Journal Watch: IEEE Transactions on Signal Processing, Oct 15^{th} Issue

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8^{th} November, 2014

Compressive Diffusion Strategies Over Distributed Networks for Reduced Communication Load

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- Setup: N sensors with measurements, $d_{i,t} = \mathbf{w}_0^T \mathbf{u}_{i,t} + v$
- Global LMS update: $\mathbf{w}_{t+1} = \mathbf{w}_t + \mu \sum_{n=1}^{N} (d_{i,t} - \mathbf{w}_t^T \mathbf{u}_{i,t})$

- Goal: To estimate the weight vector $\mathbf{w}_0$ in distributed manner

- One approach to reduce communication load: Diffusion LMS
  - combine the weights from neighboring nodes (only weights exchanged)
  - adaptively estimate using LMS
- This paper proposes further reduction
  - weight vector is transformed into a scalar/single-bit before diffusion
  - reconstructed and used for combining
- Analysis of transient, steady state and tracking behavior, show close performance to full exchange

Marginal Likelihoods for Distributed Parameter Estimation of Gaussian Graphical Models

Z. Meng and A. O. Hero, III, University of Michigan
D. Wei, IBM Research, Newyork

A. Wiesel, The Hebrew University of Jerusalem, Israel

- Estimate the pdf of the multi-variate of Gaussian distribution

$$p(\mathbf{x};\mathbf{J}) = (2\pi)^{-p/2}(\det \mathbf{J})^{1/2}\exp\left(-\frac{1}{2}\mathbf{x}^T\mathbf{J}\mathbf{x}\right).$$

- Graphical models: represent the dependence of variables in **x**
- ML estimate of inverse covariance matrix J

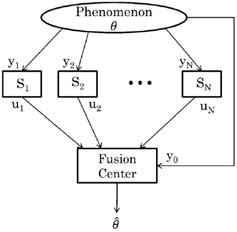
$$\begin{aligned} \widehat{\mathbf{J}}^{\mathrm{GML}} &= \arg\min_{\mathbf{J}} \langle \widehat{\mathbf{\Sigma}}, \mathbf{J}\rangle - \log\det \mathbf{J} \\ \text{s.t.} \quad \mathbf{J}_{j,k} &= 0 \quad \forall\, (j,k) \notin \widetilde{E} \\ \mathbf{J} &\succeq \mathbf{0}, \end{aligned}$$

- Loopy belief propagation is unstable and biased
- Proposes a maximum marginal likelihood estimation
- At a node i, sub-matrix of J that corresponds to marginal distribution of $\{x_j\}$'s in neighborhood of i is estimated
- Optimization problem is non-convex, employ convex relaxation
- Comparable to centralized estimator (as p and num. of samples tend to infinity)

On Quantizer Design for Distributed Bayesian Estimation in Sensor Networks

Aditya Vempaty, Hao He, Biao Chen, and Pramod K. Varshney

Syracuse University, USA



- $y_1, \ldots, y_N$ are measurements, $u_1, \ldots, u_N$ are quantized samples
- Fusion center (FC) estimates θ using $u_1, \ldots, u_N$

- Under Bayesian setting, for a given estimation procedure at FC, design an optimal strategy to quantize at individual sensors to minimize the Bayesian cost
- Contributions: For an efficient and unbiased estimator at FC and conditionally independent observations at sensors, using identical sensors is optimal
- Quantizer under rate constraint on MAC channel: binary quantizers is optimal
- Also considers location parameter estimation

Binary Symbol Recovery Via ℓ_∞ Minimization in Faster-Than-Nyquist Signaling Systems

F. M. Han and H. X. Zou, Tsinghua University, China
M. Jin, Nanjing Research Institute of Electronic Engineering, China

- Nyquist criterion: the maximum symbol rate can not exceed twice the bandwidth to avoid inter-symbol interference (ISI)
- More symbols can be packed by making modulation pulses constitute a frame for the spanned time-frequency plane
- Thus, $\mathbf{s} = \mathbf{Gb}$, where $\mathbf{b} \in \{-1, +1\}^N$, $G \in \mathcal{R}^{M \times N}$, $\mathbf{s} \in \mathcal{R}^M$, $M < N$

$$\begin{aligned} &\text{find } \boldsymbol{b} \\ &\text{s.t. } \boldsymbol{s} = \boldsymbol{G}\boldsymbol{b} \\ &b_n \in \{+1, -1\}, \quad n = 1, \ldots, N \end{aligned}$$

- Combinatorial optimization problem
- Convex relaxation

$$\hat{\boldsymbol{b}} = \arg\min \|\boldsymbol{b}\|_\infty \quad \text{s.t. } \boldsymbol{s} = \boldsymbol{G}\boldsymbol{b}$$

Other Papers

- On ArXiv: Convex Optimization for Big Data by Volkan Cevher, Stephen Becker, and Mark Schmidt