Journal Watch:

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Compressive Two Dimensional Harmonic Retrieval via Atomic Norm Minimization.

Authors: Yuejie Chi and Yuxin Chen

Affiliations: Ohio State University and Stanford University

Compressive Two Dimensional Harmonic Retrieval via Atomic Norm Minimization

- **Problem Statement:**
  - Recovery of 2D signal $\mathbf{x}$ which is (approximately) sparse under 2D Fourier Transform from its compressive measurements $\mathbf{y}$

    $$\mathbf{x}(k_1, k_2) = \frac{1}{4M+1} \sum_{i=1}^{r} d_i e^{j2\pi(f_{i,1}k_1 + f_{i,2}k_2)}$$

    where $[f_{i,1}, f_{i,2}]$ are distinct 2D frequency pairs
  - We can write $\mathbf{x} = (\mathbf{F} \otimes \mathbf{F})\mathbf{d}$, where $\mathbf{d}$ is approximately sparse, $\mathbf{F}$ being the DFT matrix
  - **Major Issue:** If true frequencies do not coincide with the hypothesized grid, the performance can degrade considerably
- **Main results:**
  - Suggests Atomic norm minimization for 2D harmonic retrieval, to resolve grid mismatch issue
  - Atomic norm: $||\mathbf{x}||_{\mathcal{A}} = \inf_{f_i \in [0,1] x [0,1], d_i \in \mathbb{C}} \{\sum_i |d_i| \ | \ \mathbf{x} = \sum_1 d_i \mathbf{c}(f_i)\}$
  - Proposes to solve the following as an SDP:

    $$\min_{\mathbf{x}} ||\mathbf{x}||_{\mathcal{A}} \ \ s.t. \ \ \mathbf{y} = \Phi\mathbf{x}$$

  - Under assumptions of minimum separation between f_i's, true $\mathbf{x}$ can be recovered provided sample complexity exceeds $\mathcal{O}(r \log r \log n)$

Bayesian Hypothesis Test Using Nonparametric Belief Propagation for Noisy Sparse Recovery.

Authors: Jaewook Kang, Heung-No Lee and Kiseon Kim

Affiliations: Gwangju Institute of Science and Technology, Republic of Korea

Bayesian Hypothesis Test Using Nonparametric Belief Propagation for Noisy Sparse Recovery

- **Problem Statement:**
  - Noisy Sparse Recovery: Recover sparse vector **x** from noisy compressive measurements **y**

$$\mathbf{y} = \Phi\mathbf{x} + \mathbf{w}$$

  - Φ is LDPC like measurement matrix
  - **Goal:** Want to do robust support detection
- **Main results:**
  - Proposes BHT-BP algorithm.
  - First detect sparse support by combination of BP and BHT, then the non zero coefficients are obtained through LMMSE estimation
  - Instead of parameterized PDF's, uniformly sampled PDF is used as messages between the variable and factor nodes (non-parametric approach is adopted)
  - Once BP has converged, the algorithm performs Binary Hypothesis Test for each index to detect a "0" or "nonzero"... Test metric is also generated using sampled distributions.
  - Shown to outperform CS-BP algorithm

Compressive Phase Retrieval via Generalized Approximate Message Passing.

Authors: Philip Schniter and Sundeep Rangan

Affiliations: Ohio State University and New York University

Compressive Phase Retrieval via Generalized Approximate Message Passing

- **Problem Statement:**
  - Phase reteival problem: Recover a sparse vector $\mathbf{x}$ from the magnitudes of noisy compressive linear measurements $\mathbf{y}$

$$\mathbf{y} = \Phi\mathbf{x} + \mathbf{w}$$

  - Why? Often easier to build detectors that measure intensity rather than the phase
- **Main results:**
  - Proposes to use GAMP framework to estimating the posterior $p(\mathbf{x}|\mathbf{y})$
  - Bernoulli Gaussian signal prior is imposed on the unknown signal vector $\mathbf{x}$
  - $p(\mathbf{y}_m|\mathbf{x})$ turns out to be Rician as $\mathbf{y}_m = |\phi_m^T\mathbf{x} + \mathbf{w}|$
  - Measurement noise variance estimated through EM algo, needed posteriors coming from GAMP framework
  - Shown to outperform GESPAR and CPRL algorithms

A State Space Approach to Dynamic Nonnegative Matrix Factorization.

Authors: Nasser Mohammadiha, Paris Smaragdis, Ghazaleh Panahandeh and Simon Doclo

Affiliations: University of Oldenberg, Germany and UIUC and KTH

A State Space Approach to Dynamic Nonnegative Matrix Factorization

- **Non negative matrix factorization (NMF):**
  - For given non negative $m \times n$ sized data matrix $\mathbf{X}$, find the factorization $\mathbf{WH}$ such that $\mathbf{X} \approx \mathbf{WH}$
  - $\mathbf{W}$ is low rank, non negative basis matrix of size $m \times r$
  - $\mathbf{H}$ is low rank, non negative coefficient matrix of size $r \times n$
  - In deterministic NMF, a cost function measuring approximation error is minimized under non-negativity constraint on $\mathbf{W}$ and $\mathbf{H}$
- **Main results:**
  - Proposes dynamic NMF algorithm (D-NMF) (probabilistic approach)
  - Columns of $\mathbf{H}$ are assumed to evolve acc. to J^{th} *order* N-VAR model:

$$f(\mathbf{h}_t|\mathbf{A}, \mathbf{h}_{t-1} \dots \mathbf{h}_{t-J}) = \mathcal{N}(\mathbf{h}_t; 0, \sum_{j=1}^{J} \mathbf{A}_j \mathbf{h}_{t-j})$$

  - Measurement model modelled as:

$$f(\mathbf{x}_t|\mathbf{W}, \mathbf{h}_t) = multinomial(\mathbf{x}_t; \sum_{k=1}^{m} x_{k,t}, \mathbf{W}\mathbf{h}_t)$$

  - Maximization of a Q function is considered: $Q = \log p(\mathbf{X}, \mathbf{H}|\mathbf{W}, \mathbf{A})$
  - EM algorithm is used to obtain MAP estimate of hidden variable $\mathbf{H}$ and ML estimates of $\mathbf{W}$ and $\mathbf{A}$

Other Interesting Papers:

- Compressive Parameter Estimation for Sparse Translation-Invariant Signals Using Polar Interpolation
- Asynchronous Adaptation and Learning Over Networks (Part-1/2/3)
- Optimal Stochastic Coordinated Beamforming for Wireless Cooperative Networks With CSI Uncertainity
- Dictionary Learning over Distributed Models
- Deterministic Constructions of Binary Measurement Matrices From Finite Geometry