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To cite this version:

HAL Id: hal-02071193
https://hal.archives-ouvertes.fr/hal-02071193
Submitted on 18 Mar 2019

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Deconvolution of fMRI Data using a Paradigm Free Iterative Approach based on Partial Differential Equations

Submission No:
3023

Submission Type:
Abstract submission

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Introduction
Functional magnetic resonance imaging (fMRI) is a technique which indirectly measures neural activations via the blood oxygenated level dependent (BOLD) signal [1]. So far, few approaches have been proposed to regularize the fMRI data, while recovering the underlying activations at the voxel level. In particular, for task fMRI, voxels time courses are fitted on a given experimental paradigm [1]. To avoid the necessity of a priori information on the pattern, supposing the brain works with blocks of constant activation, Farouj et al. [1] has developed a deconvolution approach which solves the optimizations problem by splitting it into two regularization problems, i.e. spatial and temporal. Starting from this idea, we propose a paradigm-free iterative algorithm based on partial differential equations (PDEs) which minimizes the image variations, while preserving sharp transitions (i.e. brain activations), in the space and the time dimensions at once.

Methods
We minimized image variations by iteratively smoothing the data with a gradient descent based on PDEs such that: \( \partial I/\partial t = (1-\lambda) \cdot H' \ast (I0 - I)/A + \lambda \cdot \text{div}(\nabla I)/B \), where the first term on the right is the data fitting term, which measures the correlation of the residual with the hemodynamic response function (H) [4], and the second term minimizes image variations. Moreover, I0 and I are the acquired fMRI and the denoised image respectively, \( \lambda \) is the regularization parameter, \( H' \) is the time-reversed H,
A=\| I_{0} \| \ and \ B= \| \text{div}(D \nabla I_{0}) \| \ are \ normalization \ factors \ and \ D=\nabla I \nabla I^{T}/\| \nabla I \|^{2} \cdot \ G \ is \ the \ structure \ tensor \ of \ I, \ smoothed \ by \ a \ gaussian \ kernel \ G \ (\sigma_{G}=1). \ The \ convolution \ with \ H \ and \ H' \ were \ computed \ only \ along \ the \ time \ dimension. \ Then \ if \ the \ gradient \ of \ the \ image \ was \ big \ (\| \nabla I \| >>0), \ we \ performed \ an \ anisotropic \ smoothing \ to \ smooth \ the \ image \ while \ preserving \ sharp \ edges, \ which \ can \ occur \ both \ in \ space \ and \ in \ time; \ whereas \ if \ the \ gradient \ was \ small \ (\| \nabla I \| \rightarrow 0), \ we \ isotropically \ smoothed \ the \ image \ in \ all \ the \ four \ dimensions. \ The \ validity \ of \ this \ approach \ has \ already \ been \ shown \ on \ simulated \ data \ [5]. \ Similarly \ to \ [1, \ 6] \ the \ study \ was \ conducted \ on \ the \ preprocessed \ and \ normalized \ motor \ task-fMRI \ data \ of \ a \ subject \ taken \ from \ the \ Human \ Connectome \ Project \ (HCP) \ database \ (TR=0.72 \ s) \ [7]. \ The \ reconstructed \ signals, \ u^{*}(t), \ were \ averaged \ in \ two \ regions \ of \ interest \ (ROIs) \ of \ 6 \times 6 \times 6 \ mm^{3}. \ We \ selected \ the \ task \ related \ to \ the \ tongue, \ and \ we \ chose \ one \ ROI \ centered \ in \ the \ Brodmann \ Area \ 4p \ (rBA4p; \ MNI \ coordinates: \ 62, -14, 30) \ which \ is \ supposed \ to \ be \ active \ in \ a \ tongue \ motor \ task, \ and \ another \ centered \ in \ the \ primary \ auditory \ cortex \ (TE1.2; \ 56, \ 4, \ 10) \ [8] \ in \ order \ to \ prove \ that \ our \ approach \ is \ able \ to \ differentiate \ between \ a \ region \ which \ is \ activated \ and \ one \ that \ is \ not. \ We \ compared \ the \ results \ obtained \ using \ our \ approach \ (PDEs) \ with \ the \ ones \ given \ by \ the \ total \ activation \ (TA) \ method, \ implemented \ in \ the \ iCAPs \ toolbox \ [1, \ 9]. \ To \ evaluate \ the \ results, \ Pearson \ correlation \ coefficients \ were \ computed \ between \ the \ tongue \ activation, \ simulated \ as \ a \ piecewise \ constant \ signal, \ and \ the \ recovered \ u^{*}(t) \ for \ each \ voxels, \ and \ then \ averaged \ among \ the \ voxels \ belonging \ to \ the \ gray \ matter \ (GM)-masked \ ROIs.

Results

Fig.1 \ shows \ the \ considered \ ROIs. \ Fig.2 \ shows \ the \ reconstructed \ signal \ u^{*}(t) \ and \ the \ correlations \ values \ using \ our \ approach \ and \ the \ TA. \ We \ show \ a \ higher \ correlation \ between \ the \ tongue \ activation \ and \ the \ rBA4p \ recovered \ activation \ u^{*}(t), \ which \ we \ expect \ to \ be \ involved \ in \ the \ motor \ task, \ while \ a \ low \ correlation \ is \ shown \ with \ the \ rTE12 \ which \ is \ not \ involved \ in \ the \ task. \ Whereas, \ the \ TA \ approach \ showed \ low \ correlation \ values \ for \ both \ ROIs.

Conclusions

Our \ findings \ show \ that \ the \ iterative \ approach \ based \ on \ PDEs \ allowed \ us \ to \ recover \ brain \ activations \ of \ the \ fMRI \ data \ without \ a \ priori \ knowledge \ on \ the \ experimental \ paradigm. \ This \ is \ promising \ for \ resting-state \ fMRI \ image \ which \ measures \ spontaneous \ activity \ of \ the \ brain, \ in \ order \ to \ improve \ brain \ dynamics \ recovery \ for \ future \ clinical \ application.

References


**Fig.1.** Regions of interest (ROIs) of 6×6×6 mm³ centered in the right Brodmann Area 4p (rBA4p, MNI coordinates: 62, -14, 30) in yellow and in the primary auditory cortex (rTE1.2, MNI coordinates: 56, 4, 10) in green, superimposed to the gray matter (GM) map (in red).
Fig. 2. (A) Reconstructed signals $u^*(t)$ obtained with our approach (PDEs, red) and the total activation tool (TA, blue) superimposed on the fMRI signals (green). The plot on the left is related to the region of interest (ROI) located on the Brodmann Area 4p (rBA4p), the plot on the right is associated to the ROI positioned on the primary auditory cortex (rTE1.2). All the signals were averaged among the voxels belonging to the gray-matter (GM)-masked ROIs. The grey areas represent the occurrence and the duration of the tongue movements. (B) Simulated tongue activation. (C) Mean Pearson correlation coefficients ($\mu$) and their associated standard deviations ($\sigma$) computed between the tongue activation and the recovered signals $u^*(t)$ averaged among the voxels belonging to the GM-masked ROIs (rBA4p on the left, rTE1.2 on the right). The blue curves are related to the TA approach, while the red ones to the PDEs approach.

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).