

Journal Watch

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Exact Recovery of Sparse Signals Using Orthogonal Matching Pursuit: How Many Iterations Do We Need?

Jian Wang and Byonghyo Shim

- **System model:** $\mathbf{y} = \boldsymbol{\phi}\mathbf{x}$; \mathbf{x} is K -sparse
 - T : support of \mathbf{x} , $|T| = K$
 - cK : number of OMP iterations for exact recovery, $c > 1$

Main Result

If $\boldsymbol{\phi}$ obeys RIP of order $\lfloor (c+1)K \rfloor$, for exact recovery

$$c \geq -\frac{4(1+\delta)}{1-\delta} \log \left(\frac{1}{2} - \sqrt{\frac{\delta}{2+2\delta}} \right).$$

- LB monotonically increases with the RIC δ
- Example: For Gaussian matrices $c \approx 2.8$ if $m \sim \mathcal{O} \left(K \log \frac{N}{K} \right)$

Optimal Transmit Strategy for MISO Channels With Joint Sum and Per-Antenna Power Constraints

Phuong Le Cao, Tobias J. Oechtering, Rafael F. Schaefer and Mikael Skoglund

- **Signal Model:** Point-to-point MISO channel: $y = \mathbf{x}^T \mathbf{h} + z$
- If \mathbf{x} is normal such that $\mathbf{Q} = \mathbb{E}(\mathbf{x}\mathbf{x}^T)$, the **achievable rate** is

$$R = \log \left(1 + \frac{1}{\sigma^2} \mathbf{h}\mathbf{Q}\mathbf{h} \right)$$

- **Constraints:** $\mathbf{Q} \succeq 0$, $\text{Tr}(\mathbf{Q}) \leq P_{tot}$, and $\mathbf{Q}_{ii} \leq \hat{P}_i$

Contributions

- 1 *Gaussian distributed input is capacity-achieving with the constraints*
- 2 *A simple recursive algorithm to compute the optimal \mathbf{Q}*
 - 1 *Find optimal power allocation with sum power constraint only*
 - 2 *For antennas who violate per-antenna power constraint, allocate \hat{P}_i*
 - 3 *Divide the remaining power among the other antennas with reduced constraints*

Discrete Sum Rate Maximization for MISO Interference Broadcast Channels: Convex Approximations and Efficient Algorithms

Hoi-To Wai, QiangLi, and Wing-Kin Ma

- **System Model:** M transmitters serves K receivers in a unicast manner
- **Assumption:** Gaussian input $s_q(t)$ with $W_q = \mathbb{E}\{s_q(t)s_q(t)^T\}$
- **Goal:** Find $\{W_q\}_{q=1}^{KM}$ to maximize $\sum_q \lambda_q r_q$ such that $\forall q, i$
 - Moment: $W_q \succeq 0$, $\text{Rank}\{W_q\} \leq 1$
 - Discrete rate: $r_q \in \mathcal{R}$
 - Power: $\sum_{q \in \mathcal{K}_i} \text{Tr}\{W_q\} \leq P_i$
 - SINR: $\gamma(r_q) \leq \text{SINR}_q(W)$

Proposed Solution

- *Convex approximation formulation*
- *Low-complexity and decentralized optimization algorithms*

Bayesian Learning of Degenerate Linear Gaussian State Space Models Using Markov Chain Monte Carlo

Pete Bunch, James Murphy, and Simon Godsill

- **Measurement model:**

$$\begin{aligned}x_t &= Fx_{t-1} + \epsilon_t^x; & \epsilon_t^x &\sim \mathcal{N}(0, Q) \\y_t &= Hx_t + \epsilon_t^y; & \epsilon_t^y &\sim \mathcal{N}(0, R)\end{aligned}$$

- **Goal:** Estimation of system parameter matrices F and Q

Central Idea: Gibbs sampler

Sample alternately the conditional posterior distributions

- 1 $\pi(x_{1:T} | F, Q)$: Gaussian obtained using Kalman Smoothing
- 2 $\pi(F, Q | x_{1:T})$: Matrix normal-inverse Wishart distribution

- **Contribution:** Extension to the case when Q is singular

- **Enhanced PUMA for Direction-of-Arrival Estimation and Its Performance Analysis**
 - Cheng Qian, Lei Huang, Nicholas D. Sidiropoulos and Hing Cheung So
- **Bayesian Model for Multiple Change-Points Detection in Multivariate Time Series**
 - Flore Harlé, Florent Chatelain, Cédric Gouy-Pailler and Sophie Achard
- **Compressive Detection of Random Subspace Signals**
 - Alireza Razavi, Mikko Valkama and Danijela Cabric
- **Infection Spreading and Source Identification: A Hide and Seek Game**
 - Wuqiong Luo, Wee Peng Tay and Mei Leng