Journal Watch
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Distributed Parameter Estimation With Quantized Communication via Running Average

Shanying Zhu, Yeng Chai Soh, and Lihua Xie

- Estimate a deterministic unknown θ over sensor network
  - Strongly connected directed graph
  - Quantized communication
- **Model:** $y_i = \theta + w_i$
  - $w_i \sim \mathcal{N}(0, \sigma^2)$
- **Approach:**

$$x_i(t+1) = \hat{x}_i(t) + \alpha \sum_{j \in \mathcal{N}_i} a_{ij} \left[\mathcal{Q}\left(\hat{x}_j(t)\right) - \mathcal{Q}\left(\hat{x}_i(t)\right) \right]$$

$$\hat{x}_i(t) = x_i(t) + \epsilon_i(t)$$

- **Goal:** Design $\epsilon_i(t)$ such that $x_i(t) \rightarrow$MVU estimate

- Compensation mechanism related with the left eigenvector corresponding to zero eigen value of Laplacian of the graph, ω
- **Distributed algorithm:** inter-winding two stages at each node i
  - Stage 1: Receive the estimates of ω_j for all $j \in \mathcal{N}_i$; update ω_i
  - Stage 2: compute $\epsilon_i(t)$ using estimate in stage 1.
- **Convergence analysis**
  - In mean square and almost sure sense

Optimal Estimation for Discrete-Time Linear Systems in the Presence of Multiplicative and Time-Correlated Additive Measurement Noises

Wei Liu

- **Problem:** State estimation for discrete-time linear systems

State evolution: $x_{k+1} = A_k x_k + w_k + F_k u_k$

$$\text{Measurement: } y_k = \left(C_k + \sum_{\mu=1}^{N} \tilde{C}_{\mu,k} \zeta_{\mu,k} \right) x_k + v_k + G_k u_k$$

Measurement noise: $v_{k+1} = H_k v_k + \epsilon_k$

- **Approach:** Measurement differencing method

$$z_k = y_k - H_{k-1} y_{k-1}$$
$$z_k = \phi_k x_{k-1} + v_k^* + u_k^*$$

where v_k^* and u_k^* are uncorrelated

- Optimal estimator for x_k using $\{y_t\}_{t=1}^k$ is same as that using $\{z_t\}_{t=1}^k$
- **Main result:** MSE optimal linear estimator for system state.
- **Advantages:**
  - Does not require computing the inverse of state transition matrix
  - Recursive implementation: time-independent computation and storage load

Signal Recovery on Graphs: Variation Minimization

Siheng Chen, Aliaksei Sandryhaila, José M. F. Moura, and Jelena Kovačević

- **Problem:** Recover the graph signals residing on the graph $G = (\mathcal{V}, A)$: $X = \begin{bmatrix} x^{(1)} & x^{(2)} & \dots & x^{(L)} \end{bmatrix} \in \mathbb{R}^{N \times L}$
- **Measurements:** $T = X + W + E$
  - W: noise with entries upper-bounded by a small value
  - E: sparse matrix
- Signals are smooth with respect to the representation graph G
- **Optimization problem:**

$$\hat{X}, \hat{W}, \hat{E} = \arg\min_{X,W,E} \alpha \| X - AX \|_F^2 + \beta \operatorname{rank}(X) + \gamma \| E \|_0$$

$$\text{subject to} \| W \|_F^2 \le \epsilon^2, \, T_{\mathcal{M}} = (X + W + E)_{\mathcal{M}}.$$

- Solved by relaxing l_0 norm and rank to l_1 norm and nuclear norm using alternating direction method of multipliers
- Showed how signal inpainting, matrix completion, robust principal component analysis, and anomaly detection all relate to graph signal recovery

Distributed Kalman Filtering With Dynamic Observations Consensus

Subhro Das and José M. F. Moura

- **System model:**

$$\textbf{State evolution: } x_{i+1} = Ax_i + v_i$$

$$\textbf{Sensor measurements: } z_i^n = H_n x_i + r_i^n, n = 1, \dots N$$

- Dimension of the local observations are different for different agents
- Define pseudo-observations: $\bar{y}_i = \frac{1}{N} \sum_n H_n^\mathsf{T} R_n^{-1} z_i^n$

$$\bar{y}_i = Gx_i + \frac{1}{N} H^\mathsf{T} R^{-1} r_i$$

- Distributed Kalman filter with two subroutines:
  1. Dynamic consensus on the pseudo-observations to estimate $\bar{y}_i$
  2. Distributed filtering to estimate the states x_i

Other Papers

- **Asymptotic Optimality of the Maximum-Likelihood Kalman Filter for Bayesian Tracking With Multiple Nonlinear Sensors**
  - D. Marelli, M. Fu, and B. Ninness
- **A Spatial Diffusion Strategy for Tap-Length Estimation Over Adaptive Networks**
  - Y. Zhang, C. Wang, L. Zhao, and J. A. Chambers