

AN ℓ_0 SOLUTION TO SPARSE APPROXIMATION PROBLEMS WITH CONTINUOUS DICTIONARIES



Mégane Boudineau*, Hervé Carfantan*, Sébastien Bourguignon†

*IRAP, Université de Toulouse, CNRS, UPS, CNES, Toulouse, France

†LS2N, École Centrale de Nantes/CNRS, Nantes, France



Paper's objective

Sparsity with a continuous dictionary

\mathcal{P}^C : Estimate (\mathbf{x}, δ) s.t. $\mathbf{y} \approx \sum_j x_j \mathbf{h}_j(\delta_j)$

with **sparse** \mathbf{x} and $|\delta_j| \leq \frac{\Delta}{2}$

- **Sparse amplitudes**: $\mathbf{x} \in \mathbb{R}^J$ s.t. few $x_j \neq 0$
- **Continuous atoms**: $\mathbf{h}_j(\delta_j) = \mathbf{h}(\tau_j + \delta_j)$
- **Discretization grid**: \mathcal{G} s.t. $\tau_j \in \mathcal{G}$
- **Discretization step**: $\Delta = \tau_{j+1} - \tau_j$

Main difficulties

- Nonlinearity of $\mathbf{h}_j(\cdot)$ w.r.t. δ_j
- Sparse \mathbf{x}

Linearization

with polar interpolation [2]

Linearization of $\mathbf{h}(\cdot)$

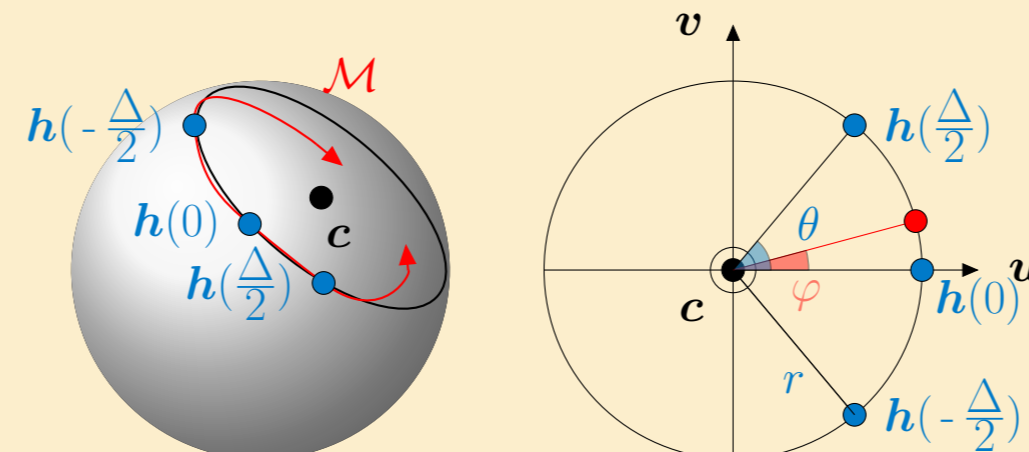
1. Taylor: $\mathbf{h}(\delta) \approx \mathbf{h}(0) + \delta \mathbf{h}'(0)$

2. Polar:

$$\varphi = \frac{2\theta}{\Delta} \delta$$

$$\downarrow$$

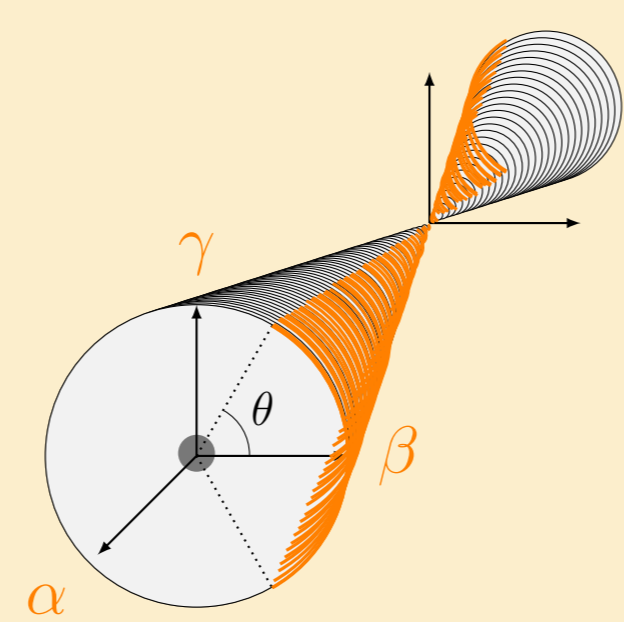
$$|\delta| \leq \frac{\Delta}{2} \Leftrightarrow |\varphi| \leq \theta$$



$$\mathbf{x} \mathbf{h}(\delta) \approx \mathbf{x} \mathbf{c} + \mathbf{x} r \cos \varphi \mathbf{u} + \mathbf{x} r \sin \varphi \mathbf{v}$$

$$\approx \alpha \mathbf{c} + \beta \mathbf{u} + \gamma \mathbf{v}$$

Bijjective change of variables



$$(\alpha, \beta, \gamma) = f(x, \delta)$$

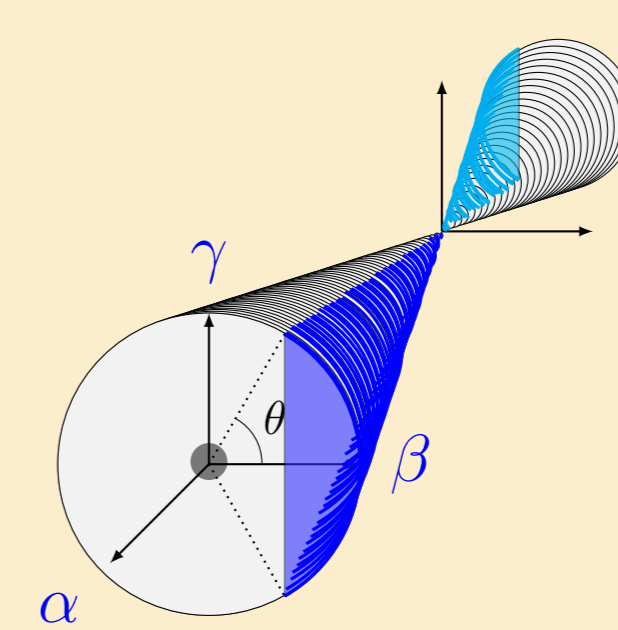
$$(x, \delta) \in (\mathbb{R} \times]-\frac{\Delta}{2}; \frac{\Delta}{2}[)$$

$$\Leftrightarrow \Omega: \begin{cases} \alpha \in \mathbb{R} \\ \beta^2 + \gamma^2 = r^2 \alpha^2 \\ \beta/\alpha \geq r \cos \theta \end{cases}$$

$$f^{-1}: x = \alpha, \delta = \frac{\Delta}{2\theta} \operatorname{atan2}\left(\frac{\gamma}{r\alpha}, \frac{\beta}{r\alpha}\right)$$

! Feasible set Ω not convex!

Feasible set's convex-relaxation



1. Relaxation: from cone's surface to cone's volume
2. Replace (α, β, γ) in Ω with

$$\begin{cases} (\alpha^+, \beta^+, \gamma^+) \text{ in } \Omega^+ \\ (-\alpha^-, -\beta^-, -\gamma^-) \text{ in } \Omega^- \end{cases}$$

Reformulation of \mathcal{P}^C

- Notations
- $\mathbf{C}, \mathbf{U}, \mathbf{V}$: matrix with column vectors $\mathbf{c}_j, \mathbf{u}_j, \mathbf{v}_j$
 - $\tilde{\mathbf{C}} = [\mathbf{C}, -\mathbf{C}]$ (same for \mathbf{U}, \mathbf{V}),
 - $\tilde{\alpha} = [\alpha^+, \alpha^-]^T$ (same for β, γ)

1. Estimate $(\tilde{\alpha}, \tilde{\beta}, \tilde{\gamma})$ s.t. $\mathbf{y} \approx \tilde{\mathbf{C}}\tilde{\alpha} + \tilde{\mathbf{U}}\tilde{\beta} + \tilde{\mathbf{V}}\tilde{\gamma}$

$$\text{s.t. } \begin{cases} \tilde{\alpha} \text{ is sparse} \\ \tilde{\alpha} \geq 0, \tilde{\beta} \geq \tilde{\alpha} r \cos \theta, \tilde{\beta}^2 + \tilde{\gamma}^2 \leq r^2 \tilde{\alpha}^2 \\ \alpha^+ \cdot \alpha^- = 0 \end{cases}$$

2. Reconstruct $\alpha = \alpha^+ - \alpha^-$ (and so for β, γ)

3. Recover $(\mathbf{x}, \delta) = f^{-1}(\alpha, \beta, \gamma)$

Differences with [3]:

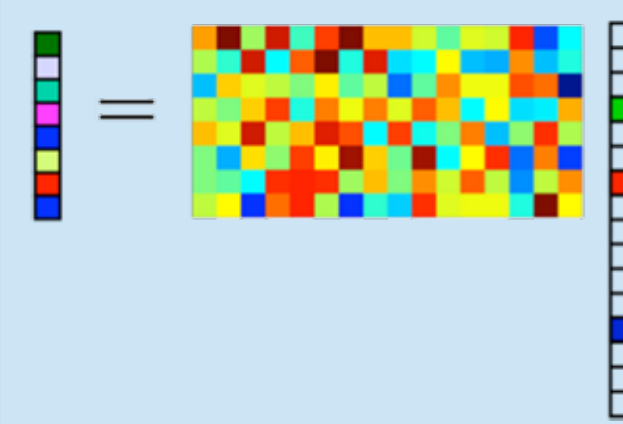
- At least α_j^+ or α_j^- is zero.
- No imposed sign for $(\beta_j^+, \beta_j^-, \gamma_j^+, \gamma_j^-)$.

Classical approach: Linear sparse approximation

Discrete model: impose $\delta_j = 0$

\mathcal{P}^D : Estimate sparse \mathbf{x} s.t.

$$\mathbf{y} \approx \mathbf{H} \mathbf{x} = \sum_{j=1}^J \mathbf{h}_j x_j \quad (\mathbf{h}_j = \mathbf{h}_j(0) = \mathbf{h}(\tau_j))$$



- Linear combinaison of *atoms* \mathbf{h}_j among a *dictionary* \mathbf{H}
- **Sparse**: few $x_j \neq 0$

$$\mathcal{P}_{2/0}^D(K_0): \min_{\mathbf{x}} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2 \text{ s.t. } \|\mathbf{x}\|_0 \leq K_0$$

$\|\mathbf{x}\|_0 = \text{Card}(j | x_j \neq 0) \rightarrow \ell_0$ pseudo-norm

\Rightarrow NP-hard problem

Suboptimal approaches

- Greedy algorithms: iterative choice of \mathbf{h}_j
- Convex relaxation: with $\|\mathbf{x}\|_1 = \sum_j |x_j|$

$$\mathcal{P}_{2+1}^D(\lambda): \min_{\mathbf{x}} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2 + \lambda \|\mathbf{x}\|_1$$

☺ (Greedy, ℓ_1) $\Leftrightarrow \ell_0$ for low sparsity level or a low-correlated *dictionary* \mathbf{H}

☹ No equivalence for correlated *dictionary* \mathbf{H}

Exact ℓ_0 resolution [1]

- Introduction of binary variables b_j s.t.

$$x_j = 0 \Leftrightarrow b_j = 0$$

- **Big-M hypothesis**: $|x_j| \leq M b_j$

\Rightarrow Reformulation of $\mathcal{P}_{2/0}^D(K_0)$:

Mixed Integer Program (MIP)

$$\mathcal{P}_{2/0}^D(K_0): \min_{\mathbf{x}, \mathbf{b}} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2 \text{ s.t. } \begin{cases} \mathbf{b} \in \{0, 1\}^J \\ -M\mathbf{b} \leq \mathbf{x} \leq M\mathbf{b} \\ \sum_{j=1}^J b_j \leq K_0 \end{cases}$$

Solution of ℓ_1 relaxation [2, 3]

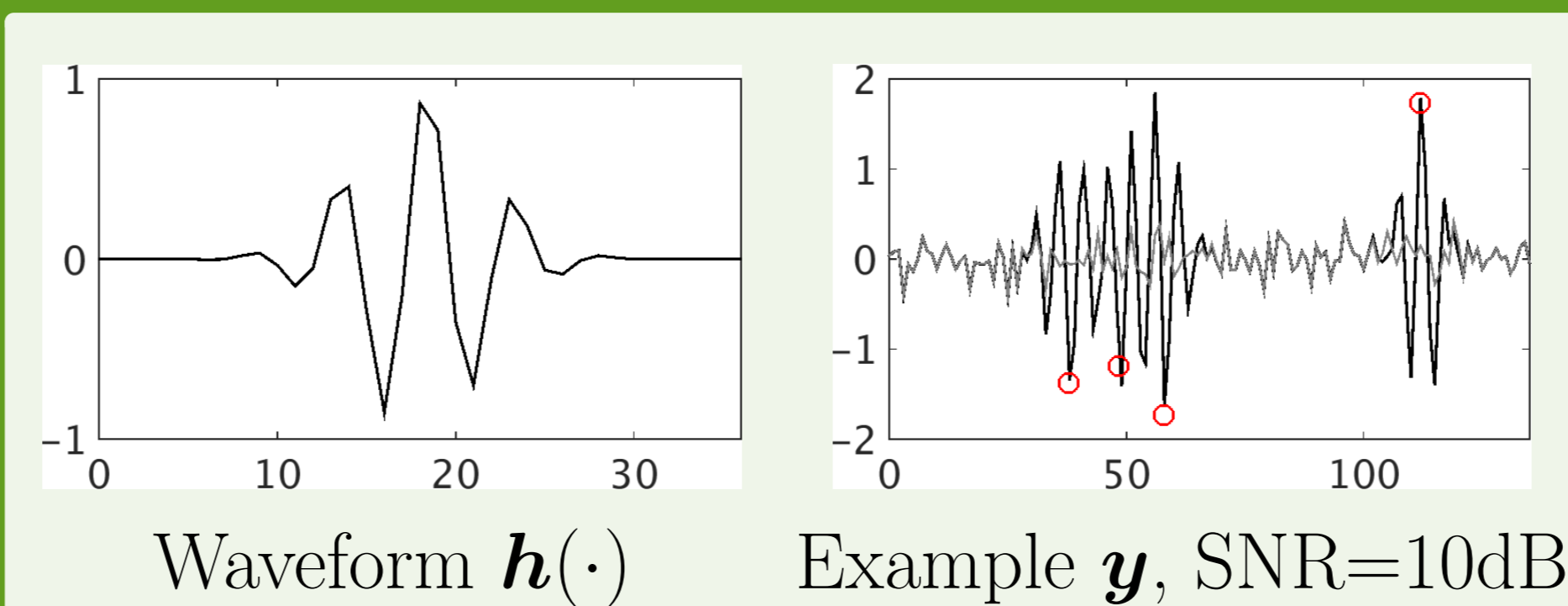
$$\mathcal{P}_{2+1}^C(\lambda): \min_{\tilde{\alpha}, \tilde{\beta}, \tilde{\gamma}} \|\mathbf{y} - \tilde{\mathbf{C}}\tilde{\alpha} - \tilde{\mathbf{U}}\tilde{\beta} - \tilde{\mathbf{V}}\tilde{\gamma}\|^2 + \lambda \|\tilde{\alpha}\|_1$$

$$\text{s.t. } \tilde{\alpha} \geq 0, \tilde{\beta} \geq \tilde{\alpha} r \cos \theta, \tilde{\beta}^2 + \tilde{\gamma}^2 \leq r^2 \tilde{\alpha}^2$$

\Rightarrow Quadratically constrained quadratic program (QCP).

+ Posterior reevaluation of polar variables on estimated support ($\mathcal{P}_{2+1}^{C*} \rightarrow \mathcal{P}_{2+1}^C$).

Description of statistical tests



Signals simulation description

- Signal model: $y_n = \sum_{k=1}^4 x_k h(n - \tau_k) + \epsilon_n$, with $\epsilon_n \sim \mathcal{N}(0, \sigma^2)$, $\tau_k \sim \mathcal{U}([0; 99])$ and $x_k \sim \pm \mathcal{U}([0.5; 2])$.
- 200 data sets simulated for SNR: 10, 20, 30 dB.
- Stopping criteria: sparsest solution s.t. the residual ρ^2 is at the noise level.

Two quality indices:

- **ELR**: the *Exact Location Recovery*.
ELR = 1 $\Leftrightarrow (\hat{K} = 4 \text{ and } \forall k, |\hat{\tau}_k - \tau_k| \leq \frac{\Delta}{2})$
- **ASD**: the *Average Spike Distance*.
compares the estimated and true spike trains, accounts for both $\hat{\tau}_k$ and \hat{x}_k estimation.

Optimization set-up: Optimization run with IBM ILOG CPLEX V12.6.0 from a Matlab interface.

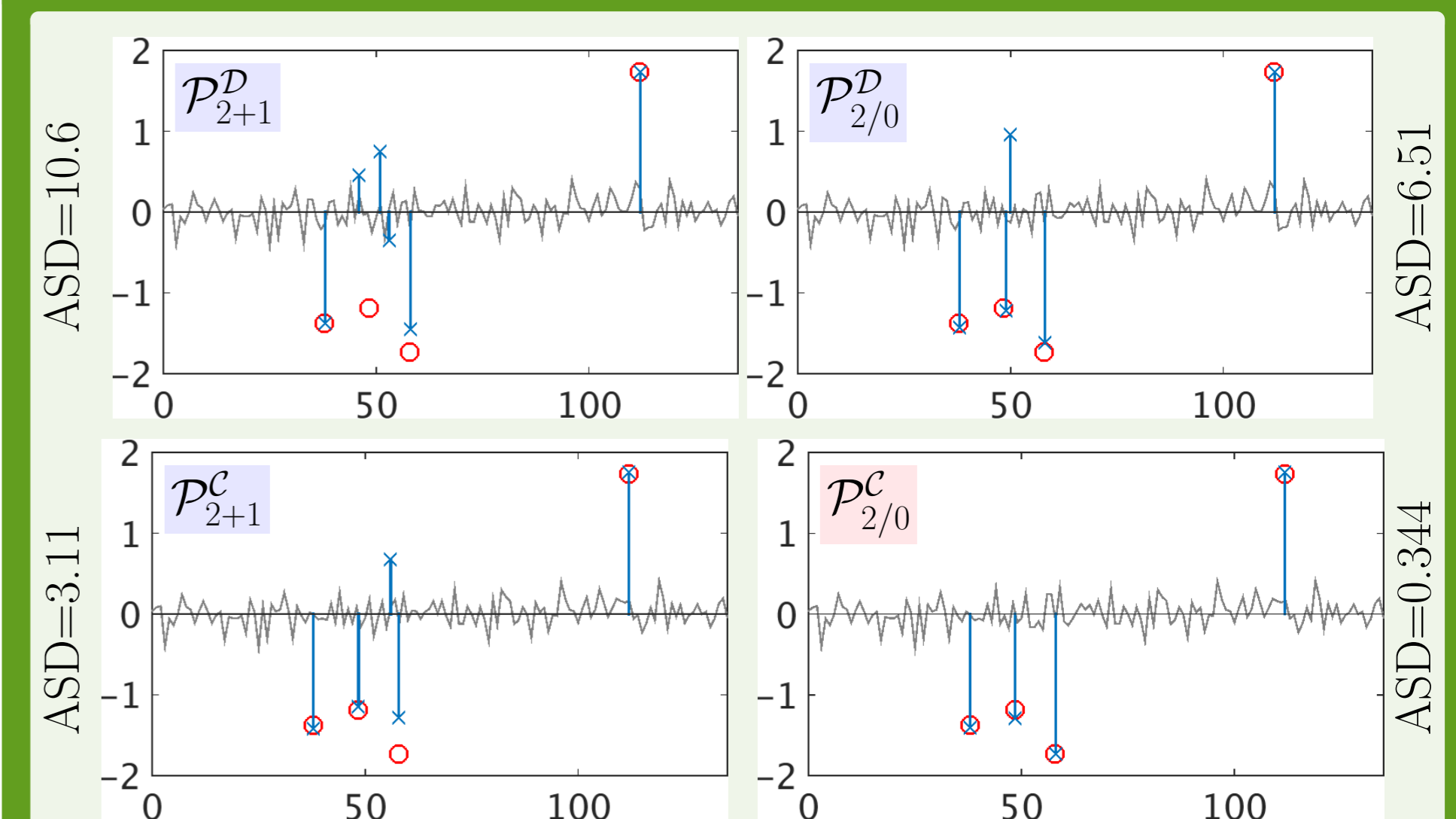
Exact ℓ_0 resolution

$$\mathcal{P}_{2/0}^C(K_0): \min_{\tilde{\alpha}, \tilde{\beta}, \tilde{\gamma}, \tilde{\mathbf{b}}} \|\mathbf{y} - \tilde{\mathbf{C}}\tilde{\alpha} - \tilde{\mathbf{U}}\tilde{\beta} - \tilde{\mathbf{V}}\tilde{\gamma}\|^2$$

$$\text{s.t. } \begin{cases} \tilde{\mathbf{b}} \in \{0, 1\}^{2J}, \tilde{\alpha} \leq M\tilde{\mathbf{b}}, \sum_{j=1}^{2J} \tilde{b}_j \leq K_0 \\ \tilde{\alpha} \geq 0, \tilde{\beta} \geq \tilde{\alpha} r \cos \theta, \tilde{\beta}^2 + \tilde{\gamma}^2 \leq r^2 \tilde{\alpha}^2 \\ \mathbf{b}^+ + \mathbf{b}^- \leq \mathbf{1} \end{cases}$$

\Rightarrow Mixed integer quadratically constrained program (MIQCP).

A result example for SNR=10dB



Estimation results for various SA methods.
Red circle : true locations.
Blue crosses: estimated locations.

Statistics results

ELR rate and ASD averaged over 200 tests for \mathcal{P}^C

SNR (dB)	% ELR			ASD(std)		
	\mathcal{P}_{2+1}^{C*}	\mathcal{P}_{2+1}^C	$\mathcal{P}_{2/0}^C$	\mathcal{P}_{2+1}^{C*}	\mathcal{P}_{2+1}^C	$\mathcal{P}_{2/0}^C$
10	24.5	31	67.5	8.1(16.6)	6.2(9.2)	3.6(7.9)
20	31	39.5	90.5	2.6(5.2)	1.6(4.1)	0.8(4.3)
30	30.5	34.5	88	1.3(5.1)	0.7(2.3)	0.05(0.3)

Computation time

- \mathcal{P}_{2+1}^C : 2s on 1.8 threads.
- $\mathcal{P}_{2/0}^C$: 400s on 3.5 threads.

References

- [1] S. Bourguignon, J. Ninin, H. Carfantan, and M. Mongeau, "Exact sparse approximation problems via mixed-integer programming: Formulations and computational performance," *IEEE Trans. Signal Process.*, vol. 64, no. 6, 2016.
- [2] C. Ekanadham, D. Tranchina, and E. P. Simoncelli, "Recovery of sparse translation-invariant signals with continuous basis pursuit," *IEEE Trans. Signal Process.*, vol. 59, no. 10, 2011.
- [3] K. Fyhn, M. F. Duarte, and S. H. Jensen, "Compressive parameter estimation for sparse translation-invariant signals using polar interpolation," *IEEE Trans. Signal Process.*, vol. 63, no. 4, 2015.