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L1-Norm Regularized Deconvolution of Functional MRI BOLD Signal

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Abstract - Deconvolution methods are used to denoise the blood oxygen level-dependent (BOLD) response, the signal that forms the basis of functional MRI (fMRI). In this work we propose a novel approach based on a temporal regularized deconvolution of the BOLD fMRI signal with the least absolute shrinkage and selection operator (LASSO) model, solved using the angle regression algorithm (LARS). In this way we were able to recover the underlying neurons activations and their dynamics.

1 Introduction

Problem

Recover brain activations and their dynamics without a-priori hypotheses.

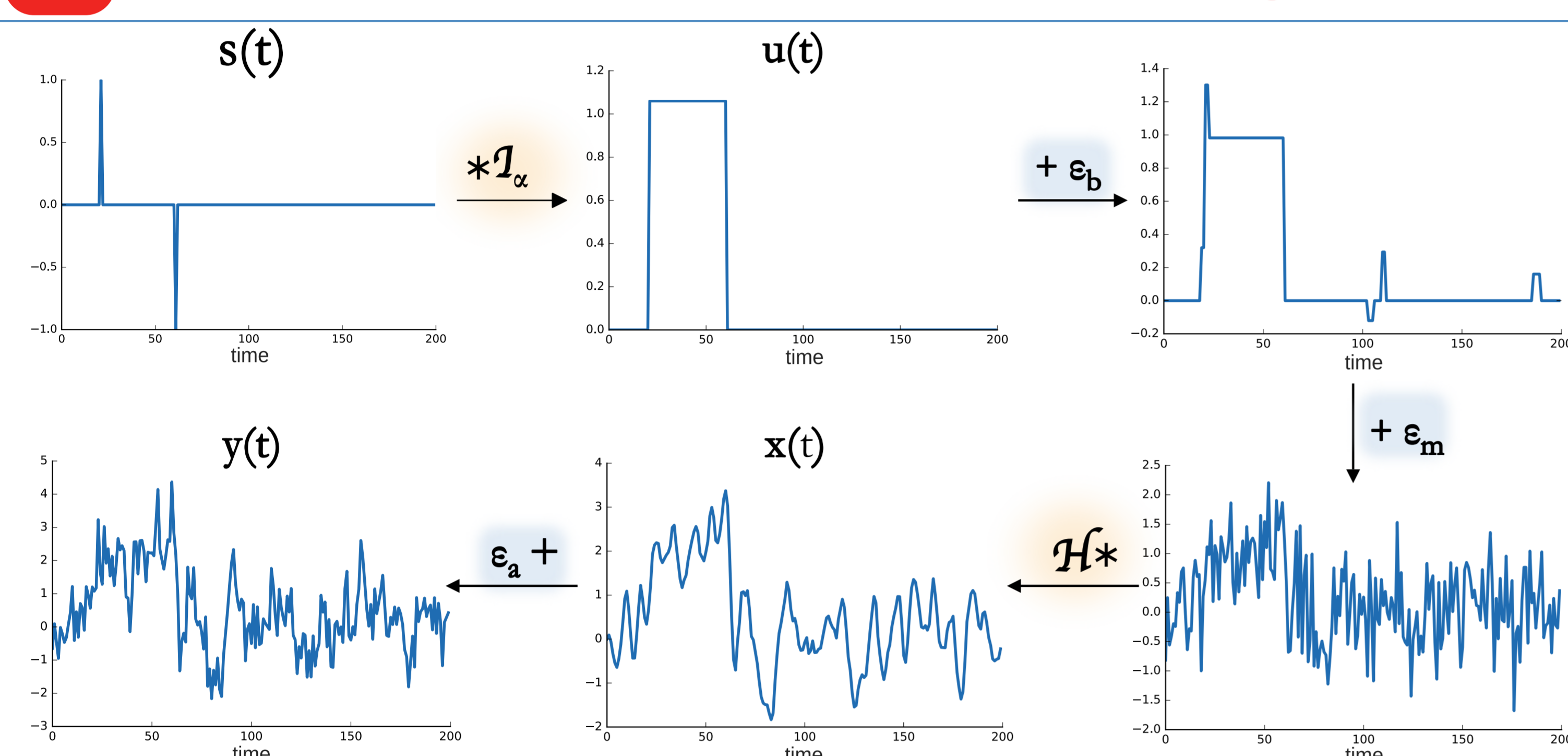
Goal

Denoise the blood oxygen level dependent (**BOLD**) functional MRI (fMRI) **response**.

Our method

Temporal regularized deconvolution of the BOLD signal with the least absolute shrinkage and selection operator (**LASSO**) model, solved using the Least-Angle Regression (**LARS**) algorithm.

2 Model of the BOLD fMRI signal



$s(t)$: innovation signal
 $u(t)$: activity-inducing signal
 $x(t)$: activity-related signal
 ϵ_b : block-type noise
 ϵ_m : model random gaussian noise
 ϵ_a : additive random gaussian noise

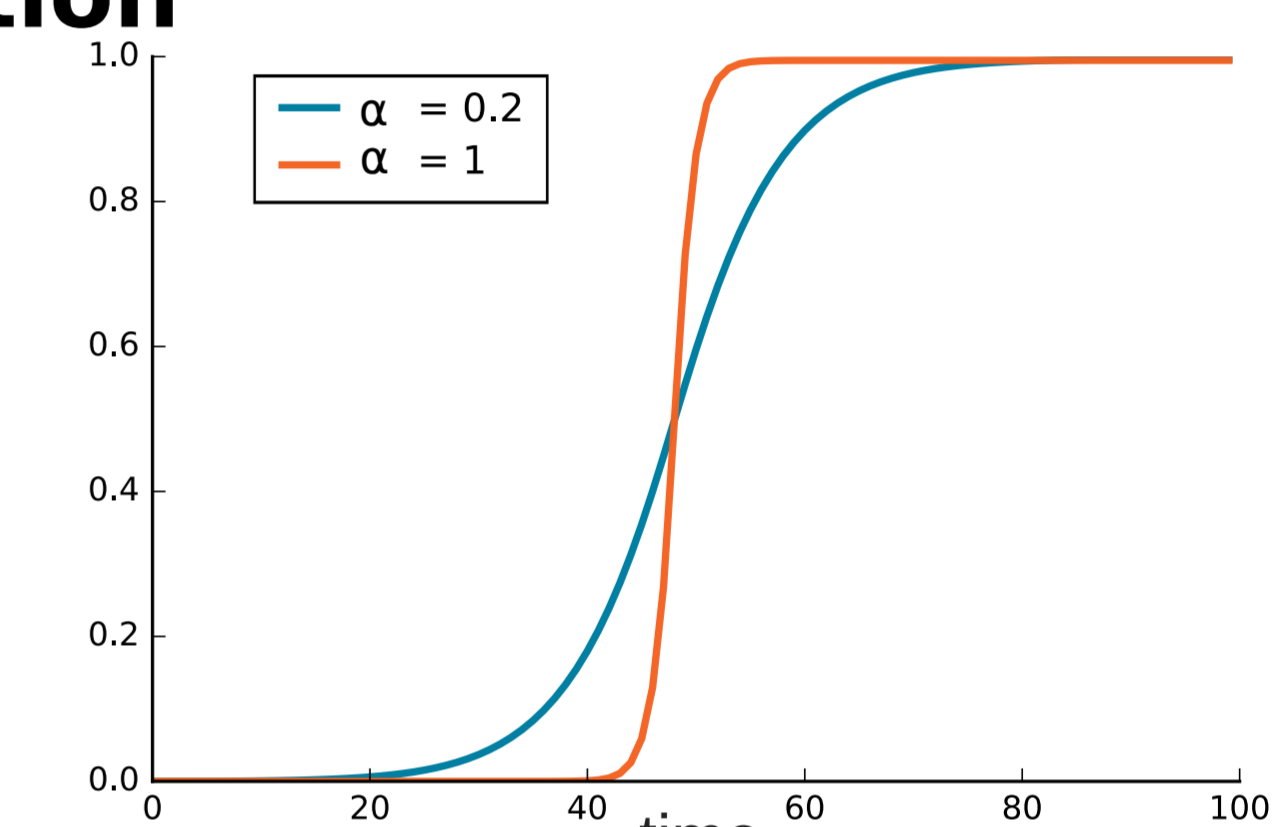
• \mathcal{H} : BOLD response

• \mathcal{I}_α : 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: normalization term

$\alpha \in [0, 3]$



3 Regularization

We exploited the sparsity of the signal $s(t)$ such that:

$$s^* = \operatorname{argmin}_s \left\{ \frac{1}{2n} \|y - \mathcal{A}s\|_2^2 + \lambda \|s\|_1 \right\}$$

$\mathcal{A}s = \mathcal{H} * \mathcal{I}_\alpha * s(t)$; λ : regularization parameter; n : signal length.

4 Solution of the inverse problem

1 LARS → All λ and their associated solutions s^* at once.

2 L-Curve → Optimal λ^* and its associated solution s^* .

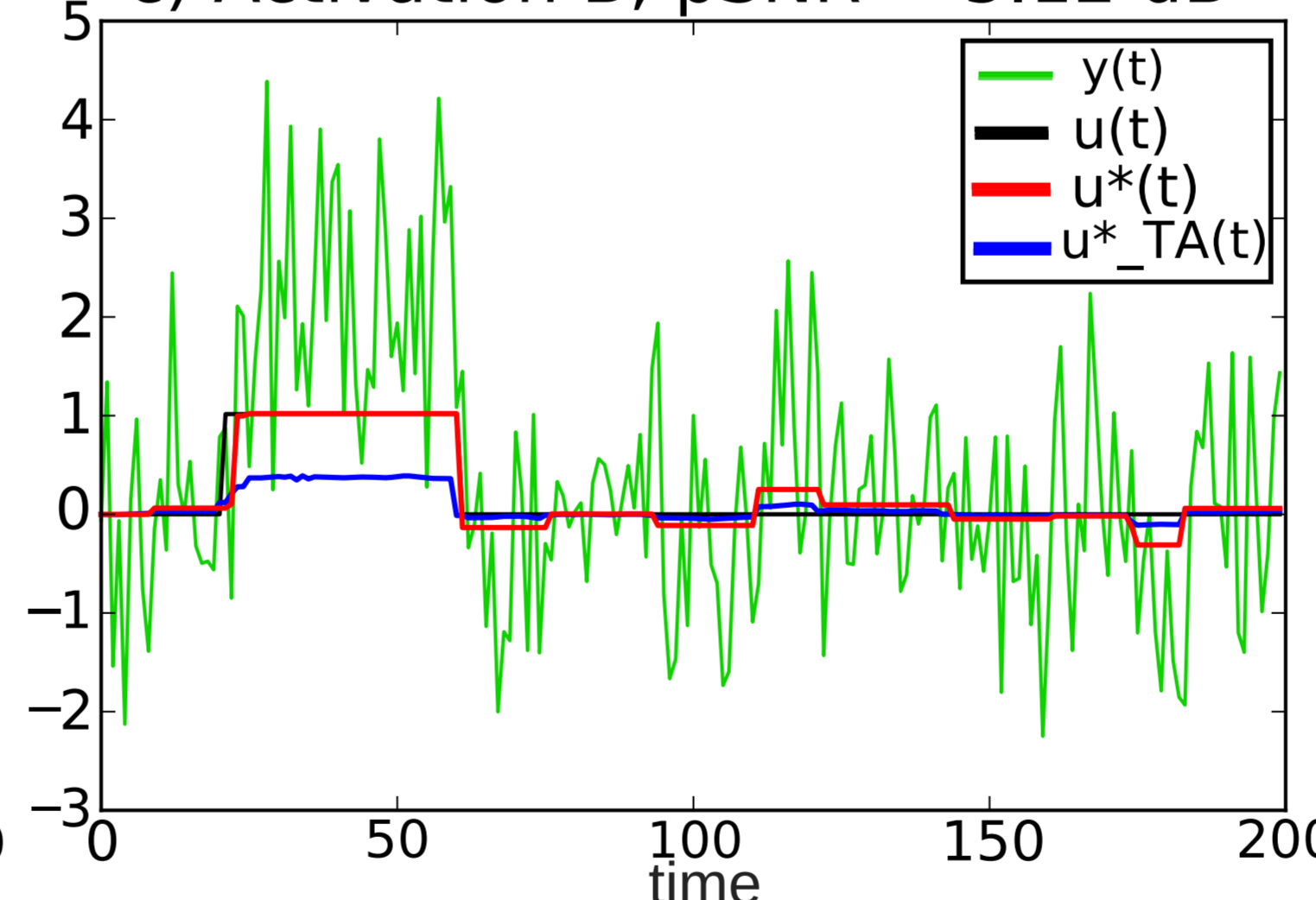
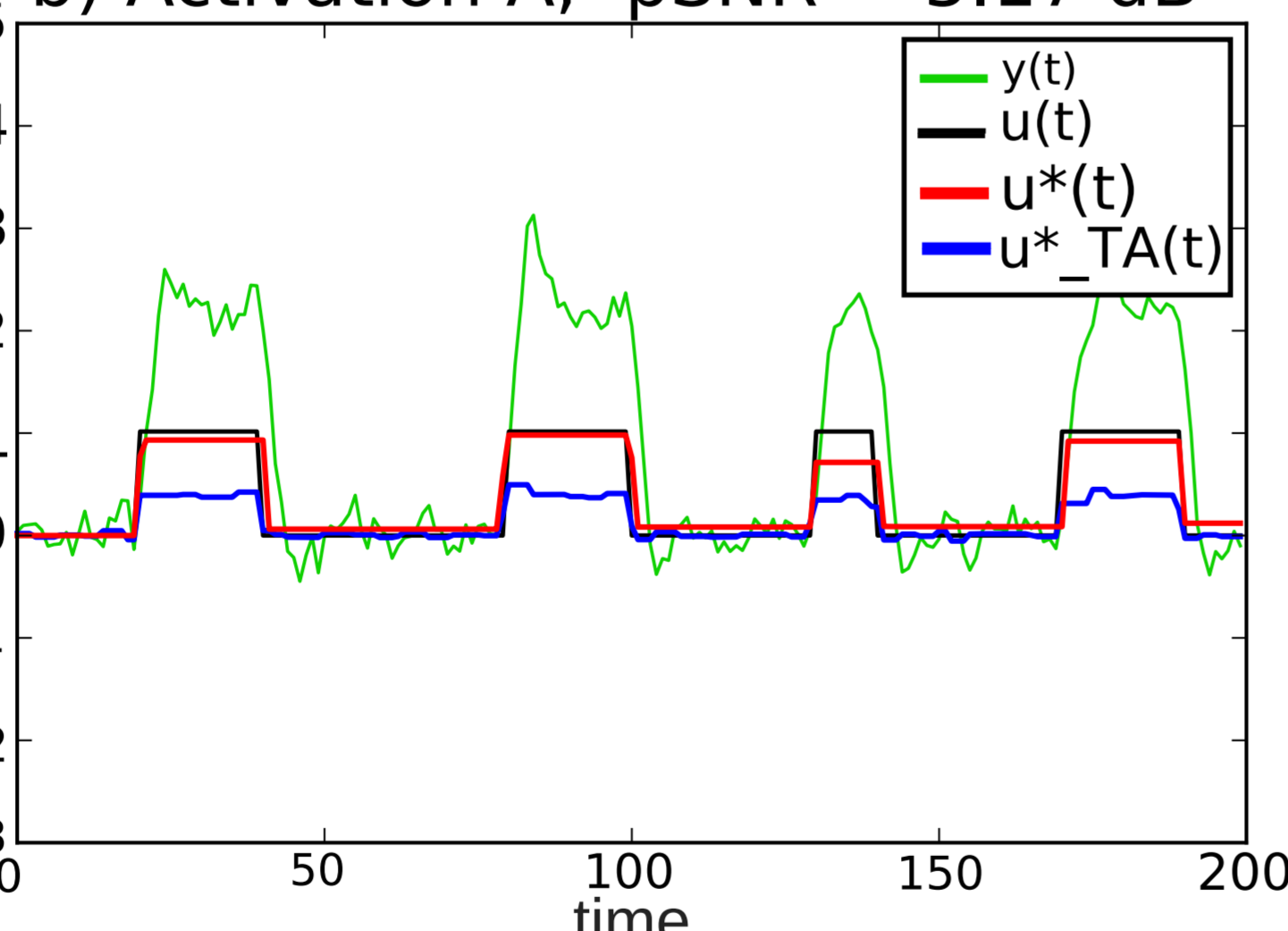
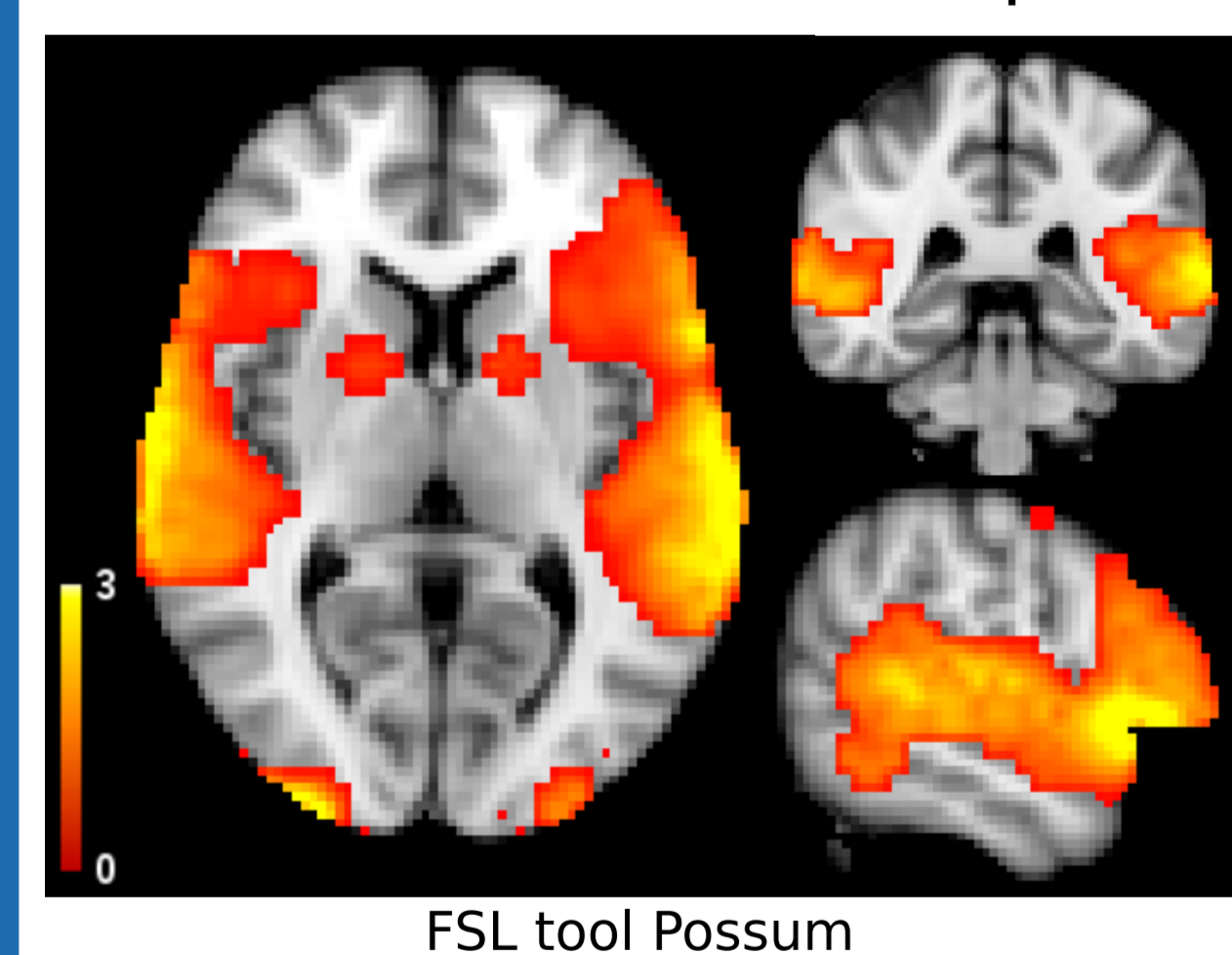
5 Simulations and Validation

SIMULATED DATA

a) 3D activation map

b) Activation A; pSNR = 5.17 dB

c) Activation B; pSNR = 5.12 dB



a) The fMRI signals $y(t)$ were simulated on a 3D activation map.

b, c) The reconstructed signals $u^*(t)$ obtained with our approach (red) and the Total Activation tool^[2] (TA, blue) are superimposed on the activation (black) and fMRI signal (green). Only the gray matter (GM) voxels were considered for analyses.

Summary of rooted MSEs and STDs.

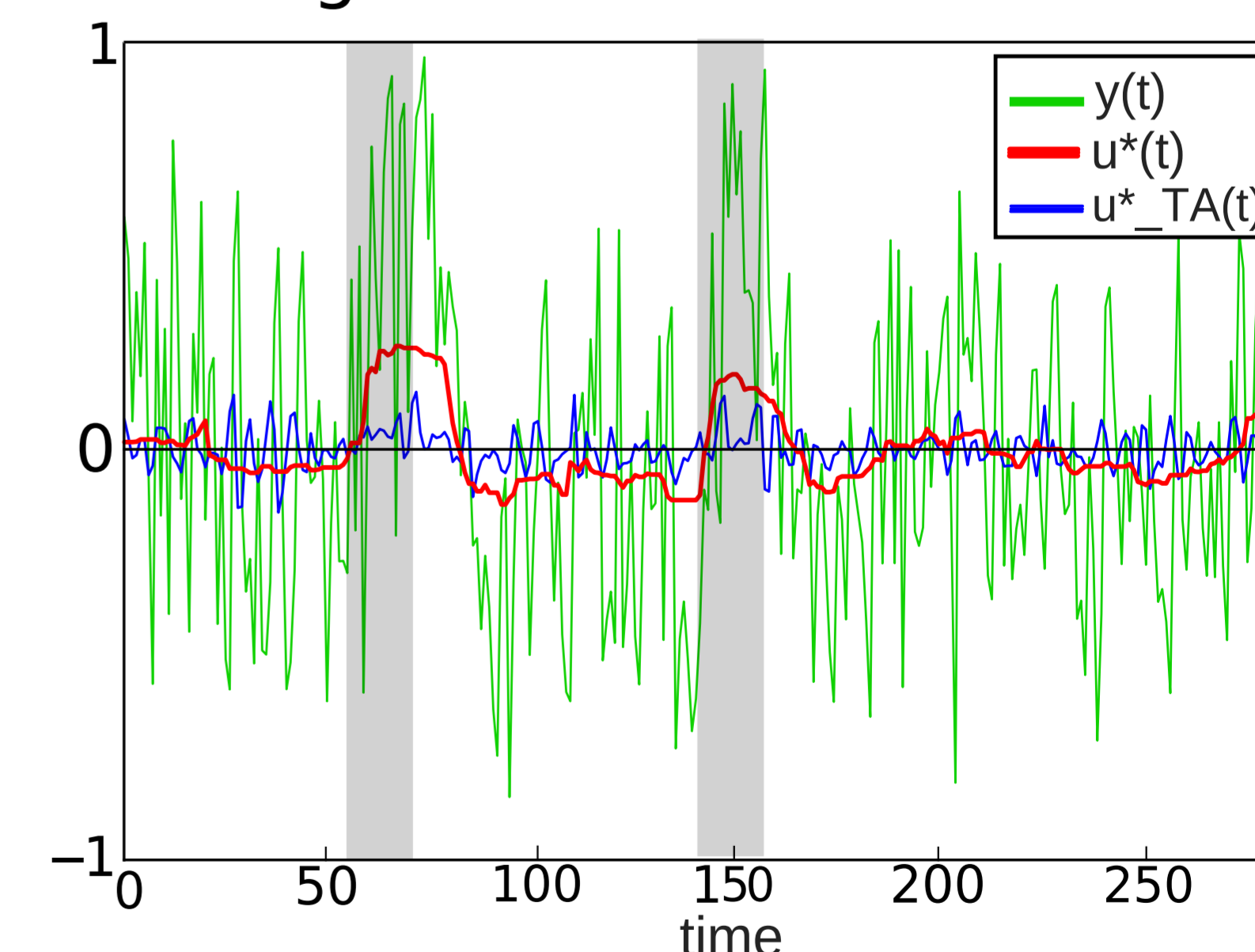
| Activation | A | | | | | B | | | | | |
|------------------------|-----------|------|------|-------------|------|------|------|-------------|-------------|------|-------------|
| | pSNR [dB] | 3.14 | 4.96 | 5.17 | 4 | 3.98 | 3.29 | 6.84 | 7.64 | 5.94 | 5.12 |
| OUR $\alpha = 0.75$ | rMSE | 0.34 | 0.15 | 0.11 | 0.22 | 0.18 | 0.31 | 0.1 | 0.05 | 0.19 | 0.14 |
| | rSTD | 0.2 | 0.14 | 0.13 | 0.16 | 0.14 | 0.17 | 0.07 | 0.05 | 0.11 | 0.08 |
| TA | rMSE | 0.36 | 0.26 | 0.24 | 0.29 | 0.3 | 0.32 | 0.2 | 0.19 | 0.24 | 0.25 |
| | rSTD | 0.33 | 0.31 | 0.31 | 0.32 | 0.33 | 0.27 | 0.23 | 0.23 | 0.24 | 0.26 |

REAL fMRI DATA

• Preprocessed HCP motor **task-fMRI data**.

• The reconstructed $u^*(t)$ were averaged in a $6 \times 6 \times 6 \text{ mm}^3$ ROI centered in BA4p.

• The gray areas represents the duration of the tongue movements.



6 Conclusion

• The **joint** use of the **LARS** algorithm and the **L-curve** allowed us to choose the optimal **solution** among all those **outputted at once**.

• We **decreased** the **computation time** and **avoided** a need of defining **λ a priori**.

• We improved brain dynamics recovery for future clinical applications.

• Future works will involve also a spatial regularization.

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