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-Forward Regression (LARS) algorithm.

2 Model of the BOLD fMRI signal

\[ y(t) = u(t) * g(t) + s(t) \]

\[ u(t) \]: activity-inducing signal  
\[ v(t) \]: BOLD response  
\[ s(t) \]: innovation signal  
\[ \gamma(t) \]: Exponential accumulation function

\[ \gamma(z) = S \left[ \frac{e^{-az} - 1}{1 - e^{-az} - 1} \right] \]

\[ S \]: normalization term  
\[ \alpha \in [0, 3] \]

3 Regularization

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

\[ s = \arg \min_s \left\{ \frac{1}{2n} \| y - A s \|^2 + \lambda \| s \|_1 \right\} \]

\[ A_s = A + \lambda \| s(t) \| \lambda \text{ regularization parameter; } n \text{: signal length.} \]

4 Solution of the inverse problem

1 LARS  
All \( \lambda \) and their associated solutions \( s^* \) at once.

2 L-Curve  
Optimal \( \lambda^* \) and its associated solution \( s^* \).

5 Simulations and Validation

a) 3D activation map  
b) Activation A; pSNR = 5.17 dB  
c) Activation B; pSNR = 5.12 dB  

- The fMRI signals \( y(t) \) were simulated on a 3D activation map.
- The reconstructed signals \( u^*(t) \) were averaged over a ROI.

Summary of root mean square errors and standard deviations:

<table>
<thead>
<tr>
<th>Activation</th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>pSNR [dB]</td>
<td>3.14</td>
<td>4.56</td>
</tr>
<tr>
<td>OUR</td>
<td>0.15</td>
<td>0.13</td>
</tr>
<tr>
<td>STD</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>TA</td>
<td>0.39</td>
<td>0.26</td>
</tr>
</tbody>
</table>

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 \( \lambda \) a priori.
- We improved brain dynamics recovery for future clinical applications.
- Future works will involve also a spatial regularization.

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