Journal Watch
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Goal

- Estimating sparsity level in a single snapshot case

Contributions

- Result for matrices with a Khatri-Rao structure
- Design for Vandermonde matrices with low coherence

System Model

$$\mathbf{b} = \mathbf{A}\mathbf{x} + \mathbf{n}, \mathbf{b} \in \mathcal{C}^{\mathbf{N}}$$

$$B = [b_1 b_2 \ldots b_k] \in \mathcal{C}^{lxk}$$

$$b_i = [b_{1+p(i-1)}, b_{2+p(i-1)}, \ldots, b_{l+p(i-1)}]^T \in \mathcal{C}^l$$

Idea is that for a suitably chosen A, rank(B) = K for any K-sparse x

Theorem for Non-Overlapping Blocks

For k blocks of length l and any r $\leq$ min(k,l), the following results are valid:

- For all s $\leq$ r and all s-sparse x, it holds that k-rank(B) $=$ s
- $A = \phi \odot \psi$ for some $\phi \in \mathcal{C}^{kxN}, \psi \in \mathcal{C}^{lxN}$ with k-rank(ϕ) $\geq$ r and k-rank(ψ) $\geq$ r

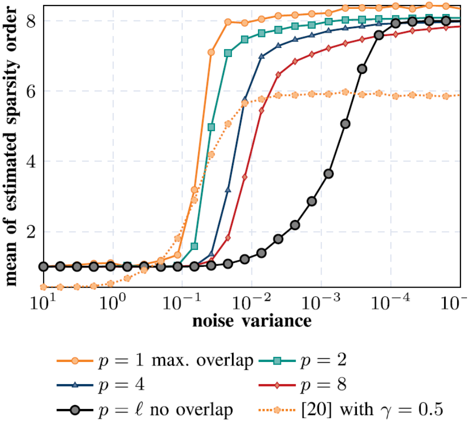
Theorem for Overlapping Blocks

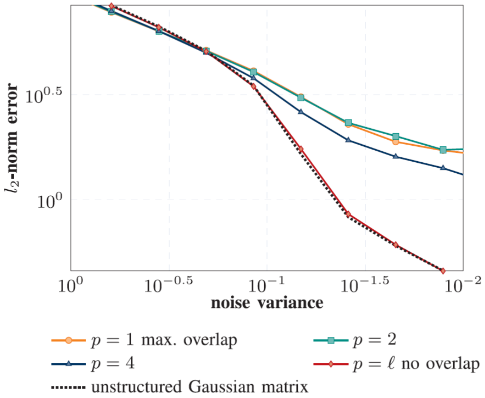
For k overlapping blocks of length l, block advance p and any r $\leq$ min(k,l), the following results are valid:

- For all s $\leq$ r and all s-sparse x, it holds that k-rank(B) $=$ s
- A consists of the first m rows of $V \odot \psi$ for some $\psi \in \mathcal{C}^{pxN}$ with V being a Vandermonde matrix such that V restricted to its first k rows has k-rank r

Noisy case

With AWGN, B is full rank with probability 1.
Knowing the statistics of noise, Eigenvalue Threshold Test/Exponential Fitting Test can be used for finding the "effective" rank of B.


mean of estimated sparsity order
8
6
4
2
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-}
noise variance
$p = 1$ max. overlap
$p = 2$
$p = 4$
$p = 8$
$p = \ell$ no overlap
[20] with $\gamma = 0.5$


l_2-norm error
$10^{0.5}$
10^{0}
10^{0}
$10^{-0.5}$
10^{-1}
$10^{-1.5}$
10^{-2}
noise variance
$p = 1$ max. overlap
$p = 2$
$p = 4$
$p = \ell$ no overlap
unstructured Gaussian matrix

A Fast Non Iterative Algorithm for Compressive Sensing Using Binary Measurement Matrices

Goal

- Sparse signal recovery with usage of a binary measurement matrix
- Single pass recovery with no iterations
- Guarantees for stable recovery of all sparse vectors with a few measurements

System Model

1. $y = Ax + n, A \in \{0, 1\}^{mxn}$
2. Assumption: Every column of A has exactly q non-zero entries

New Recovery Algorithm

```
for j ∈ [n] do
    Construct the reduced measurement vector ȳ_j.
    Find the number of the elements of ȳ_j that are
    nonzero;
  call it ν.    ▷ (In implementation, we find the number of
  elements that are greater than some tolerance δ.)
    if ν > q/2 then
        Find a group of q/2 elements in ȳ_j that are equal;
  call this value θ_j. ▷ (In implementation, we allow some
  tolerance here.)
        x̂_j = θ_j.
    else
        x̂_j = 0
    end
end
```

Results

- Proposed Algorithm with complexity of $\mathcal{O}(nklog(k))$
- Proposed Algorithm requires $m = q^2$ measurements, where $q \geq max(4k, n^{2/3})$
- For n = 20,000 and k = 6, l_1 norm min. requires m = 1369, expander graph requires m = 7921 whereas proposed algorithm requires m = 841

PERFORMANCE OF NEW ALGORITHM AND ℓ_1-NORM MINIMIZATION WITH ADDITIVE SHOT NOISE

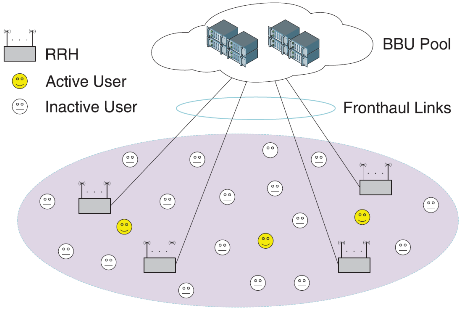
	New Algorithm		ℓ_1-norm minimization	
Alpha	**Err.**	**Time**	**Err.**	**Time**
10^{-5}	0	0.1335	3.2887e-06	26.8822
10^{-4}	0	0.1325	3.2975e-05	26.6398
10^{-3}	0	0.1336	3.3641e-04	28.1876
10^{-2}	0	0.1357	0.0033	23.1727
10^{-1}	0	0.1571	0.033	28.9145
10	0	0.1409	1.3742	26.6362
20	0	0.1494	1.3967	26.5336

Compressive Channel Estimation and Multi-User Detection in C-RAN With Low-Complexity Methods

Goal

- Low complexity methods for estimating CSI in a Cloud-Radio Access Network

Architecture



System Model

$$R = H\Lambda P + N_1 \Rightarrow B = AX + N$$

$$\mathbf{X} = \begin{bmatrix} \mathbb{1}_1 \mathbf{H}_{1,1}^H & \cdots & \mathbb{1}_1 \mathbf{H}_{G,1}^H \\ \cdots & \cdots & \cdots \\ \mathbb{1}_K \mathbf{H}_{1,K}^H & \cdots & \mathbb{1}_K \mathbf{H}_{G,K}^H \end{bmatrix}$$

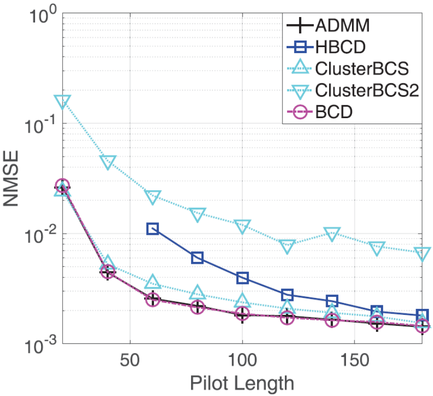
Strategy

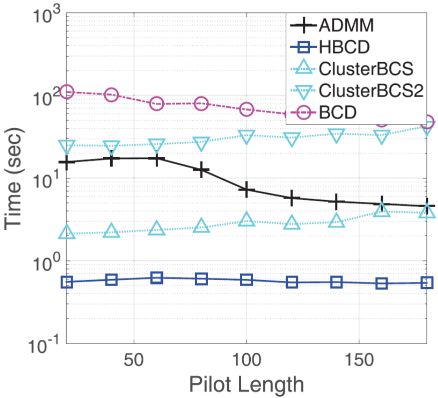
$$\min_{\mathbf{X}} \ \alpha_1 \sum_{i=1}^{K} \boldsymbol{w}_i \left\|\mathbf{X}_i\right\|_F + \alpha_2 \sum_{i=1}^{K} \sum_{j=1}^{G} \mathbf{W}_{i,j} \left\|\mathbf{X}_{i,j}\right\|_F + \frac{1}{2} \left\|\mathbf{A}\mathbf{X} - \mathbf{B}\right\|_F^2$$

$$\min_{\mathbf{x}} \ \alpha_1 \sum_{k=1}^{K} \left\|\mathbf{x}^{(k)}\right\|_F + \alpha_2 \left\|\mathbf{x}\right\|_1 + \frac{1}{2} \left\|\bar{\mathbf{A}}\mathbf{x} - \mathbf{b}\right\|_F^2$$

Solution

- Alternating Direction Method of Multipliers
- Block Coordinate Descent
- Hybrid Block Coordinate Descent


NMSE
Pilot Length
ADMM
HBCD
ClusterBCS
ClusterBCS2
BCD
10^0
10^{-1}
10^{-2}
10^{-3}
50
100
150


Time (sec)
Pilot Length
ADMM
HBCD
ClusterBCS
ClusterBCS2
BCD
10^3
10^2
10^1
10^0
10^{-1}
50
100
150

Other Interesting Papers

TSP Aug. 1:

1. A Framework for Clustered and Skewed Sparse Signal Recovery
2. Multilayer Convolutional Sparse Modeling - Pursuit and Dictionary Learning
3. DOA Estimation Using Compressed Sparse Array
4. Hybrid Beamforming With Selection for Multiuser Massive MIMO Systems

TWC June:

1. Estimation of Broadband Multiuser Millimeter Wave Massive MIMO-OFDM Channels by Exploiting Their Sparse Structure
2. Joint Optimization of Hybrid Beamforming for Multi-User Massive MIMO Downlink
3. Channel Estimation for TDD/FDD Massive MIMO Systems With Channel Covariance Computing
4. Joint Optimization of Computation and Communication Power in Multi-User Massive MIMO Systems