

fMRI Deconvolution via Temporal Regularization using a LASSO model and the LARS algorithm

Isa Costantini, Patryk Filipiak, Kostiantyn Maksymenko, Samuel Deslauriers-Gauthier, Rachid Deriche

▶ **To cite this version:**

Isa Costantini, Patryk Filipiak, Kostiantyn Maksymenko, Samuel Deslauriers-Gauthier, Rachid Deriche. fMRI Deconvolution via Temporal Regularization using a LASSO model and the LARS algorithm. EMBC'18 - 40th International Engineering in Medicine and Biology Conference, Jul 2018, Honolulu, United States. hal-01855467

HAL Id: hal-01855467
https://inria.hal.science/hal-01855467

Submitted on 8 Aug 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

fMRI Deconvolution via Temporal Regularization using a LASSO model and the LARS algorithm

Isa Costantini, Patryk Filipiak, Kostiantyn Maksymenko, Samuel Deslauriers-Gauthier, Rachid Deriche
Inria Sophia Antipolis-Méditerranée, Université Côte d'Azur, France

***Abstract*— In this work we propose a novel approach to deconvolve the blood oxygenated level dependent (BOLD) signal to recover underlying neurons activations and their dynamics.**

I. INTRODUCTION

Deconvolution methods are used to denoise the blood oxygen level-dependent (BOLD) response, the signal that forms the basis of functional MRI (fMRI) [1]. In this work we propose a temporal regularized deconvolution of BOLD fMRI signal with the least absolute shrinkage and selection operator (LASSO) model, solved using the Least-Angle Regression (LARS) algorithm.

II. METHODS

We implemented the deconvolution exploiting the sparsity of the innovation signal s(t) [2], and we built a LASSO model:

$$s^* = \underset{s}{\operatorname{argmin}} \left\{ \frac{1}{2n} \left\| y - HI_\alpha s \right\|_2^2 + \lambda \|s\|_1 \right\}$$

where n is the signal length, H represents the hemodynamic response function [3] and λ is the regularization parameter. I_α is the exponential accumulation function given by:

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

such that the activity-inducing signal $u(t) = I_\alpha * s(t)$, normalized by the factor S. We chose $\alpha = 0.75$ experimentally within the range [0, 3]. We minimized the objective function using LARS [4], that outputs all λs of interest and their associated solutions. We used the L-curve to estimate the λ^* corresponding to the optimal solution s^*. Then, as in [2], we scaled a 3D activation map computed with FSL in the range [0, 3], with a 2-mm isotropic resolution (Fig.1b). We multiplied it by two block-type signals of 200s, u(t): A) with 4 onsets, and B) with one long onset. We corrupted the signals with model and block-type noise, we convolved them with H and we added Gaussian noise thus simulating the fMRI time series y(t). We solved the inverse problem and we recovered $u^*(t) = I_\alpha * s^*(t)$ as described above. Finally, to evaluate the results, we computed the root of the mean square errors (MSE) and standard deviation (STD) between u(t) and $u^*(t)$ averaged among the voxels belonging to the grey matter masked activation. We compared our results with those obtained with the temporal regularization implemented in the Total Activation (TA) toolbox [1]. We tested the above procedure on the preprocessed task-fMRI image of one subject taken from the Human Connectome Project (HCP) database [5]. The reconstructed $u^*(t)$ were averaged in a ROI of 6 × 6 × 6 mm^3 centered in the Brodmann Area 4p (MNI coordinates: 62, -14, 30).

III. RESULTS

Table I shows that the MSEs±STDs change for different peak-SNRs (pSNRs) and that they are lower than the ones obtained using the TA toolbox. Fig.1.a and c show examples of the reconstructed activity inducing signal using our approach (u^*) and the approach in [1] (u^*_{TA}).

TABLE I. SUMMARY OF ROOTED *MSES AND STDS*

Activation		**A**			**B**		
pSNR [dB]		5.17	4	3.98	7.64	5.94	5.12
OUR $\alpha = 0.75$	*RMSE*	**0.11**	0.22	0.18	**0.05**	0.19	**0.14**
	STD	**0.13**	0.16	0.14	**0.05**	0.11	**0.08**
TA	*RMSE*	0.24	0.29	0.3	0.19	0.24	0.25
	STD	0.31	0.32	0.33	0.23	0.24	0.26

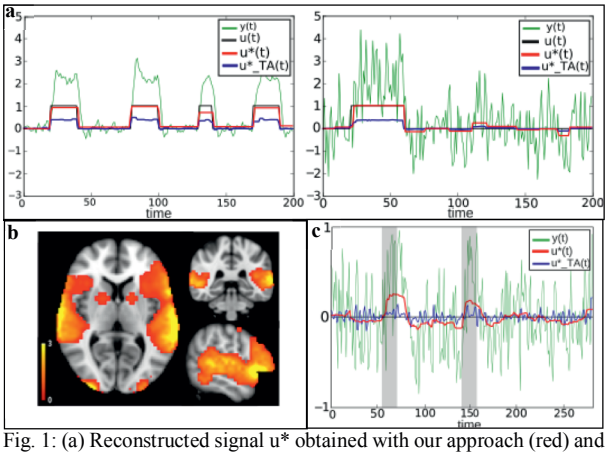


Fig. 1: (a) Reconstructed signal u* obtained with our approach (red) and the TA (blue) superimposed on the activation (black) and fMRI signal (green). The plots are related to different activations and pSNRs: activation A, pSNR = 5.17 dB (left); activation B, pSNR = 5.12 dB (right). (b) Activation map. (c) Results of HCP data. Same legend of panel (a); the grey areas represent the duration of the tongue movements.

IV. DISCUSSION & CONCLUSION

Our findings show that the joint use of LARS and the L-curve for solving our optimization problem allowed us to choose the optimal λ^* and related solution among all those outputted by the algorithm. Thus, we decreased the computation time and avoided a need of defining λs a priori, allowing to improve brain dynamics recovery in future clinical application.

REFERENCES

[1] F. I. Karahanolu, *Total activation: fMRI deconvolution through spatio-temporal regularization.* Neuroimage, 2013.
[2] Y. Farouj, *Regularized spatiotemporal deconvolution of fMRI data using gray-matter constrained total variation,* ISBI 2017.
[3] I. Khalidov, *Activelets: Wavelets for sparse representation of hemodynamic responses,* Signal Processing, 2011.
[4] B. Efron, *Least angle regression,* The Annals of statistics, 2004.
[5] D.C. Van Essen, *The WU-Minn HCP,* NeuroImage, 2013.

ACKNOWLEDGMENTS - 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).