asymptotic Normality Consider the CIGLRT algorithm under Assumptions A.1-A.4, and the sequence $\{\mathbf{z}(t)\}$. We then have under P_{θ^*} , for all $\|\theta^*\| > 0$,

$$\sqrt{t+1} \left(z_n(t) - \frac{\mathbf{h}^{\top}(\theta_N^*) \Sigma^{-1} \mathbf{h}(\theta_N^*)}{2N} \right) \xrightarrow{\mathcal{D}} \mathcal{N} \left(0, \frac{\mathbf{h}^{\top}(\theta_N^*) \Sigma^{-1} \mathbf{h}(\theta_N^*)}{N^2} \right), \forall n$$

where $\theta_N^* = \mathbf{1}_N \otimes \theta^*$, $\mathbf{h}(\theta_N^*) = [\mathbf{h}_1^{\top}(\theta^*) \cdots \mathbf{h}_N^{\top}(\theta^*)]^{\top}$ and $\xrightarrow{\mathcal{D}}$ refers to convergence in distribution (weak convergence).

Theorem 2: Error Analysis Consider the decision rule of CIGLRT. For all θ^* which satisfy $\frac{\mathbf{h}^{\top}(\theta_N^*) \Sigma^{-1} \mathbf{h}(\theta_N^*)}{2N} > \frac{(\frac{1}{N} + \sqrt{Nr}) \sum_{n=1}^N M_n}{2}$, we have the following choice of the thresholds $\frac{(\frac{1}{N} + \sqrt{Nr}) \sum_{n=1}^N M_n}{2} < \eta < \frac{\mathbf{h}^{\top}(\theta_N^*) \Sigma^{-1} \mathbf{h}(\theta_N^*)}{2N}$ for which we have that $P_{M, \theta^*}(t) \rightarrow 0$ and $P_{FA}(t) \rightarrow 0$ as $t \rightarrow \infty$. Specifically, $P_{FA}(t)$ decays to zero exponentially with the following large deviations exponent

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log (P_0(z_n(t) > \eta)) \leq -LE(\min\{\lambda^*, 1\}),$$

where $LE(\lambda) = \frac{\eta \lambda}{\frac{1}{N} + \sqrt{Nr}} + \left(\frac{\sum_{n=1}^N M_n}{2} \right) \log \left(1 - \frac{\lambda (\frac{1}{N} + \sqrt{Nr})}{\frac{\mathbf{h}^{\top}(\theta_N^*) \Sigma^{-1} \mathbf{h}(\theta_N^*)}{2N}} \right)$,

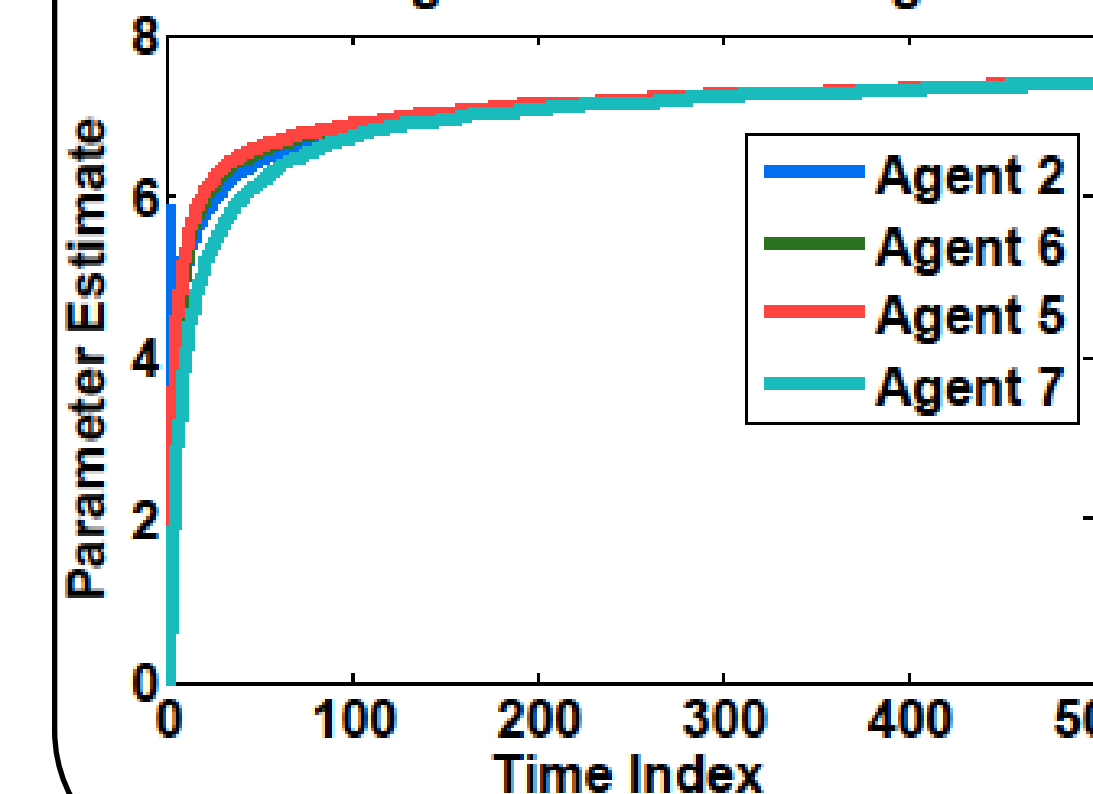
$$\lambda^* = \frac{\frac{1}{N} + \sqrt{Nr}}{\frac{1}{N} + \sqrt{Nr}} - \frac{(\frac{1}{N} + \sqrt{Nr}) \sum_{n=1}^N M_n}{2\eta}.$$

Simulation Results

- Linear Scalar Model: $\mathbf{h}_n(\theta) = h_n \theta$.
- Network of 10 agents: 5 are defective, only observe noise.
- Scaling factors of the other 5 agents: 1, 1.5, 0.8, 2, 0.9
- $\theta^* = 7.8$, noise power = 3.
- Random geometric network: $\|\mathbf{I} - \delta \mathbf{L} - \frac{1}{N} \mathbf{1} \mathbf{1}^{\top}\| = 0.9161$.

Convergence Analysis

Convergence of different agents



Probability of Miss

Probability of Miss of different agents

