

Journal watch

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Performance Analysis and Optimization for Interference Alignment Over MIMO Interference Channels With Limited Feedback

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Singapore University of Technology and Design

- Performance analysis framework for IA
 - ▶ Limited CSI feedback
 - ▶ MIMO interference channels
 - ▶ Maximize average transmission rate (variables: f/b amount, transmission modes)
 - ★ Closed form expressions for SINR (and average trans. rate) in the presence of IA leakage
 - ★ Tools: Random vector quantization
 - ▶ Greedy allocation of feedback bits
 - ▶ Dynamic mode selection scheme
- Asymptotic analysis on average transmission rate
 - ▶ Trade-off between feedback amount and rate loss
 - ▶ Increase in antennas is useful only if the feedback budget is also increased
 - ▶ Interference limited scenarios: Single data stream is optimal

Greedy Algorithms for Joint Sparse Recovery

Authors:

Jeffrey D. Blanchard, Michael Cermak, David Hanle, and Yirong Jing

Grinnell College, IA, USA

- Extension and investigation of “well-known” greedy algorithms to MMV setup
 - ▶ IHT, NIHT, HTP, NHTP, CoSamp
- Sufficient conditions based on the Asymmetric-RIP to guarantee joint sparse recovery
 - ▶ Results in terms of lower and upper RIC
 - ▶ Smallest and largest singular values deviate in asymmetric fashion
 - ▶ Much weaker sufficient conditions
 - ▶ Sufficient conditions agree with the SMV counterparts
- Bounds on recovery error
- Simulation results
 - ▶ Good performance
 - ▶ Theoretical results are quite pessimistic, empirical average case provides much more information

Decomposition Approach for Low-Rank Matrix Completion and Its Applications

Authors:

Rick Ma, Nafise Barzigar, Aminmohammad Roozgard, and Samuel Cheng

Hong Kong University of Science and Technology
Univ. of Oklahoma

- Low rank matrix completion algorithm
 - ▶ Significantly reduces complexity and storage requirements
 - ▶ Does not use SVD or norm-minimization
 - ▶ Can be applied with finite field incomplete matrices also
 - ▶ Extensive numerical simulations to test the algorithm
- Overview of main algorithmic components
 - ▶ Decompose a incomplete matrix into u -diagonalizable matrices.
 - ★ Cluster all known entries into block diagonal structure
 - ★ Conditions for u -diagonalizability ?
 - ▶ Complete, each cluster using a “trimming” procedure
 - ★ Involves finding out if a particular column belongs to the column space of some matrix
 - ★ Find “basis” columns of cluster sub-matrix
 - ★ Zero out the incomplete entries in basis columns
 - ★ Complete the remaining columns using the linear combinations of basis columns
 - ▶ Complete all off-diagonal entries using completed clusters

On the Linear Convergence of the ADMM in Decentralized Consensus Optimization

Authors:

Wei Shi, Qing Ling, Kun Yuan, Gang Wu, and Wotao Yin

University of Science and Technology of China, Hefei
UCLA

- Decentralized consensus optimization problem is considered
 - ▶ $\min_x \sum_{i=1}^L f_i(x)$, L n/w agents, common optimization variable x .
 - ▶ To solve the above in a decentralized fashion
- ADMM is applied to the decentralized setup
- Main contributions
 - ▶ A linear convergence rate has been established for ADMM in decentralized setup
 - ▶ Dependence of the rate on n/w topology, properties of objective functions is established
 - ▶ Algorithm parameter choices to get higher convergence rates is discussed

Smoothing and Decomposition for Analysis Sparse Recovery

Authors:

Zhao Tan, Yonina C. Eldar, Amir Beck and Arye Nehorai

Washington Univ., St Louis, USA
Technion Israel

- Algorithms and recovery guarantees for “Analysis” sparse model

$$\min_{x \in \mathbb{R}^n} \|\mathbf{D}^H x\|_1 \quad \text{subject to} \quad \|\mathbf{A}x - b\| < \epsilon$$

- Main contributions

- ▶ Extensions of FISTA to the above setting is considered
 - ★ Fast iterative shrinkage-thresholding algorithm (First order method)
 - ★ Unlike, ADMM and NESTA does not require \mathbf{A} to have particular structure
- ▶ General recovery guarantees for these algorithms based on D-RIP