Journal Watch: IEEE Transactions on Information Theory, Vol. 60, No. 10, Oct. 2014

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11 Oct., 2014

- The Performance of Successive Interference Cancellation in Random Wireless Networks

Authors: X. Zhang and M. Haenggi

Affiliations: University of Texas at Austin and University of Notre Dame, USA

- Provides a unified framework to study performance of SIC[1] in wireless network
    - Arbitrary fading distribution
    - Power law path loss
- Models active transmitters by a PPP with power law density function
- Considers SIC as a pure receiver end technique

[1] Successive interference cancelation: similar to onion peeling

- Contributions
  - Fading does not affect the performance of SIC in a large class of interference limited networks
  - In noisy networks, fading always reduces decoding probability
  - Closed form bounds on the prob. of successively decoding at least k users
  - Also shows how to apply these results to heterogeneous cellular networks

- Minimum Variance Estimation of a Sparse Vector Within the Linear Gaussian Model: An RKHS Approach

  Authors: A. Jung, Member, S. Schmutzhard, F. Hlawatsch, Z. Ben-Haim, and Y. C. Eldar

- Sparse linear Gaussian model (SLGM)

$$\mathbf{y} = \mathbf{Hx} + \mathbf{n} \in \mathcal{R}^M$$

  - $\mathbf{x}$ is S-sparse
  - $\mathbf{H}$ is known and any set of S columns of $\mathbf{H}$ is linearly independent
  - When $\mathbf{H} = \mathbf{I}$: model is termed as sparse signal in noise model (SSNM)
- Goal: Estimating the value $g(\mathbf{x})$ of a known vector-valued function $g(\cdot)$ evaluated at $\mathbf{x}$

- Framework: Reproducing kernel Hilbert[2] spaces (RKHS)
- Contributions
  - Characterizing the RKHS associated with the SLGM
  - This helps to obtain a new lower bound on the variance of estimators for the SLGM
  - Lower bound results are specialized to CS measurement matrices
  - SSNM: minimum achievable variance (Barankin bound) at a given parameter vector and the locally minimum variance estimator

[2] Q: What is yellow, linear, normed, and complete? A: Bananach space

- Robust Spectral Compressed Sensing via Structured Matrix Completion

Authors: Yuxin Chen and Yuejie Chi

Affiliations: Stanford University and Ohio State University, USA

- Spectral compressed sensing problem: $x(t)$ is assumed to be a weighted sum of complex sinusoids
- Motivation: Basis mismatch
  - CS needs sparse representation of the signal in a finite discrete dictionary
  - In many cases the true parameters may be specified in a continuous dictionary
- To overcome this problem, this paper proposes an algorithm called EMaC[3]
  - Shift invariance property of harmonic structures
  - Spectral sparsity of signals

[3] enhanced matrix completion

- Problem is viewed as a low-rank Hankel structured matrix completion problem
- Under mild incoherence conditions, proposed algorithm enables recovery of the multi-dimensional unknown frequencies
- Result on Hankel matrix completion: first theoretical guarantee that is close to the information-theoretical limit

- Capacity-Achieving Distributions in Gaussian Multiple Access Channel With Peak Power Constraints

  Authors: B. Mamandipoor, K. Moshksar, and A. K. Khandani

- Gaussian MAC channel with peak power constraints at transmitters
- Capacity of MAC with average power constraint is known
- Discrete distribution with finite number of mass points achieves points of the boundary of the capacity region

- M. Braverman and A. Rao: Information Equals Amortized Communication
- N. Jiang, Y. Yang, A. Host-Madsen, and Z. Xiong: On the Minimum Energy of Sending Correlated Sources Over the Gaussian MAC
- A. Javanmard and A. Montanari: Hypothesis Testing in High-Dimensional Regression Under the Gaussian Random Design Model: Asymptotic Theory