TSP SEP. 1, 2015 JW by Chandra Murthy

ITERATIVE REWEIGHTED L2/L1 RECOVERY ALGORITHMS FOR COMPRESSED SENSING OF BLOCK SPARSE SIGNALS

- Zeinalkhani, Z.; Banihashemi, A.H., Carleton Univ., Canada
- The problem:
 - Block boundaries assumed known
- Weighted 12/11 minimization:
- Two choices for the weighting:
 - Inversely proportional to 12 norms of the blocks
 - Truncate 12 norms of the blocks to a threshold
- Show that, as block length increases, performance approaches the Wu-Verdu theoretical limit

$$\begin{split} \mathbf{\bar{x}} &= [\mathbf{\bar{u}}_{1}^{T}, \mathbf{\bar{u}}_{2}^{T}, \dots, \mathbf{\bar{u}}_{L}^{T}]^{T} \\ &= \mathop{\arg\min}_{\mathbf{u}_{1}, \dots, \mathbf{u}_{L}} \quad |\{i: \|\mathbf{u}_{i}\|_{2} \neq 0, i = 1, \dots, L\}| \\ &\text{s.t.} \| \mathbf{y} - \mathbf{Ax} \|_{2} \leq \alpha. \\ \\ &\hat{\mathbf{x}} = [\hat{\mathbf{u}}_{1}^{T}, \hat{\mathbf{u}}_{2}^{T}, \dots, \hat{\mathbf{u}}_{L}^{T}]^{T} \\ &= \mathop{\arg\min}_{\mathbf{u}_{1}, \dots, \mathbf{u}_{L}} \sum_{i=1}^{L} \omega_{i} \|\mathbf{u}_{i}\|_{2} \quad \text{s.t.} \ \|\mathbf{y} - \mathbf{Ax}\|_{2} \leq \alpha, \end{split}$$



SIMPLE AND FAST CONVEX RELAXATION METHOD FOR COOPERATIVE LOCALIZATION IN SENSOR NETWORKS USING RANGE MEASUREMENTS

- Soares, C. ; Xavier, J. ; Gomes, J., Univ. of Lisbon, Portugal
- The problem: minimize
- Contributions:
 - Convex lower bound for the cost function
 - Synchronous & distributed algorithm that optimizes the lower bound; proof of convergence
 EDM completion
 - Asynchronous variant, a.s. convergence
 - Analysis of iteration complexity
 - Performance via simulations



 $f(x) = \sum_{i \sim j} \frac{1}{2} (\|x_i - x_j\| - d_{ij})^2 + \sum_{i \sim k \in \mathcal{A}_i} \frac{1}{2} (\|x_i - a_k\| - r_{ik})^2$

TSP AUG. 15, 2015 Some More Papers

COMPRESSIVE PERIODOGRAM RECONSTRUCTION USING UNIFORM BINNING

- Ariananda, D.D.; Romero, D.; Leus, G.
- Problem: reconstruction of periodogram using uniform bins
 - Does not assume periodogram is sparse, but that there are a small number of "sources" that result in the periodogram
 - Goal: Reconstruction from as few samples as possible
- Compressive sampling of the periodogram
- Reconstruction of the correlation matrix (from which the periodogram can be found)
- Bias and variance analysis
- Demonstrate efficacy through simulations



FUSING CENSORED DEPENDENT DATA FOR DISTRIBUTED DETECTION

- H. He; P. Varshney, Syracuse Univ.
- GLRT framework for fusion of censored, dependent data based on "coupola theory"
 - Coupolas: parametric coupling of marginals to form joint distbns
 - Data dependency structure assumed unknown
 - Data quantized before sending to FC

| Copulas | | Parametric Form | | Parameter Range |
|------------------------|-------------|--|---|--|
| Elliptical copulas | Gaussian | $\Phi_{\Sigma}(\Phi^{-1}(v_1), \dots, \Phi^{-1}(v_N)),$ | $ \Phi_{\Sigma}(\mathbf{x}) = \int_{0}^{\mathbf{x}} \mathcal{N}(\mathbf{x}; 0, \Sigma) d\mathbf{x}, \ \mathbf{x} \in \mathbb{R}^{N} \\ \Phi^{-1}(v) = \inf_{x \in \mathbb{R}} \{ u \leq \int_{0}^{x} \mathcal{N}(x; 0, 1) dx \} $ | $\begin{split} \boldsymbol{\Sigma} &= [\rho_{mn}], m, n = 1, \dots, N\\ \rho_{mn} \in [-1, 1] \end{split}$ |
| | Student-t | $t_{\nu,\Sigma}(t_{\nu}^{-1}(v_1),\ldots,t_{\nu}^{-1}(v_N)),$ | $t_{\nu,\Sigma}$: multivariate Student- t CDF t_{ν}^{-1} : inverse CDF of univariate Student- t | ν : degrees of freedom, $\nu \ge 3$ |
| Archimedean copulas | Clayton | $\left(\sum_{n=1}^{N} v_n^{-\phi} - 1\right)^{-\frac{1}{\phi}}$ | | $\phi \in [-1,\infty) \backslash \{0\}$ |
| | Frank | $-\frac{1}{\phi} \log \left(1 + \frac{\prod_{n=1}^{N} \left[\exp\left\{-\phi v_n\right\} - 1\right]}{\exp\left\{-\phi\right\} - 1}\right)$ | | $\phi \in \mathbb{R} \setminus \{0\}$ |
| | Gumbel | $\exp \left\{-\left(\sum_{n=1}^{N}(-\ln v_n)^{\phi}\right)^{\frac{1}{\phi}}\right\}$ | | $\phi \in [1,\infty)$ |
| | Independent | $\prod_{n=1}^{N} v_n$ | | - |

- Optimal GLRT hard to implement; propose to use "controlled" noise
 - Sub-optimal but computationally efficient detector

SENSOR NETWORK TOMOGRAPHY: THE REVENGE OF THE DETECTED

- Marano, S.; Matta, V.; Willett, P.
- S sensors deployed at unknown locations
- At time t, Nt sensors detect a target; Nt is revealed to the target. Total number of sensors is also known
- By collecting {Nt, t = 1, 2, ...}, can the target localize the sensors?
- Consider MSE in localization as performance metric
- Optimal ML detector: combinatorial complexity. Viable alternatives proposed, and their performance studied via sims
 - A trellis based estimator is found to offer the best performance

POISSON GROUP TESTING: A PROBABILISTIC MODEL FOR BOOLEAN COMPRESSED SENSING

• Emad, A.; Milenkovic, O.