Journal Watch

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1. Robust Sparse Recovery in Impulsive Noise via l_p-l_1 Optimization

Authors: Fei Wen, Peilin Liu, Yipeng Liu, Robert C. Qiu and Wenxian Yu

Goal: Robust sparse recovery in compressive sensing (CS) in the presence of impulsive measurement noise.

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{n} \ (\mathbf{m} < \mathbf{n});\ \mathbf{x} \in \mathbb{R}^{\mathbf{n}};\ \mathbf{y}, \mathbf{n} \in \mathbb{R}^{\mathbf{m}}$$

n - Impulsive noise

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \ \text{ s.t. } \ \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \le \epsilon.$$

$$\min_{\mathbf{x}} \left\{ \frac{1}{\mu} \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_p^p + \|\mathbf{x}\|_1 \right\}.$$

$$0 \le p < 2$$

$$f(\mathbf{n}) = \frac{v^N}{[2\sigma_n \Gamma(\frac{1}{v})]^N} \exp\left(-\frac{\|\mathbf{n}\|_v^v}{\sigma_n^v} \right).$$

$$0 \le v < 2$$

- Generalized Gaussian distribution
- v controls the distribution shape.
- $v < 2$: heavy tail & suitable for impulsive noise

1. Problem formulation

$$\min_{\mathbf{x},\mathbf{v}} \left\{ \frac{1}{\mu}\|\mathbf{v}\|_p^p + \|\mathbf{x}\|_1 \right\} \text{ subject to } \mathbf{A}\mathbf{x} - \mathbf{y} = \mathbf{v}.$$

$$\mathcal{L}_\rho(\mathbf{v}, \mathbf{x}, \mathbf{w}) = \frac{1}{\mu}\|\mathbf{v}\|_p^p + \|\mathbf{x}\|_1 - \langle \mathbf{w}, \mathbf{A}\mathbf{x} - \mathbf{y} - \mathbf{v} \rangle + \frac{\rho}{2}\|\mathbf{A}\mathbf{x} - \mathbf{y} - \mathbf{v}\|_2^2$$

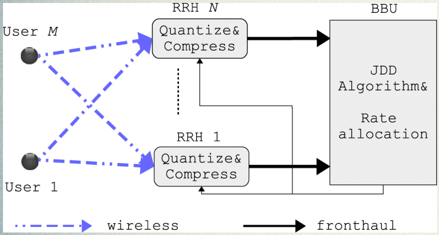
w-dual variable, ρ- penalty parameter

Contributions

- Efficient Alternating direction method (L_p-ADM) algo is derived.
- Unified framework for both the convex and nonconvex cases.
- Convergence Conditions for convex and nonconvex are analysed.
- State of the art robust performance for particular choice of p ($p < 1$) in highly impulsive noise.

Authors: Thang X. Vu, Hieu Duy Nguyen, Tony Q. S. Quek and Sumei Sun

Goal: Design of fronthaul in C-RAN uplink by focusing on the compression and optimization in fronthaul uplinks based on the statistics of wireless fading channels.



- BBU - baseband unit, RRH -remote radio head
- M users $m \in \{1, 2, ..., M\}$, N RRHs $n \in \{1, 2, ..., N\}$,

- C-RAN enables adaptive load balancing via virtual base station pool.
- Block Error Rate(BLER) - performance metric for C-RAN systems.

2. Contd.

$$y_n = \sum_{m=1}^{M} h_{nm}\sqrt{P_{nm}}c_m + z_n$$
$$= \mathbf{h}_n \mathbf{\Lambda}_n \mathbf{c} + z_n,$$

c-codeword

Decoding at the BBU:

$$\hat{\mathbf{c}} = \arg\max_{\mathbf{c}} \Pr\{\mathbf{c}\} \prod_{n=1}^{N} \Pr\{\tilde{y}_n | \mathbf{c}\},$$

Union bound on the BLER:

$$\mathrm{BLER} \leq \frac{1}{|\mathcal{S}|^M} \sum\sum_{\mathbf{c},\tilde{\mathbf{c}} \in \mathcal{S}^M, \tilde{\mathbf{c}} \neq \mathbf{c}} \overline{\mathrm{PEP}}_{\mathbf{c} \to \tilde{\mathbf{c}}},$$

Minimization of Fronthaul Transmission Rate:

$$\min_{\{Q_n : Q_n \geq 1\}_{n=1}^{N}} \sum_{n=1}^{N} Q_n \ \texttt{s.t.}$$

$$\frac{1}{|\mathcal{S}|^M} \sum\sum_{\mathbf{c},\tilde{\mathbf{c}} \in \mathcal{S}^M, \mathbf{c} \neq \tilde{\mathbf{c}}} \overline{\mathrm{PEP}}_{\mathbf{c} \to \tilde{\mathbf{c}}} \leq \zeta,$$

2. Contributions

- Derived the system BLER under Rayleigh fading channels
  - upper and lower bounds of the BLER in closed-form
- Proposed two adaptive compression schemes to minimize the fronthaul transmission rate subject to a BLER constraint
- Fronthaul rate allocation is proposed to minimize the system BLER

3. Generalized Coprime Sampling of Toeplitz Matrices for Spectrum Estimation

Authors: Si Qin, Yimin D. Zhang, Moeness G. Amin and Abdelhak M. Zoubir

Goal: Spectrum estimation of wide-sense stationary (WSS) processes utilizing the Toeplitz property of the covariance matrix.

- X(t), t $\in$ R: zero-mean WSS process
- X[l]- sampled signal of X(t), l$\in$[L]

$$\mathbf{R_x} = \mathrm{E}\left[\mathbf{x}_L[l]\mathbf{x}_L^H[l]\right]$$

$$= \begin{pmatrix} r[0] & r[-1] & \dots & r[-L+1] \\ r[1] & r[0] & \dots & r[-L+2] \\ \vdots & \vdots & \dots & \vdots \\ r[L-2] & r[L-3] & \dots & r[-1] \\ r[L-1] & r[L-2] & \dots & r[0] \end{pmatrix}$$

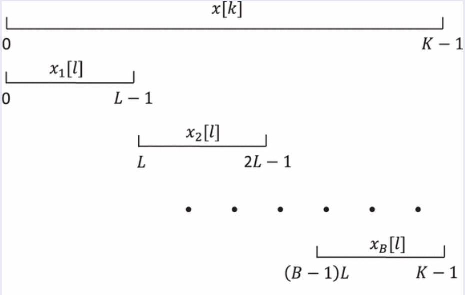
$$r[\tau] = E[x[l]x^*[l-\tau]]$$

$\hat{\mathbf{R}}_{\mathbf{x}}$ *is LxL covariance matrix*

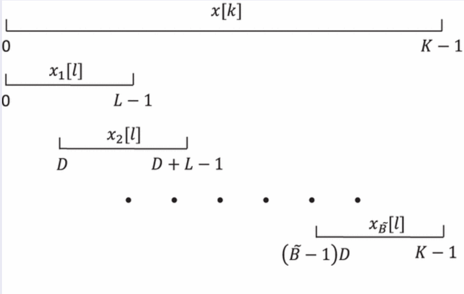
3. Contd.

$x_L(l) = [x(l), x(l+1), ..., x(l+L-1)]^T$ be a realized vector of X(l).

Nonoverlap Segmentation



Overlap Segmentation



Each block $x_b = [x_b(0), x_b(1), ..., x_b(L-1)]^T$, b∈[B]

3. Contd.

$$\mathbf{y} = \mathbf{A}_s \mathbf{x}_b, b \in [B], BL = K,$$

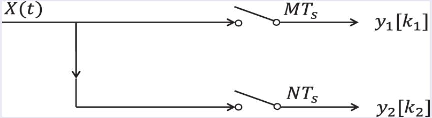
$\mathbf{A}_s$: *VxL Sampling matrix* $(V << L)$

$\hat{\mathbf{R}}_\mathbf{y}$ *is VxV covariance matrix*

$$\hat{\mathbf{R}}_\mathbf{y} = \frac{1}{B} \sum_{b=1}^{B} \mathbf{y}_b \mathbf{y}_b^H$$

Recover $\hat{\mathbf{R}}_\mathbf{x}$ from $\hat{\mathbf{R}}_\mathbf{y}$

Coprime Sampling



M,N are coprimes

Spectrum estimation

-Estimating the PSD

$$P[f] = \sum_{\tau=-\infty}^{\infty} r[\tau] e^{-j2\pi\tau f / f_s}$$

4. Compressed and Quantized Correlation Estimators

Authors: Augusto Gabriel Zebadua, Pierre-Olivier Amblard, Eric Moisan, and Olivier J. J. Michel

Goal: Estimation of correlation functions between sensors using compressed acquisition and one-bit-quantization.

Compressed estimator b/n x &y

$C_N = (\Phi x)^T (\Phi y), \ \Phi : MxN \ (M \leq N) \ \& \ x, y \in \mathbf{R}_N$

- Statistical information content of zero crossings of a stochastic process is very close to the information content of the process itself.
- Implemented correlation estimates of a process using one-bit quantized measurements
- compressed acquisition and one-bit-quantization can decrease the need for computation and communication resources for correlation estimation

For Further Interesting Papers

- Theoretical Bounds in Minimax Decentralized Hypothesis Testing.
  G. Gul and A. M. Zoubir
- Learning-Based Distributed Detection-Estimation in Sensor Networks With Unknown Sensor Defects
  Q. Zhou, D. Li, S. Kar, L. M. Huie, H. V. Poor, and S. Cui
- Closed-Loop Autonomous Pilot and Compressive CSIT Feedback Resource Adaptation in Multi-User FDD Massive MIMO Systems
  A. Liu, F. Zhu, and V. K. N. Lau
- Cooperative Simultaneous Localization and Mapping by Exploiting Multipath Propagation
  H. Naseri and V. Koivunen

Thank You