Journal Watch
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Chirag Ramesh
SPC Lab, Indian Institute of Science

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Quasi-Static and Time-Selective Channel Estimation for Block-Sparse Millimeter Wave Hybrid MIMO Systems: Sparse Bayesian Learning (SBL) Based Approaches

Contributions

- SBL approaches proposed for channel estimation of mmWave hybrid MIMO system with MMV under quasi-static and temporally correlated scenarios.
- Online recursive Bayesian Kalman Filter proposed for time-selective channel estimation.
- Cramér-Rao bounds derived for estimation schemes for the two scenarios.

System Model

- Received signal $\mathbf{Y} = \mathbf{W}^H\mathbf{H}\mathbf{F}\mathbf{X} + \mathbf{V} = \sqrt{P}\mathbf{W}^H\mathbf{H}\mathbf{F} + \mathbf{V}$.

- Channel model:

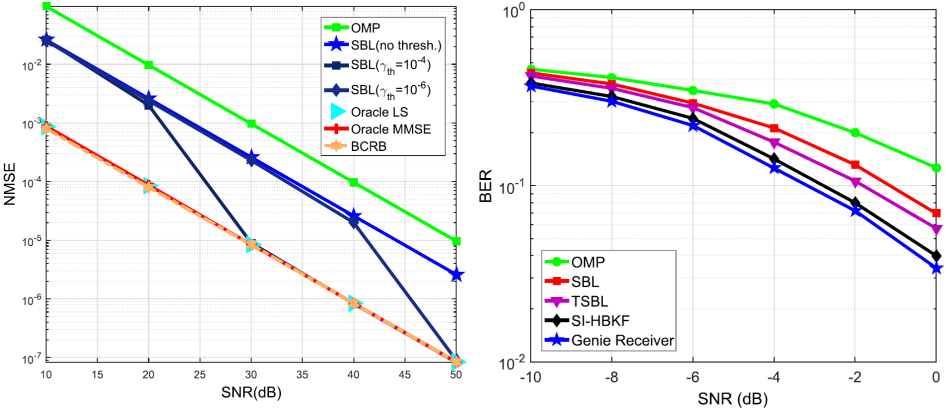
$$\mathbf{H} = \sum_{l=1}^{N_p} \alpha_l \mathbf{a}_R(\theta_{R,l}, \phi_{R,l}) \mathbf{a}_T^H(\theta_{T,l}, \phi_{T,l})$$
$$= \overline{\mathbf{A}}_R \overline{\mathbf{H}}_b \overline{\mathbf{A}}_T^H \approx \mathbf{A}_R \mathbf{H}_b \mathbf{A}_T^H$$
$$\Rightarrow \mathbf{y} = \sqrt{P}(\mathbf{F}^T \otimes \mathbf{W}^H) vec(\mathbf{H}) + \mathbf{n} = \mathbf{Q}\mathbf{h}_b + \mathbf{v}$$

- SBL for quasi-static channels: $\mathbf{h}_b \sim \mathcal{CN}(\mathbf{0}_{G^2}, \boldsymbol{\Gamma})$.
- Algorithm based on EM proposed to evaluate $\mathbf{h}_b$.
- Extended to the block-sparse case.

- SBL for temporally correlated channels: $\mathbf{h}_{b,M} \sim \mathcal{CN}(\mathbf{0}_{MG^2}, \mathbf{\Gamma} \otimes \mathbf{B})$.
- SBL for time-selective channels:

$$\begin{aligned} \boldsymbol{y}[n] &= \mathbf{Q}\mathbf{h}_b[n] + \boldsymbol{v}[n] \\ \mathbf{h}_b[n] &\sim \mathcal{CN}(\mathbf{0}_{G^2}, \mathbf{\Gamma}[n]) \\ \mathbf{h}_b[n] &= \rho\mathbf{h}_b[n-1] + \sqrt{1-\rho^2}\mathbf{w}[n] \end{aligned}$$

- Bayesian Kalman Filter proposed for the above.
- Design of precoders and combiners based on $\hat{\mathbf{H}}$.
- Cramér-Rao bounds analyzed for all the proposed estimation schemes.


OMP
SBL(no thresh.)
SBL(γ_{th}=10^{-4})
SBL(γ_{th}=10^{-6})
Oracle LS
Oracle MMSE
BCRB
NMSE
SNR(dB)
OMP
SBL
TSBL
SI-HBKF
Genie Receiver
BER
SNR (dB)

Sparse Signal Recovery via Generalized Entropy Functions Minimization

Contributions

- Generalized entropy functions used as regularizers for sparse signal recovery.
- Proved that generalized Shannon entropy with $p \neq 1$ can lead to sparser solutions than $p = 1$.
- Non-convex problem converted to a series of ℓ_1 problems and solved with FISTA.

Model

- Problem: $\min_{\mathbf{x}} \ \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda f(\mathbf{x})$

- Shannon entropy function:

$$f(\mathbf{x}) = h_p(\mathbf{x}) = -\sum_{i=1}^{N} \frac{|x_i|^p}{\|\mathbf{x}\|_p^p} \log \frac{|x_i|^p}{\|\mathbf{x}\|_p^p}, p > 0$$

- Rényi entropy function:

$$f(\mathbf{x}) = h_{p,\alpha}(\mathbf{x}) = \frac{1}{1-\alpha} \log \left(\sum_{i=1}^{N} \left(\frac{|x_i|^p}{\|\mathbf{x}\|_p^p} \right)^{\alpha} \right), p, \alpha > 0 \,\&\, \alpha \neq 1$$

- Sparsity and energy promoting analysis performed for both noisy and noiseless cases.
- It is proved that the local minimas of the entropy functions only occur at the boundaries of each orthant in $\mathbb{R}^N$.

- The regularizers are non-convex and non-smooth.
- Recast into a series of reweighted ℓ_1 problems and solved using inexact proximal gradient method (IPGM) and accelerated inexact proximal gradient method (FISTA).
- Choice of λ is analyzed.
- Analysis of optimal p and α performed.
- Performance of image recovery is compared with OMP, CoSaMP, BP and IHT.

Online Forecasting Matrix Factorization

Contributions

- Goal is to forecast high dimensional time series data in an online setting.
- Recursive MMSE estimator is derived based on AR model.

System Model

- Time series data to be factorized as $\mathbf{X} = \mathbf{U}^T\mathbf{V}$.
- $\mathbf{X} \in \mathbb{R}^{M\times T}, \mathbf{U} \in \mathbb{R}^{d\times M}, \mathbf{V} \in \mathbb{R}^{d\times T}, d = \text{rank}(\mathbf{X})$.
- At each instant, one column $\mathbf{x}_t$ of $\mathbf{X}$ is observed.

- AR model of order P used:

$$\begin{aligned}\mathbf{v}_t &= \theta_1 \mathbf{v}_{t-1} + \cdots + \theta_P \mathbf{v}_{t-P} + \mathbf{n}_{\mathbf{v},t},\\ \mathbf{U}_t &= \mathbf{U}_{t-1} + \mathbf{n}_{\mathbf{U},t},\\ \mathbf{x}_t &= \mathbf{U}_t^T \mathbf{v}_t + \mathbf{n}_{\mathbf{x},t}.\end{aligned}$$

- $\bar{\mathbf{v}} = \sum_{p=1}^{P} \theta_p \mathbf{v}_{t-p} = \mathbf{P}_t \boldsymbol{\theta}$.
- $\hat{\boldsymbol{\theta}}_{LMMSE}$ is found and used to evaluate $\bar{\mathbf{v}}$ and hence $\mathbf{v}_t$.
- Fixed Penalty Constraint:

$$\min_{\mathbf{U}_t, \mathbf{v}_t} \|\mathbf{x}_t - \mathbf{U}_t^T \mathbf{v}_t\|_2^2 + \rho_U \|\mathbf{U}_t - \mathbf{U}_{t-1}\|_F^2 + \rho_v \|\mathbf{v}_t - \bar{\mathbf{v}}\|_2^2.$$

- Fixed Tolerance Constraint:

$$\begin{aligned} \min_{\mathbf{U}_t, \mathbf{v}_t} \quad & \|\mathbf{U}_t - \mathbf{U}_{t-1}\|_F^2 + \rho_v \|\mathbf{v}_t - \bar{\mathbf{v}}\|_2^2 \\ \text{s.t.} \quad & \|\mathbf{x}_t - \mathbf{U}_t^T \mathbf{v}_t\|_2^2 \leq \epsilon. \end{aligned}$$

- Zero Tolerance Constraint:

$$\begin{aligned} \min_{\mathbf{U}_t, \mathbf{v}_t} \quad & \|\mathbf{U}_t - \mathbf{U}_{t-1}\|_F^2 + \rho_v \|\mathbf{v}_t - \bar{\mathbf{v}}\|_2^2 \\ \text{s.t.} \quad & \mathbf{x}_t = \mathbf{U}_t^T \mathbf{v}_t. \end{aligned}$$

- Algorithms proposed for the above problems based on coordinate descent.

Other Interesting Papers

1. Compressed Training Based Massive MIMO
2. A Hybrid Lower Bound for Parameter Estimation of Signals With Multiple Change-Points
3. Low Rank and Structured Modeling of High-Dimensional Vector Autoregressions
4. Receive Spatial Modulation in Correlated Massive MIMO With Partial CSI
5. Recursive Maximum Likelihood Algorithm for Dependent Observations
6. Online Learning With Inexact Proximal Online Gradient Descent Algorithms