

## Overview

- > We apply a **Blind Source Separation** technique to differentiate between signal and noise on MALDI spectra.
- > We look for efficient representations in a redundant composite of two transforms with different statistical properties, one adapted to represent the signal, the other the noise.
- > Results show a clean separation between signal and noise with joint perfect reconstruction of the original signal

## Sparse approximation on a composite of bases

- MALDI spectra is typically affected by several sources of noise: chemical background, electrical noise, peak broadening, contaminants...
- The signal of interest usually has statistical properties that differ from those of most of the sources of noise.
- The sparse approximation problem is defined as minimising the error of approximating the data as a linear combination of a limited number of functions taken from an overcomplete base (one with more coefficients than elements in the original signal)

We use a **blind-source separation approach to differentiate between signal and noise by looking for sparse representations in a composite domain constructed from several bases, each one adapted to represent efficiently one of those sources.**

- We implement the solution to the associated sparse approximation problem by using an iterated algorithm based on **Iterative Shrinkage Methods**, which iterates between
  - A thresholding operation in the transformed domain to enforce sparseness
  - A projection back to the transformed subspace of perfect reconstruction of the original signal
- By doing so, we hope to **capture each feature of the raw signal with the corresponding base** that is more adapted to its statistical properties.

## Experimental Methods

### Sample preparation and acquisition:

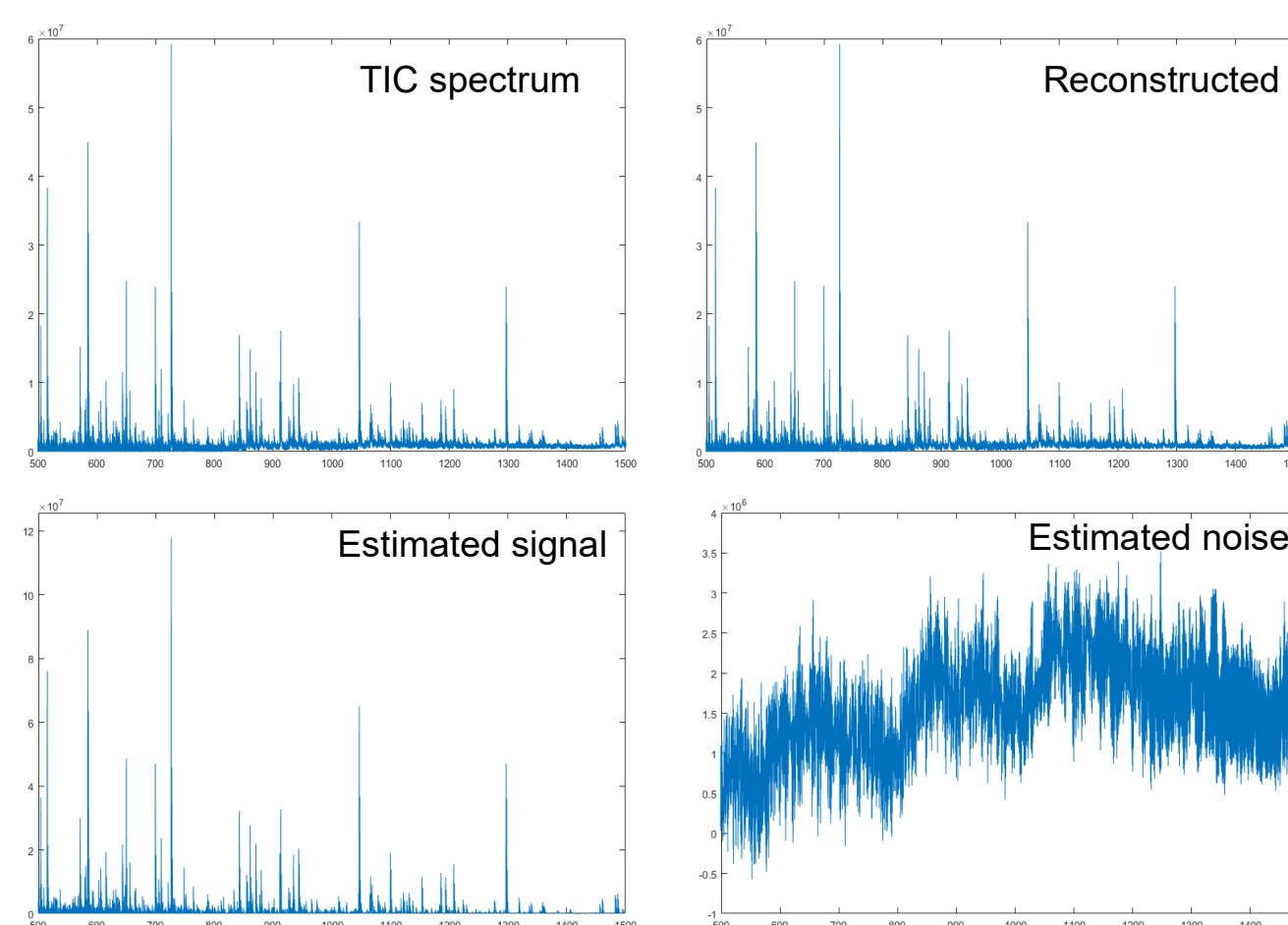
- > The proposed algorithm has been tested on MALDI-MSI datasets of mouse brain tissue sections. Serial mouse brain sections at 12  $\mu\text{m}$  thickness were mounted on ITO glass slides for MALDI.
- > Tissue sections were sprayed using the SunCollect (Sunchrom) for trypsin and matrices deposition.  $\alpha$ -Cyano-4-hydroxycinnamic acid matrix was used for in-situ digested protein imaging respectively.
- > MALDI images were acquired using a MALDI TOF-TOF instrument (MALDI-7090, Shimadzu, UK) in linear or reflectron mode for protein imaging and in-situ digest imaging samples, respectively at 30  $\mu\text{m}$  resolution.

### Processing:

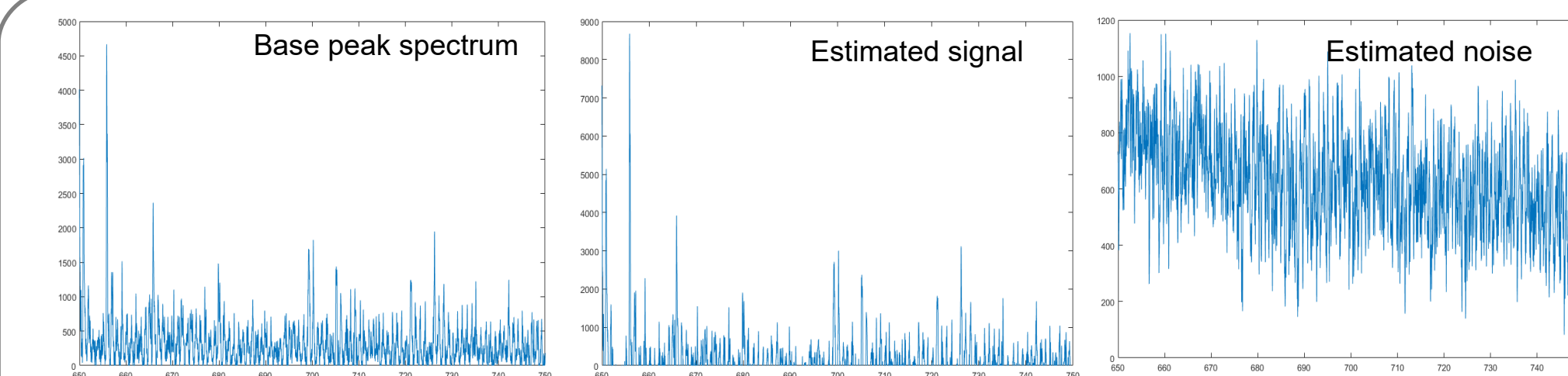
- > Raw data were loaded in IonView software (Shimadzu, UK) and TIC and Basepeak spectra were exported to ASCII format for further processing in Matlab.

## Results & discussion

- > Representations used:
  - 1D Dual-Tree Complex Wavelet transform
    - Represented by matrix **W**
    - **Efficiently represents signal**
  - 1D Discrete Fourier Transform
    - Represented by matrix **F**
    - **Efficiently represents noise**
- > Algorithm
  - **x**; input raw spectrum
  - **A**: composite orthogonal transform
    - Column-wise concatenation of  $\alpha\mathbf{W}$  and  $\beta\mathbf{F}$ , with  $\alpha, \beta$  two scalars
  - $\mathbf{a}^{(0)} = \mathbf{Ax}$ ,  $i = 0$ ,  $\theta^{(0)} = \max(\text{abs}(\mathbf{a}^{(0)}))$ ,  $\gamma$  in (0,1)
  - Until convergence repeat:
    - Form  $\mathbf{b}^{(i)}$  by thresholding  $\mathbf{a}^{(i)}$  with threshold  $\theta$
    - Form  $\mathbf{x}_s^{(i+1)}$  and  $\mathbf{x}_n^{(i+1)}$  by transforming  $\mathbf{b}^{(i)}$  to the original signal domain of **W** and **F** respectively
    - Form  $\mathbf{a}^{(i+1)}$  by projecting  $\mathbf{b}^{(i)}$  to the subspace of perfect reconstruction of **x**
    - $\theta^{(i+1)} = \gamma\theta^{(i)}$
  - Use  $\mathbf{x}_s^{(\text{end})}$  as estimate of noise-free signal



**Figure 1:** Noise separation result using a TIC spectrum from a mouse brain protein digest image. Mass range is showed from 500 to 1500 Da for feature visibility. Scalar parameters were set at  $\alpha = 0.4$ ,  $\beta = 0.6$ ,  $\gamma = 0.9$ . From top to bottom and left to right: original TIC spectrum, reconstructed spectrum from final sparse representation, estimated noise-free signal component, estimated noise component.



**Figure 2:** Same settings as in Figure 1 but applied to the Base peak spectrum. Mass range is showed from 650 to 750 Da for feature visibility.

## Additional result: Data reduction

- > Additionally, this technique helps to reduce the disk size required to store spectra.
- > This is thanks to the maximization of sparseness in the resulting representation in the transformed domain
- > Compression results for the examples shown in this poster:

Example	Original data size	Compressed data size	Estimated signal data size	% of data reduction
TIC spectrum	2.03 MBytes	0.15 MBytes	0.06 MBytes	97.07%
Basepeak spe.	2.03 MBytes	0.70 MBytes	0.17 MBytes	91.53%

## Conclusions

- > This seems to be a promising approach to separate signal from noise in MALDI spectra. Noise-sources captured include random noise and baseline
- > It is an iterative algorithm but it has the potential to be highly accelerated.
- > It provides an estimation of the noise in the same range as the signal, which can be used to estimate noise power, calculate signal to noise ratios, etc.
- > As side result, it provides the potential for highly compressing the data.

## References

- [1] J. Bobin, J-L Starck, J. Fadili, Y. Moudden. IEEE Trans. on Image Proc. (2007), 16: 2662-74
- [2] A.N. Krutchinsky, B.T. Chait. J. Am. Soc. Mass Spectrom. (2002) 13(2):129-34.