IEEE Transactions on Signal Processing
15 Dec. 2018

Journal Watch

Geethu Joseph
SPC, IISc

Exploiting Sparsity in Tight-Dimensional Spaces for Piecewise Continuous Signal Recovery

Hiroki Kuroda, Masao Yamagishi and Isao Yamada

Sparsity Piecewise Continuous Signal Recovery

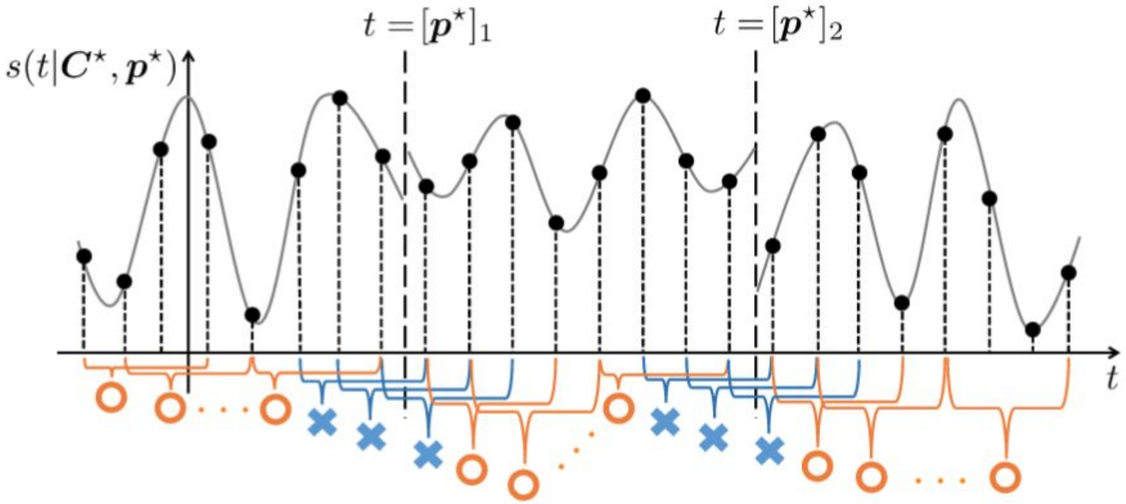
$$s(t|\boldsymbol{C}^\star, \boldsymbol{p}^\star)$$

$$:= \begin{cases} \sum_{k=1}^{K} [\boldsymbol{C}^\star]_{k,1} \varphi_k(t), & (t \in (-\infty, [\boldsymbol{p}^\star]_1)), \\ \vdots & \\ \sum_{k=1}^{K} [\boldsymbol{C}^\star]_{k,\ell} \varphi_k(t), & (t \in [[\boldsymbol{p}^\star]_{\ell-1}, [\boldsymbol{p}^\star]_\ell)), \\ \vdots & \\ \sum_{k=1}^{K} [\boldsymbol{C}^\star]_{k,L+1} \varphi_k(t), & (t \in [[\boldsymbol{p}^\star]_L, \infty)), \end{cases}$$

Measurement model: Linear and Noisy

Obtain $\hat{\boldsymbol{s}} \approx \boldsymbol{s}^\star$ → Obtain $\hat{\boldsymbol{p}} \approx \boldsymbol{p}^\star$ → Obtain $\hat{\boldsymbol{C}} \approx \boldsymbol{C}^\star$

Sparsity Piecewise Continuous Signal Recovery



1. Design **W** such that **Ws*** is sparse
2. Identify **p***
3. Estimate **C*** using least squares

Detection Theory for Union of Subspaces

Muhammad Asad Lodhi, Waheed U. Bajwa

Detection Theory for Union of Subspaces

- Model

$$\mathcal{H}_0 : \quad \mathbf{y} = \mathbf{n};$$
$$\mathcal{H}_k : \quad \mathbf{y} = \mathbf{x} + \mathbf{n},\ \mathbf{x} \in S_k; \quad k = 1, \ldots, K_0.$$

- Problem 1: signal detection
- Problem 2: active subspace detection
- Generalized likelihood ratio tests for detection (GLRT)

Detection Theory for Union of Subspaces

- Analysis: Colored Gaussian noise with full rank covariance matrix
    - Known noise statistics
    - Unknown variance, known correlation
    - Unknown variance, known correlation
- Performance metric: probabilities of
    - Detection
    - Classification
    - False alarm

A New Sequential Optimization Procedure and Its Applications to Resource Allocation for Wireless Systems

Augusto Aubry, Antonio De Maio, Alessio Zappone, Meisam Razaviyayn, and Zhi-Quan Luo

Sequential Optimization Procedure

$$\begin{aligned} \max_{\boldsymbol{x}_1,\ldots,\boldsymbol{x}_K} \quad & f(\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_K) \\ \text{s.t.} \quad & \phi_{i,h}(\boldsymbol{x}_h) \geq 0, h = 1, 2, \ldots, K \\ & \qquad\qquad i = 1, \ldots, K_{1,h} \end{aligned}$$

- Existing ideas
  - Alternating minimization
  - Maximum block improvement (MBI)
- Proposal: Join MBI and sequential method

$$\widetilde{\phi}_{i,h}(\boldsymbol{y}; \boldsymbol{x}_h) \leq \phi_{i,h}(\boldsymbol{y}), \forall i = 1, \ldots, K_{1,h};$$

$$\widetilde{\phi}_{i,h}(\boldsymbol{x}_h; \boldsymbol{x}_h) = \phi_{i,h}(\boldsymbol{x}_h), \forall i = 1, \ldots, K_{1,h}.$$

Sequential Optimization Procedure

1: **Input:** A feasible starting point $\boldsymbol{x}^{(0)} = (\boldsymbol{x}_1^{(0)}, \ldots, \boldsymbol{x}_K^{(0)})$.

2: set $n = 1$.

3: **repeat**

4: for $h = 1, 2, \ldots, K$, let $\nu_h^{(n)}$ and $\boldsymbol{y}_h^{(n)}$ be, respectively, the optimal value and an optimal solution to problem

$$\mathcal{P}^h_{(\boldsymbol{x}^{(n-1)})} \begin{cases} \max\limits_{\boldsymbol{y}} \; f_h(\boldsymbol{y}; \boldsymbol{x}^{(n-1)}) \\ \text{s.t.} \quad \widetilde{\phi}_{i,h}(\boldsymbol{y}; \boldsymbol{x}_h^{(n-1)}) \geq 0, h = 1, 2, \ldots, K, \\ \qquad\; i = 1, \ldots, K_{1,h} \end{cases}$$

5: Let $k^\star = \arg \max\limits_{k=1,2,\ldots,K} \nu_k^{(n)}$. Define $\boldsymbol{x}_h^{(n)} = \boldsymbol{x}_h^{(n-1)}$ for all $h \neq k^\star$ and $\boldsymbol{x}_{k^\star}^{(n)} = \boldsymbol{y}_{k^\star}^{(n)}$, i.e.,

$$\boldsymbol{x}^{(n)} = \left[\boldsymbol{x}_1^{(n-1)}, \ldots, \boldsymbol{x}_{k^\star-1}^{(n-1)}, \boldsymbol{y}_{k^\star}^{(n)}, \boldsymbol{x}_{k^\star+1}^{(n-1)}, \ldots, \boldsymbol{x}_K^{(n-1)}\right]^T;$$

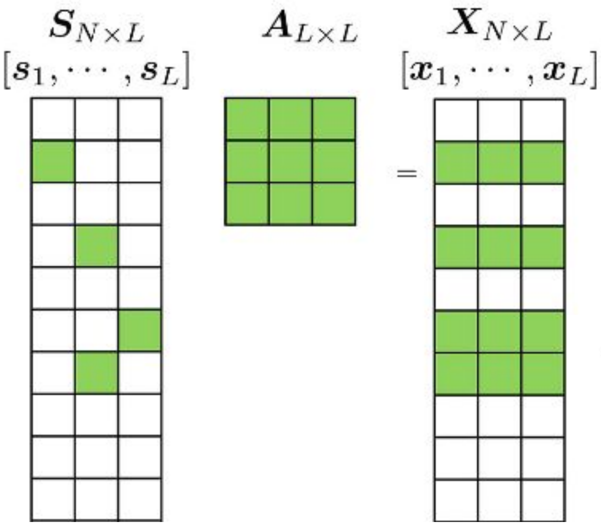
6: **until** Convergence

7: **Output:** $\boldsymbol{x}_h^\star = \boldsymbol{x}_h^{(n)}, h = 1, 2, \ldots, K$.

A Recovery of Independent Sparse Sources From Linear Mixtures Using Sparse Bayesian Learning

Seyyed Hamed Fouladi, Sung-En Chiu, Bhaskar D. Rao, and Ilangko Balasingham

Recovery of Independent Sparse Sources From Linear Mixtures



$$\boldsymbol{Y} = \boldsymbol{\Phi X}, \ \boldsymbol{X} = \boldsymbol{SA}.$$

$$\min_{\boldsymbol{S},\boldsymbol{A}} \sum_{i=1}^{L} \|\boldsymbol{s}_i\|_0, \text{ subject to } \boldsymbol{Y} = \boldsymbol{\Phi S A}, \boldsymbol{X} = \boldsymbol{SA}$$

$$\text{and } \sqrt{\sum_{j=1}^{L} \left(\boldsymbol{A}_{(i,j)}\right)^2} = 1. \qquad ($$

Recovery of Independent Sparse Sources From Linear Mixtures

- Uniqueness conditions

$$\max_i \{r_i\} + \sum_{j=1}^{L} r_j < \text{Spark}(\Phi).$$

- SBL-based recovery algorithm
    - Hyperparamters: $\Theta = \{\Gamma, \sigma^2, A\}$
    - Closed form expressions for EM updates
- Analysis of global minima and local minima of SBL cost function

Other Interesting Papers

- **Discreteness-Aware Approximate Message Passing for Discrete-Valued Vector Reconstruction**
  - R. Hayakawa and K. Hayashi
- **Bayesian Detection for MIMO Radar in Gaussian Clutter**
  - J. Liu, J. Han, Z.-J. Zhang, and J. Li
- **Source Counting and Separation Based on Simplex Analysis**
  - B. Laufer-Goldshtein, R. Talmon, and S. Gannot

Thank You!