Deconvolution of fMRI BOLD signal in time-domain using an exponential operator and Lasso optimization

Isa **Costantini**[1], Patryk **Filipiak**[1], Kostiantyn **Maksymenko**[1], Rachid **Deriche**[1], and Samuel **Deslauriers-Gauthier**[1]

[1] Inria Sophia-Antipolis Méditerranée - Université Côte d'Azur, France

Contacts: isa.costantini@inria.fr

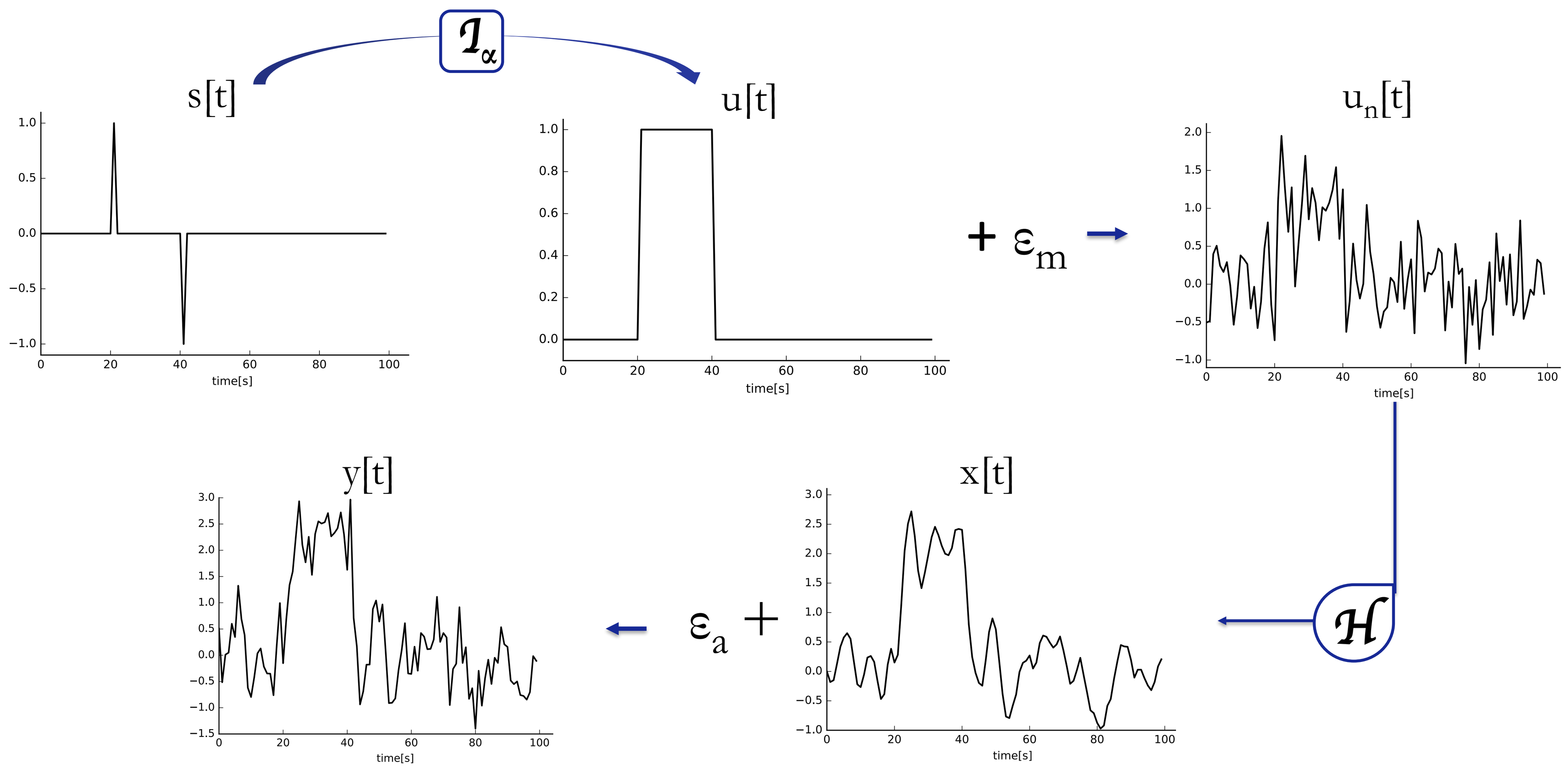
https://team.inria.fr/athena/

1. Introduction

Many techniques have been explored so far in the study of neural activations using the blood oxygenated level dependent (BOLD) signal in order to investigate spontaneous brain activity. Among them, deconvolution methods are powerful since they do not require *a priori* knowledge about timing and duration of activations[1]. In this work we propose a regularized deconvolution technique which uses an exponential operator, whose shape and performance can be adjusted by tuning an appropriate parameter, and the Least-Angle Regression (LARS) algorithm, by using the least absolute shrinkage and selection operator (LASSO) model.

2. Methods

MODEL



- The activity-inducing signal u[t] is simulated as a piece-wise constant signal, so its derivative s[t] is sparse[1,2].
- The activity-related signal is the convolution of a linear time-invariant system, $\mathcal{H}$, which describes the BOLD activation[1,2,4], and the noisy activity-inducing signal.
- The operator $\mathcal{I}_\alpha$ is an exponential accumulation function:

$$\mathcal{I}_\alpha(z) = S\left[\frac{e^{-\alpha}z^{-1}}{(1-e^{-\alpha}z^{-1})^2} - \frac{e^{-\alpha}z}{(1-e^{-\alpha}z)^2}\right]\frac{1}{(1-z^{-1})^2}$$

- S is the normalization term
- ε_m and ε_a are, respectively, the model (peak-SNR=8dB) and the additive Gaussian noise (peak-SNR=16dB).
- y[t] was simulated $n_r = 200$ times.

PROBLEM

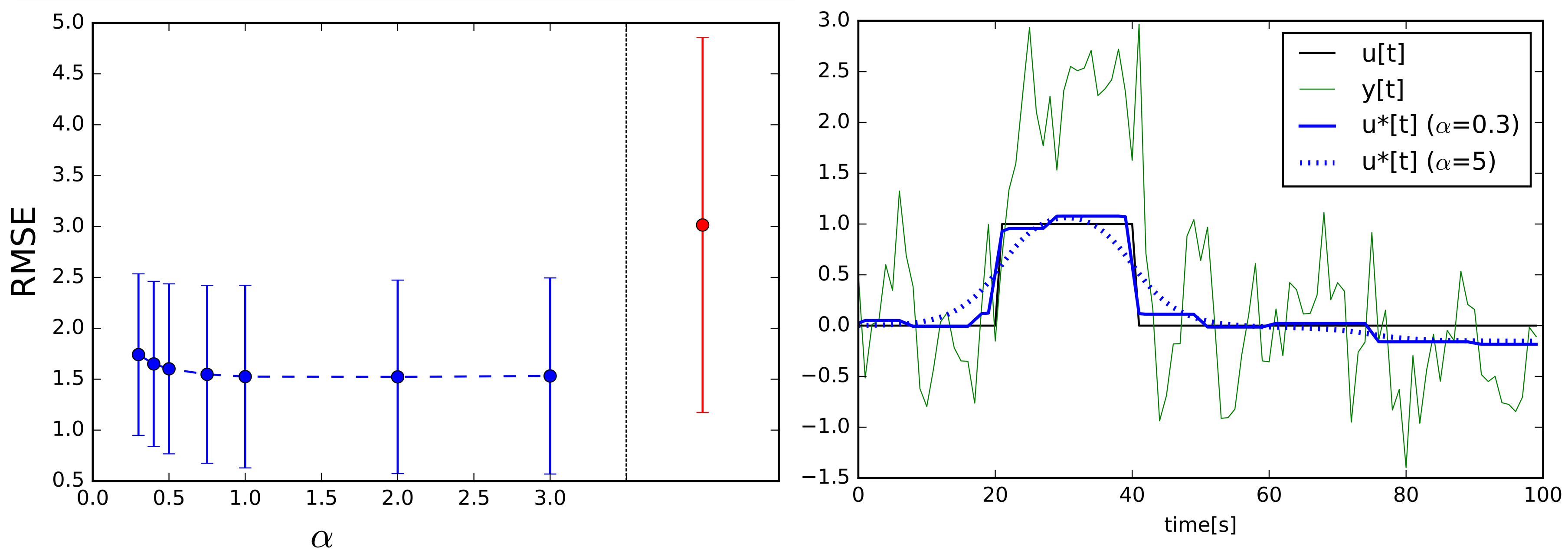
Solve: $$\tilde{s} = \underset{s}{\operatorname{argmin}}\left\{\frac{1}{2N}\|y - As\|_2^2 + \lambda\|s\|_1\right\},$$

where N is the number of samples, $As = \mathcal{H}\{\mathcal{I}_\alpha\{s\}\}$, and λ is the regularization parameter.

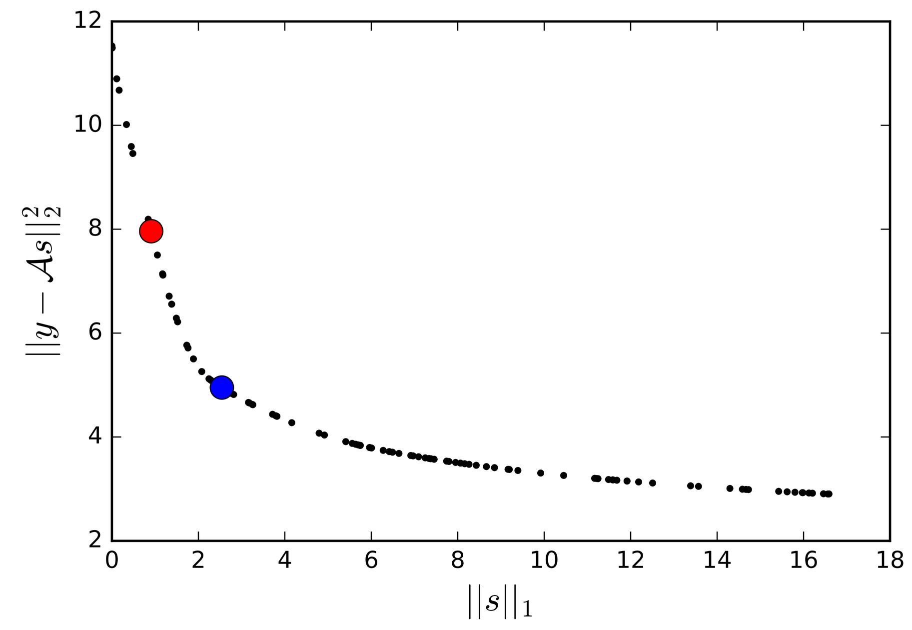
SOLUTION

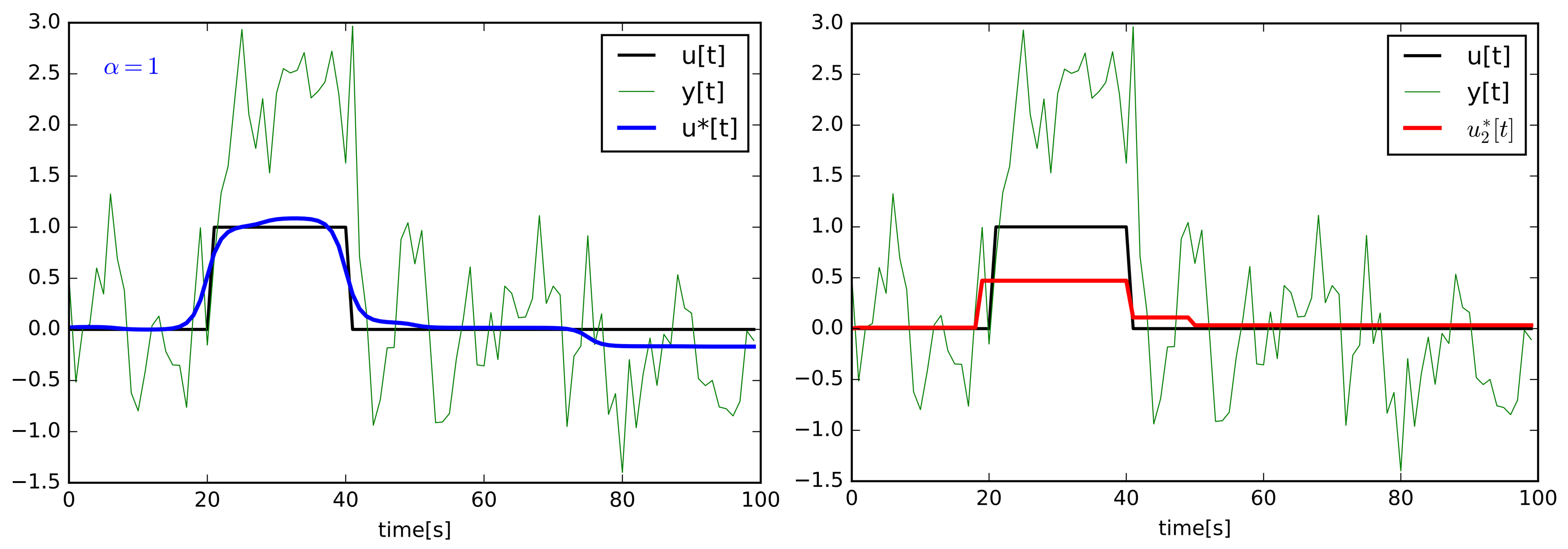
- **LARS** algorithm by computing the **Lasso** path along the regularization parameter. This outputs all λs of interest and their associate solutions $\tilde{s}$ [5].
- L-curve is used for estimating the optimal solution $\tilde{s}^*$. The optimal λ is selected as the nearest one to $(0, 0) \in \mathcal{R}^2$.

3. Results



On the left: square roots of MSE ± STD over n_r repetitions, computed for different αs, between u[t] and the recovered $u^*[t] = \mathcal{I}_\alpha\{\tilde{s}^*\}[t]$ (blue line) and the ones obtained using the λ selection method from [2] (red line). On the right: the recovered activity-inducing signal u*[t] for α = 0.3 (blue dotted line) and 5 (blue solid line).





At the top: the L-curve (black dotted line) with the solution computed with our approach (blue dot) and the one defined in [2] (red dot). At the bottom: the reconstructed activity-inducing signals obtained using our approach with α = 1 (u*[t]; in blue), and using the method from [2] ($u_2^*[t]$; in red), superimposed on the simulated activity-inducing signal (in black) and the noisy fMRI time series (in green).

4. Discussion and Conclusion

- Using Lasso for solving the optimization objective allowed us to obtain all the important λs and their relative solutions in one step, thus decreasing the computation time. This way, we avoided the necessity of defining λ *a priori.*
- The use of an exponential operator depending on a parameter α, with respect to the finite difference, is worth exploring. It can improve results particularly in presence of noise.
- Future works will incorporate the spatial regularization[2].

Acknowledgements

This work has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (ERC Advanced Grant agreement No 694665 : CoBCoM - Computational Brain Connectivity Mapping).

References

[1] Karahanoğlu, F. I., Caballero-Gaudes, C., Lazeyras, F., & Van De Ville, D. (2013). Total activation: fMRI deconvolution through spatio-temporal regularization. Neuroimage, 73, 121-134.
[2] Farouj, Y., Karahanoğlu, F. I., & Van De Ville, D. (2017, April). Regularized spatiotemporal deconvolution of fMRI data using gray-matter constrained total variation. In Biomedical Imaging (ISBI 2017), 2017 IEEE 14th International Symposium on (pp. 472-475). IEEE.
[3] Karahanoglu, F. I., Bayram, I., & Van De Ville, D. (2011). A signal processing approach to generalized 1-D total variation. IEEE Transactions on Signal Processing, 59(11), 5265-5274
[4] Khalidov, I., Fadili, J., Lazeyras, F., Van De Ville, D., & Unser, M. (2011). Activelets: Wavelets for sparse representation of hemodynamic responses. Signal Processing, 91(12), 2810-2821.
[5] Efron, B., Hastie, T., Johnstone, I., & Tibshirani, R. (2004). Least angle regression. The Annals of statistics, 32(2), 407-499.