



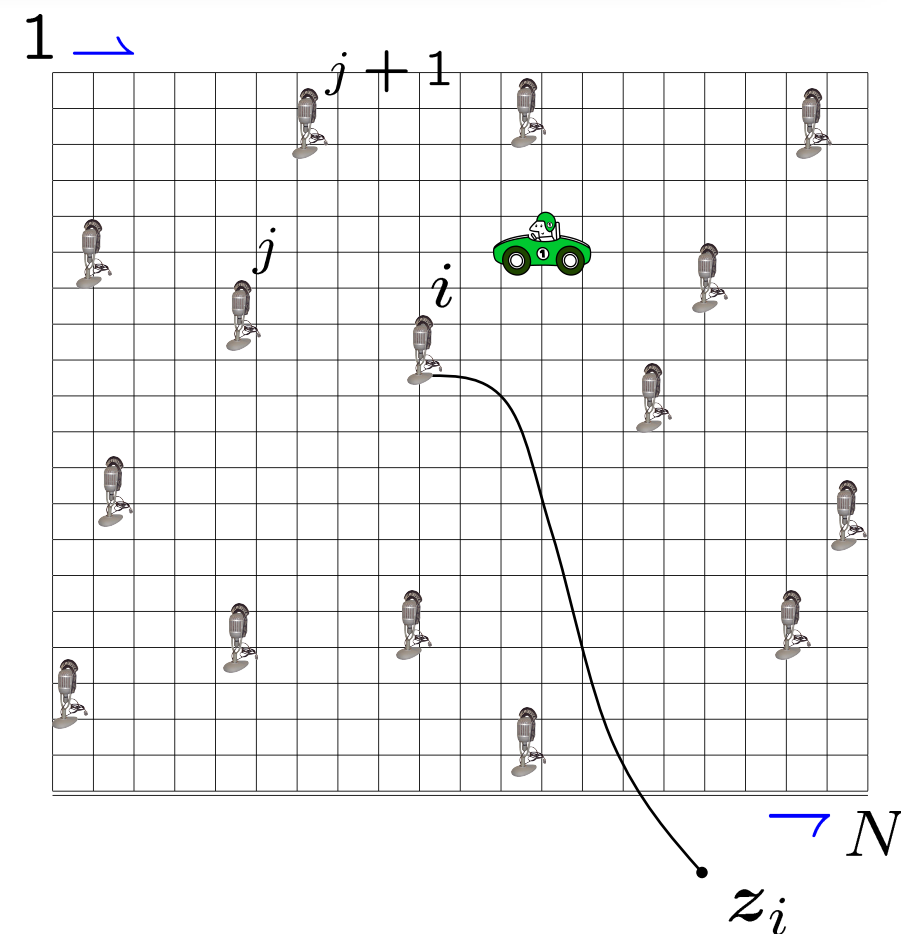
# Localization and Bearing Estimation via Structured Sparsity Models

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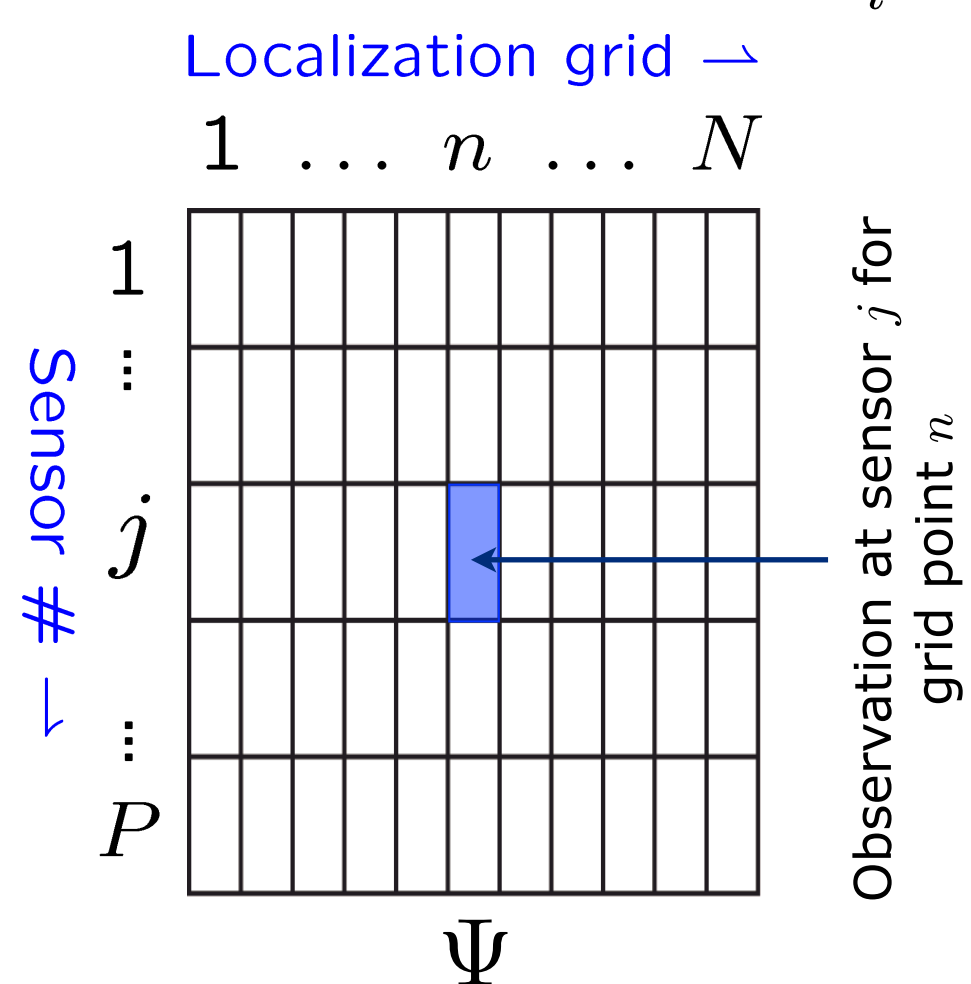
## Sparsity-Based Localization

- Build  $N$ -sample grid  $\{z_i\}_{i=1}^N$  to **discretize** localization space (field, range of orientations...)
- A **small number of targets**  $K$  is assumed to be present at locations within grid
- Build **localization dictionary** by collecting observations at  $P$  sensors for a target located at each of the grid points  $z_i$
- Recorded observations can be expressed as product of localization dictionary and **sparse location vector**  $c$ :



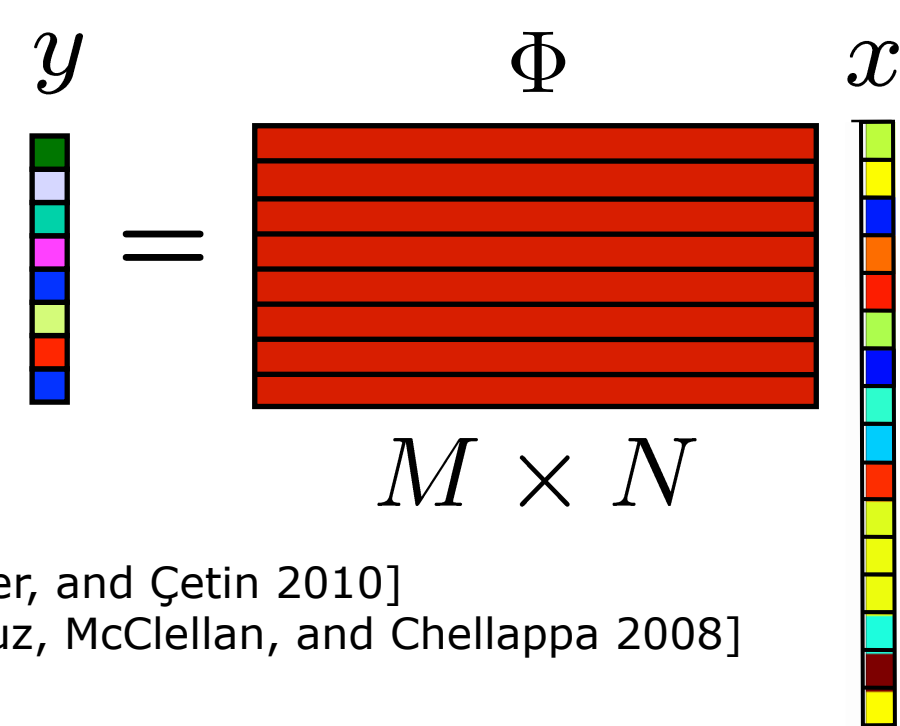
$$x = \Psi c, \quad c \in \Sigma_K$$

- Sparse vector  $c$  encodes locations in its **support** (indices of nonzero entries)
- Use **sparse approximation** to obtain target locations from collected observations (e.g., IHT, CoSaMP, ...)
- Can be combined with **compressive sensing** to reduce dimensionality of acquired data:



$$y = \Phi x = \Phi \Psi c$$

Requires  $M = \mathcal{O}(K \log(N/K))$  random measurements



[Gorodnitsky and Rao 1997][Potter, Ertin, Parker, and Cetin 2010]  
[Cevher, Duarte, Baraniuk 2008][Cevher, Gurbuz, McClellan, and Chellappa 2008]  
Many others...

## Issues with Sparsity

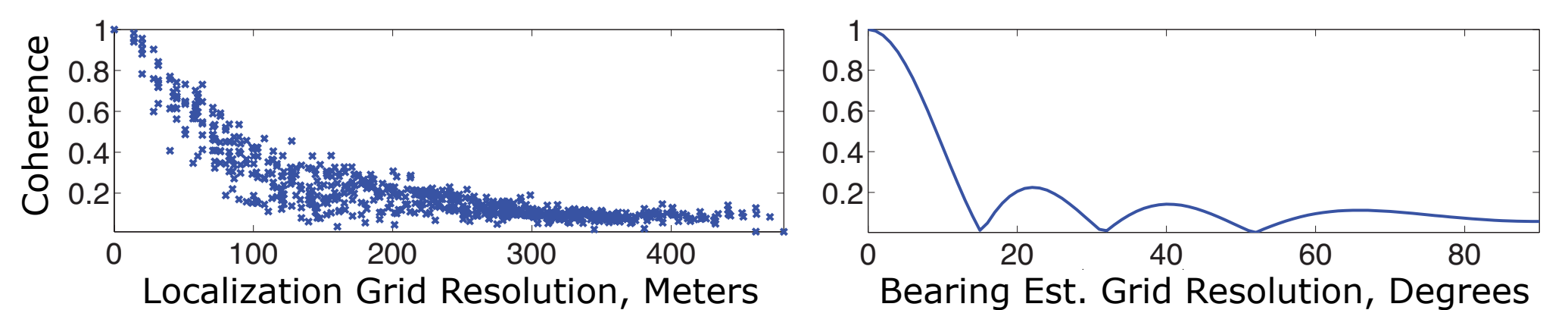
- Coherence** measures similarity between columns of sparsity dictionary: for  $\Psi = [\psi_1 \ \psi_2 \ \dots \ \psi_N]$ ,

$$\mu(\Psi) = \max_{1 \leq i, j \leq N, i \neq j} \frac{|\langle \psi_i, \psi_j \rangle|}{\|\psi_i\|_2 \|\psi_j\|_2}$$

- Connection between dictionary coherence and performance of sparse approximation: *one can recover a  $K$ -sparse vector  $c$  from  $x = \Psi c$  if*

$$K \leq \frac{1}{2} \left( 1 + \frac{1}{\mu(\Psi)} \right) \quad [\text{Donoho and Elad 2003}]$$

- Discretization requires that actual target locations are within (or sufficiently close to) grid samples, which **requires fine resolution** in dictionary
- As dictionary grid resolution increases, coherence **approaches maximum value** of 1



Resolution **tradeoff**:

- increased resolution **enlarges** set of configurations that provide  $x \approx \Psi c$  for a  $K$ -sparse vector  $c$
- increased resolution **worsens** coherence, **limits** values of  $K$  for which the  $K$ -sparse vector  $c$  can be recovered
- Connection between coherence in localization dictionary and **resolution/ambiguity issues** present in standard localization/bearing estimation algorithms
- These issues are **exacerbated** with compressive sensing

## Structured Sparsity Models

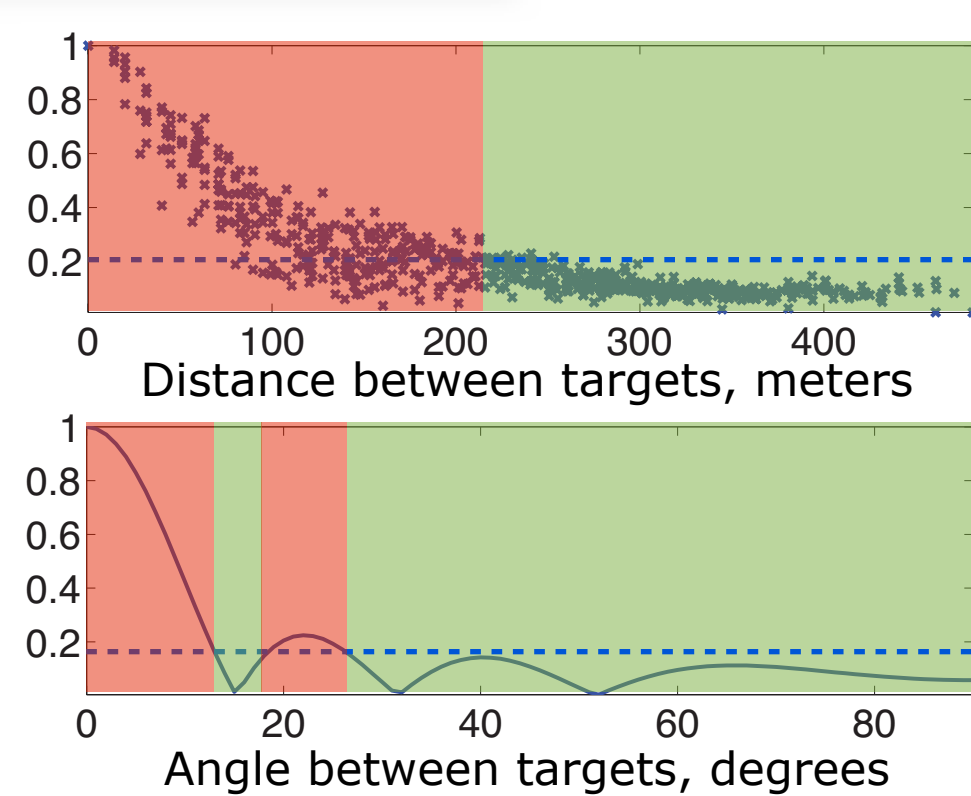
- A structured sparsity model  $\mathcal{M}_K \subseteq \Sigma_K$  **restricts** possible locations of nonzero coefficients of  $c \in \Sigma_K$  so that they exhibit some desirable additional structure
- Structure can be enforced during sparse approximation (and compressive sensing recovery) by replacing usual thresholding steps by **structured thresholding**:

$$\mathbb{M}_K(c) = \arg \min_{\hat{c} \in \mathcal{M}_K} \|c - \hat{c}\|_2$$

- Example: Structured Iterative Hard Thresholding (IHT)

$$\hat{c}_t = \mathbb{M}_K(\hat{c}_{t-1} + \Psi^T \Phi^T (y - \Phi \Psi c))$$

- The **stronger** the structure assumed, the **larger the reductions** in the number of measurements required for signal recovery in compressive sensing
- We restrict set of nonzeros to include **only indices that correspond to incoherent columns** of localization dictionary:



$$x \in \mathcal{M}_K \text{ if } x = \sum_{i=1}^K c_i \Psi_{n_i}, \quad \frac{|\langle \Psi_{n_i}, \Psi_{n_j} \rangle|}{\|\Psi_{n_i}\|_2 \|\Psi_{n_j}\|_2} \leq \mu_0$$

for all  $i \neq j, n_i \in \{1, \dots, N\}, i, j = 1, \dots, K.$

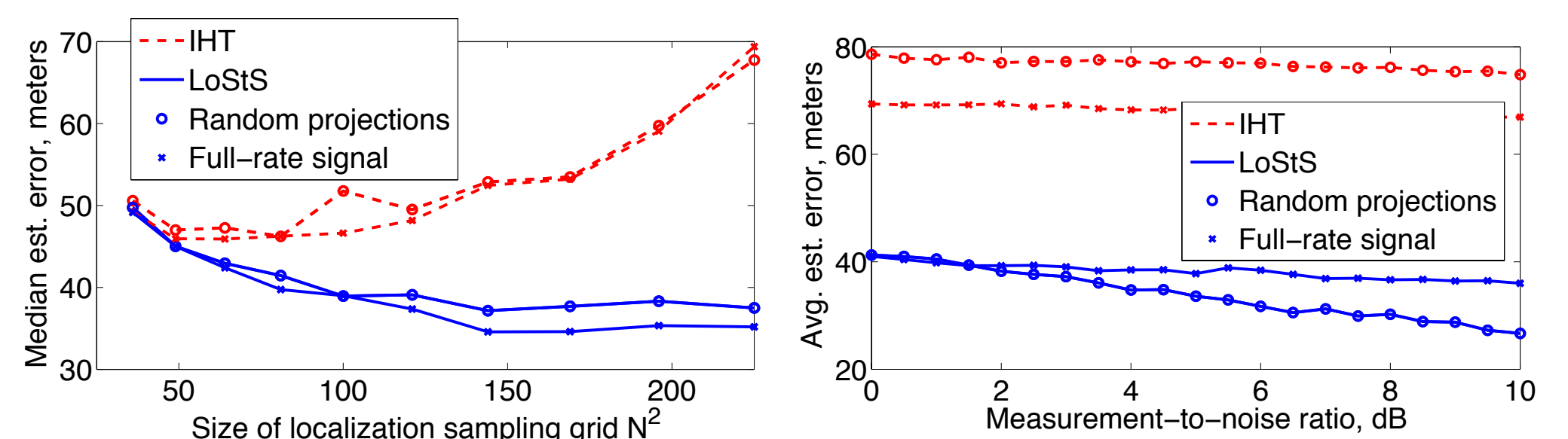
- This coherence-inhibiting structured sparsity model shows a **connection** between localization resolution and sparse approximation
- For this model, structured thresholding can be performed via **linear programming** or approximated via **heuristics**

[Baraniuk, Cevher, Duarte, and Hegde 2010][Duarte and Baraniuk 2011]

## Numerical Results

**Localization via Structured Sparsity (LoStS) Simulation:**

- Randomly deployed  $K = 5$  sources and  $P = 20$  microphones
- Regular grid of  $\sqrt{N} \times \sqrt{N}$  locations in  $340 \times 340$  m field
- Sources transmit MSK-modulated binary sequence
- Localization via standard sparsity (IHT) and LoStS from full-rate signal and from  $M = 100$  random measurements



**Bearing Estimation via Structured Sparsity (BESTs) Simulation:**

- Randomly deployed  $K = 5$  far-field sources
- Linear array of  $P = 10$  microphone sensors, 25 cm spacing
- Regular grid of  $N$  bearings/angles in range  $[0, 360]$
- Sources transmit beacon at 500 kHz frequency
- Bearing estimation via IHT and BESTs from full-rate signal and from  $M = 100$  random measurements

