

# Atom Selection in Continuous Dictionaries : Reconciling Polar and SVD Approximations

Frédéric Champagnat and Cédric Herzet  
Contact : [frederic.champagnat@onera.fr](mailto:frederic.champagnat@onera.fr)

## Problem Statement

A generic problem :  
Atom selection in a continuous dictionary

$$\mathbf{a}_{\max} \in \arg \max_{\mathbf{a} \in \mathcal{A}} \langle \mathbf{a}, \mathbf{r} \rangle$$

- $\mathcal{A}$  dictionary of **infinitely uncountable** atoms  $\mathbf{a}(\theta)$  in some Hilbert space  $\mathcal{H}$  indexed on an interval  $\Theta$  of  $\mathbb{R}^d$
- $\mathbf{r}$  is some iteration dependent « residual » vector in  $\mathcal{H}$
- Such a problem typically occurs in critical steps of BLASSO or OMP on continuous dictionaries
- **Typical applications : particle imaging (PIV, PALM-STORM)**

A common assumption

“Some efficient scheme to find  $\mathbf{a}_{\max}$  exists”

Proposed approach

- **A general framework for continuous dictionary approximation**  
*Piecewise linear approximation*
- **Efficient atom selection through Polar approximation**  
*Accurate closed-form expression*
- **$\|\cdot\|$ -optimal linear approximation framework (i.e. SVD)**  
*Raised-cosine dictionary kernels yield Polar approximation*

## Dictionary Approximation Piecewise Linear Approximation

$$\hat{\mathcal{A}} = \bigcup_{\ell=1}^L \hat{\mathcal{A}}_{\ell} \quad \hat{\mathcal{A}}_{\ell} = \left\{ \sum_{k=1}^K c_k \mathbf{v}_k : c \in \mathcal{C} \right\} \quad \mathbf{v}_k \in \mathcal{H} \text{ and } \mathcal{C} \subseteq \mathbb{R}^K$$

- $\hat{\mathcal{A}}_{\ell}$  is an approximation of some subdictionary  $\mathcal{A}_{\ell} = \{\mathbf{a}(\theta) : \theta \in \Theta_{\ell}\}$ .

$$\max_{\mathbf{a} \in \hat{\mathcal{A}}} \langle \mathbf{a}, \mathbf{r} \rangle = \max_{\ell} \max_{\mathbf{a} \in \hat{\mathcal{A}}_{\ell}} \langle \mathbf{a}, \mathbf{r} \rangle$$

- **Accurate atom selection promotes  $K \geq 3$  (1D case)**
  - piecewise constant ( $K=1$ ) : no discrimination within  $\Theta_{\ell}$
  - Taylor 1st order ( $K=2$ ) : optimal argument at the boundary of  $\Theta_{\ell}$

- **Polar approximation**  $\hat{\mathcal{A}}_{\ell} = \left\{ \mathbf{v}_1 + \cos(\omega\tau)\mathbf{v}_2 + \sin(\omega\tau)\mathbf{v}_3 : \tau \in \left[-\frac{\Delta}{2}, \frac{\Delta}{2}\right] \right\}$

$$\arg \max_{\tau \in \left[-\frac{\Delta}{2}, \frac{\Delta}{2}\right]} \langle \mathbf{v}_1, \mathbf{r} \rangle + \cos(\omega\tau)\langle \mathbf{v}_2, \mathbf{r} \rangle + \sin(\omega\tau)\langle \mathbf{v}_3, \mathbf{r} \rangle$$

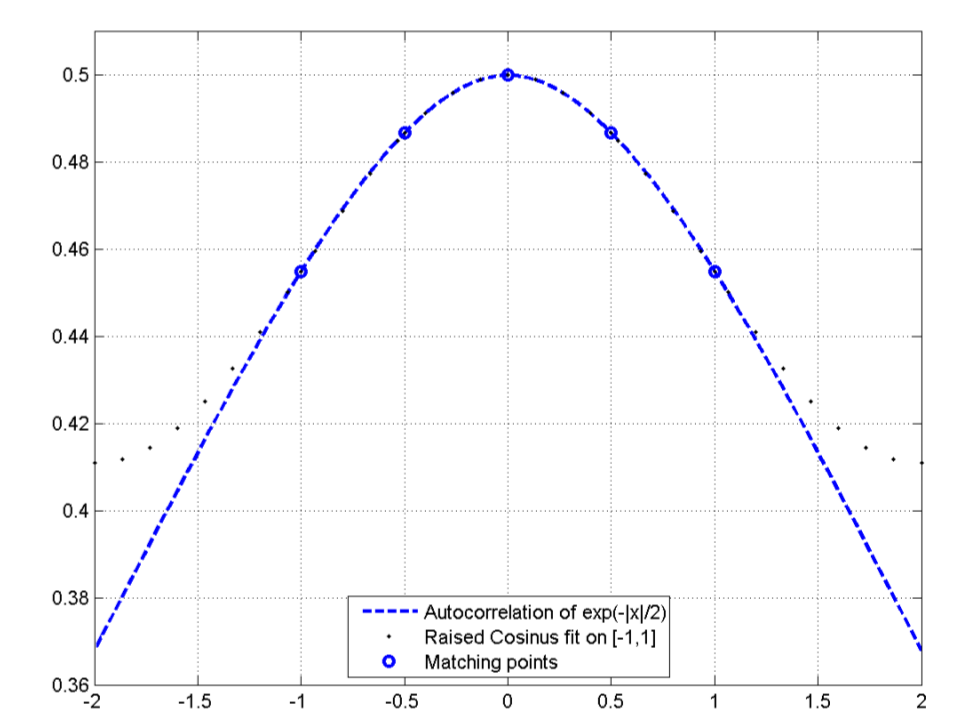
Admits a closed-form expression

## Numerical Experiments

1D Deconvolution :  $\mathbf{a}(\theta) = h(\cdot - \theta)$  ( $h =$  convolution kernel)  
 $\kappa(\theta, \theta') = \kappa(\theta - \theta') =$  autocorrelation of  $h$

### Raised-cosine approximation of $\kappa(\theta - \theta')$

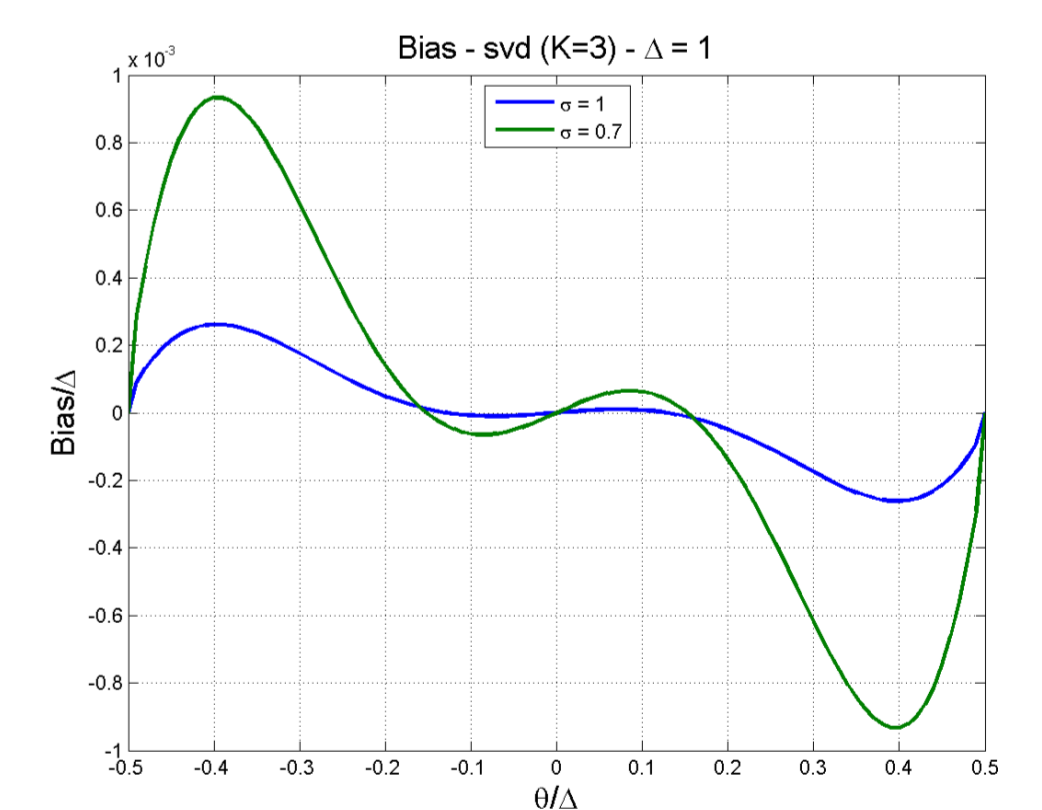
- Most autocorrelations are smooth near zero
- True also for Laplacian kernel despite singularity
- Closed-form expression by matching at  $0, \Delta/2, \Delta$



### Performance measures

- Bias on location error for  $\mathbf{r} = \mathbf{a}(\theta^*)$ 
  - Sensitive to location and approximation error
- Averaged Projection MSE

$$\int_{\Theta_{\ell}} \|\mathbf{a}(\theta) - P_V(\mathbf{a}(\theta))\|^2 d\theta.$$



## $\|\cdot\|$ -optimal Approximation (SVD)

- **Determine optimal**  $V = \text{span}(\{\mathbf{v}_\ell\}_{\ell=1}^K)$  **through**

$$V_{\text{opt}}^K = \arg \min_{V: \dim(V)=K} \int_{\Theta_{\ell}} \|\mathbf{a}(\theta) - P_V(\mathbf{a}(\theta))\|^2 d\theta. \quad P_V(\mathbf{a}) \triangleq \arg \min_{\tilde{\mathbf{a}} \in V} \|\mathbf{a} - \tilde{\mathbf{a}}\|$$

- **Solution : spectral decomposition of kernel operator**

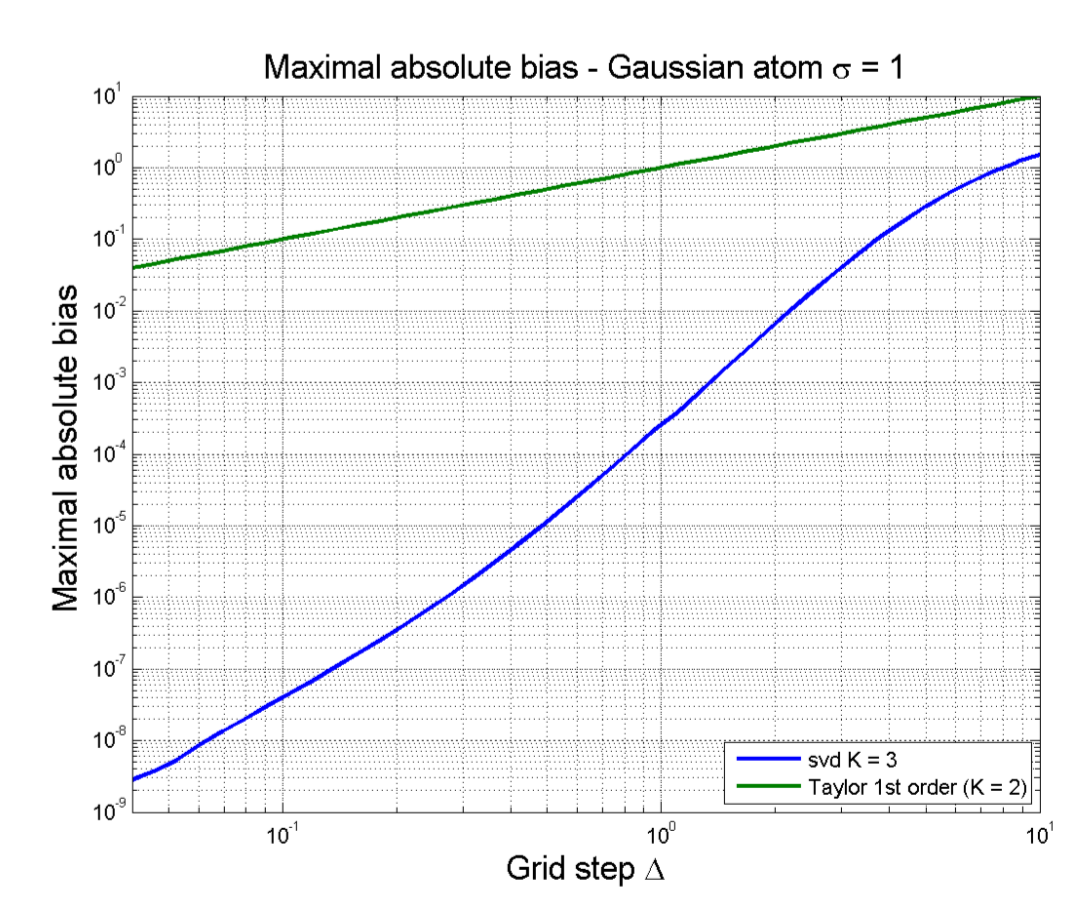
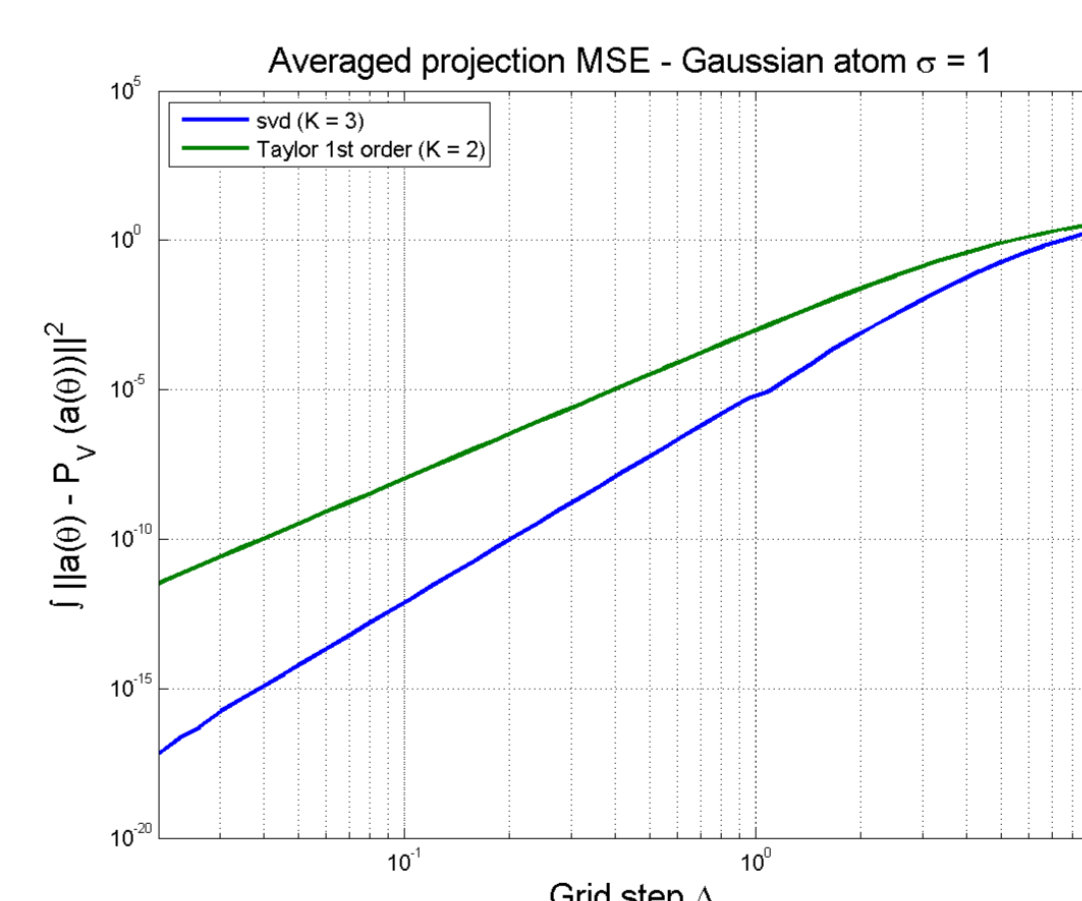
$$\kappa(\theta, \theta') \triangleq \langle \mathbf{a}(\theta), \mathbf{a}(\theta') \rangle \quad \begin{matrix} \rightarrow R: L_2(\Theta_{\ell}) \rightarrow L_2(\Theta_{\ell}) \\ u(\theta) \mapsto \int_{\Theta_{\ell}} \kappa(\theta, \theta') u(\theta') d\theta' \end{matrix} \quad \begin{matrix} \rightarrow \{\mathbf{u}_k\}_{k=1}^K \\ \text{K largest eigenfunctions of R} \end{matrix}$$

$$\mathbf{v}_k \triangleq \int_{\Theta_{\ell}} \mathbf{a}(\theta) \mathbf{u}_k(\theta) d\theta,$$

- **Special case : raised-cosine kernel**  $\kappa(\theta, \theta') = a + b \cos(\omega(\theta - \theta'))$ ,

$$\{P_{V_{\text{opt}}}(\mathbf{a}(\theta)) : \theta \in \Theta_{\ell}\} = \left\{ \mathbf{v}_1 + \cos(\omega\theta)\mathbf{v}_2 + \sin(\omega\theta)\mathbf{v}_3 : \theta \in \left[-\frac{\Delta}{2}, \frac{\Delta}{2}\right] \right\}$$

Polar approximation =  $\|\cdot\|$ -optimal approximation



### SVD / Polar approximation accurate for

- Atom MSE approximation  $\rightarrow$  grid methods (Continuous BP)
- Atom Selection  $\rightarrow$  off the grid methods (Continuous OMP, BLASSO)

## Perspectives

- **Towards Polar and SVD approximations in higher dimensions**

- **Coarse to fine strategies for**  $\max_{\mathbf{a} \in \hat{\mathcal{A}}} \langle \mathbf{a}, \mathbf{r} \rangle = \max_{\ell} \max_{\mathbf{a} \in \hat{\mathcal{A}}_{\ell}} \langle \mathbf{a}, \mathbf{r} \rangle$

## References

- C. Ekanadham et al., Recovery of sparse translation-invariant signals with continuous basis pursuit, TSP, 2011
- K. Knudson et al., Inferring sparse representations of continuous signals with orthogonal matching pursuit, NIPS, 2014
- Q. Denoyelle et al., The Sliding Frank-Wolfe Algorithm and its Application to Super-Resolution Microscopy, 2018. (hal-01921604)
- C. Herzet et al., Gather and Conquer: Region-based Strategies to Accelerate Safe Screening Tests, TIP, 2019