# Journal Watch:

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# Sparsity-Aware Sphere Decoding: Algorithms and Complexity Analysis.

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# Sparsity-Aware Sphere Decoding: Algorithms and Complexity Analysis (1/2)

- **Problem Statement:**
  - Integer Least Squares (ILS) problem:

$$\mathbf{x}^* = \underset{\mathbf{x} \in \mathbb{Z}^m}{\mathbf{arg\,min}} ||\mathbf{y} - \mathbf{H}\mathbf{x}||_2^2$$

    where $\mathbf{x}$ is k-sparse.
- **Main Contributions:**
  - Proposes Sparsity-Aware Sphere Decoding algorithm which exploits sparsity of $\mathbf{x}$.
  - Proposed algorithm is computationally more efficient than conventional sphere decoding.
  - Exact characterization of algorithm complexity in terms of:
    - Expected number of lattice points for which ML metric is evaluated.
    - Variance of number of lattice points for which ML metric is evaluated.
  - Algorithm applied to sparse channel estimation problem.

# Sparsity-Aware Sphere Decoding: Algorithms and Complexity Analysis (2/2)

- **Sphere Decoding:**
  - Restricted sequential search over lattice to find lattice point which lies inside the sphere $d^2 \geq ||\mathbf{y} - \mathbf{Hx}||_2^2$ and for which the ML metric is minimum.
  - Say $\mathbf{H}$ admits QR decomposition, $\mathbf{H} = \mathbf{QR}$.
  - Then, candidate lattice point must satisfy $d^2 \geq ||\mathbf{Q}^H\mathbf{y} - \mathbf{Rx}||_2^2$ which yields a series of ever tightening feasibility conditions.

    $$d^2 \geq ||\mathbf{Q}^H\mathbf{y} - \mathbf{Rx}||_2^2 = (z_m - \mathbf{R}_{m,m}\mathbf{x}_m)^2 + (z_{m-1} - \mathbf{R}_{m-1,m}\mathbf{x}_m\mathbf{R}_{m-1,m-1}\mathbf{x}_{m-1})^2 \ldots..$$

    where $\mathbf{z} = \mathbf{Q}^H\mathbf{y}$.
- **Sparsity-Aware Sphere Decoding:**
  - At each iteration of sphere decoding algorithm, the non sparse candidates are pruned.
  - Coloring of lattice points and pruning is done using D-ary trees (D is the alphabet set used for lattice generation)

# Joint Sparse Decomposition-and-Synthesis Approach and Acheivable DoF Regions for K-User MIMO Interference Channels (1/2).

Authors: Jiayi Chen, Q.T.Zhang and Guarong Chen

Affiliations: City University of Hong Kong, Kowloon

# Joint Sparse Decomposition-and-Synthesis Approach and Acheivable DoF Regions for K-User MIMO Interference Channels (2/2)

- **Problem Statement:**
  - $K$-User MIMO interference channel with $K$ pairs of transmitters and receivers.
  - $i^{th}$ pair transmitter has $N_i$ antennas and receiver has $M_i$ antennas.
  - Goal-1: Design precoding matrices $\{\mathbf{V}_i\}_{i=1}^{k}$, one for each transmitter such that sum DoF is maximized.
  - Goal-2: Characterize the DoF region for K-user MIMO interference channel.
- **Main Contributions:**
  - Proposes Joint Space Decomposition and Synthesis Approach for finding out the precoding matrices.
  - Exact characterize of the DoF region for 2-user and 3 user MIMO interference channel.
  - Upper and lower bounds derived for general K-user MIMO interference channel.

# Joint Sparse Decomposition-and-Synthesis Approach and Acheivable DoF Regions for K-User MIMO Interference Channels

- **Joint Sparse Decomposition-and-Synthesis Approach**
  - Channel matrix for all transmitter/receiver pairs is assumed to be known apriori on both sides.
  - At $i^{th}$ receiver:

$$\mathbf{y}_i = \mathbf{H}_{ii}\mathbf{V}_i\mathbf{s}_i + \sum_{j \neq i} \mathbf{H}_{ij}\mathbf{V}_j\mathbf{s}_j + \mathbf{w}_i$$

  - Observe that $span(\mathbf{H}_{ii}\mathbf{V}_i) \subseteq span(\mathbf{H}_{ii})$ and $span(\mathbf{H}_{ii}^{'}\mathbf{V}_i^{'}) \subseteq span(\mathbf{H}_{ii}^{'})$, where $\mathbf{H}_{ii}^{'}\mathbf{V}_i^{'}$ is compact representation of interference terms at $i^{th}$ receiver.
  - $span(\mathbf{H}_{ii})$ and $span(\mathbf{H}_{ii}^{'})$ may or may not overlap.
  - QSVD algorithm used to identify basis function for non-overlapping sub-spaces of $span(\mathbf{H}_{ii})$ and $span(\mathbf{H}_{ii}^{'})$.
  - These identified basis functions then used to construct precoding matrices which ensure signal and inteference are observed at receiver in disjoint sub-spaces.

# Reconstruction of Signals Drawn From a Gaussian Mixture Via Noisy Compressive Measurements (1/2).

Authors: Francesco Renna, Robert Caldetrbach, Lawrence Carin, Miguel R.D.Rodrigues

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# Reconstruction of Signals Drawn From a Gaussian Mixture Via Noisy Compressive Measurements (1/1).

- **Problem Setup:**
  - Noisy linear measurement model $\mathbf{y} = \Phi\mathbf{x} + \mathbf{w}$, where $\mathbf{w} \sim N(0, \sigma^2\mathbf{I})$.
  - $\mathbf{x}$ is drawn from a *Gaussian Mixture Model* (GMM) i.e., $\mathbf{x} \sim \sum_{k=1}^{K} p_k \mathcal{N}(\boldsymbol{\mu}^k, \Sigma^k)$.
  - Since $s_k = rank(\Sigma^k) << n$, $\mathbf{x}$ is sparse under a suitable change of basis.
- **Main Contributions:**
  - Characterize *MMSE phase transition* under low-noise regime ($\sigma^2 \to 0$).
  - Understand the impact of measurement matrix design on *MMSE phase transition*.
- **Main Results:**
  - For low noise regime and $m$ independent measurements:-
  - $MMSE^G(\sigma^2) = M_\infty^G + \mathcal{D}^G\sigma^2 + o(\sigma^2)$.
  - When $m < s_{\max}, s_{\max} = \max\{s_k\}$, then $MMSE^{GM}(\sigma^2)$ converges to an error floor as $\sigma^2 \sim 0$.
  - When $m > s_{\max}$, then $MMSE^{GM}(\sigma^2)$ converges to zero $\sigma^2 \sim 0$.
  - When $m = s_{\max}$, then $MMSE^{GM}(\sigma^2)$ may or maynot converges to zero.

  - The design of measurement matrix elements has no impact on MMSE phase transition curve.

# Sequential Bayesian Estimation with Censored Data for Multi-Sensor Systems.

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# Sequential Bayesian Estimation with Censored Data for Multi-Sensor Systems (1/2)

- **Problem Statement:**
  - Multiple nodes want to track a common state vector using local noisy linear measurements.
  - Common State model: $\mathbf{x}_{k+1} = \mathbf{F}_k \mathbf{x}_k + \mathbf{u}_k$
  - Local meas model at $i^{th}$ node: $\mathbf{y}_k^i = \mathbf{H}^i \mathbf{x}_k + \mathbf{w}_k^i$
  - A fusion center exists which receives raw measurements from each node and performs joint state tracking.
  - All nodes may not send data to fusion center in order to save communication traffic per time epoch.
- **Big Questions:**
  1. What rule to use to censor data at each node?
  2. How to handle missing data at fusion center to improve state tracking performance? The action of censoring data itself conveys **some information** about state !!
- **Main Contributions:**
  - A distributed Kalman Filter framework proposed which addresses these two questions.

# Sequential Bayesian Estimation with Censored Data for Multi-Sensor Systems (2/2)

- **When to censor data at each node?**
  - If variance of innovation is greater than *threshold*, transmit raw measurements to fusion center.
  - *threshold* chosen offline such that expected number of nodes transmitting at each time epoch is $L$.
- **How to handle missing data at Fusion Center?**
  1. Fusion Center runs a particle filter with aposterior pdf of state vector given measurement approximated by a pmf.
  2. If data is not available from a censor, it conveys information about current state vector.
  3. $p(\mathbf{y}_k^{obs}, \text{binary censor vector} | \mathbf{x}_k)$ is used to update aposterior state pdf.

# Other Interesting Papers:

- *Information and Energy Cooperation in Cognitive Radio Networks*, Gan Zheng ; Ho, Z. ; Jorswieck, E.A. ; Ottersten, B.
- $\ell_{1/2}$ *Regularization: Convergence of Iterative Half Thresholding Algorithm*, Jinshan Zeng ; Shaobo Lin ; Yao Wang ; Zongben Xu
- *Adaptive Double Subspace Signal Detection in Gaussian BackgroundâPart I: Homogeneous Environments* Weijian Liu ; Wenchong Xie ; Jun Liu ; Yongliang Wang
- *Adaptive Double Subspace Signal Detection in Gaussian BackgroundâPart II: Partially Homogeneous Environments* Weijian Liu ; Wenchong Xie ; Jun Liu ; Yongliang Wang
- *Distributed Localization of Coverage Holes Using Topological Persistence* Chintakunta, H. ; Krim, H.
- *Deepest Minimum Criterion for Biased Affine Estimation* Cernuschi-Frias, B. ; Gama, F. ; Casaglia, D.

***Thank You !!!***