

Parameter-Free Spatio-Temporal Filtering of fMRI Data

Shing-Chung Ngan, Stephen M. LaConte, William F. Auffermann and Xiaoping Hu
Center for Magnetic Resonance Research, University of Minnesota, Minneapolis, MN 55455

INTRODUCTION

A prime difficulty in performing data analysis in event-related fMRI is the low signal-to-noise ratio (SNR) inherent in the data. To improve the SNR, various signal processing techniques such as low-pass filtering in the time domain and anisotropic diffusion in the spatial domain have been previously exploited. While useful, most of these techniques involve parameters that need to be manually tuned for data sets obtained under different experimental settings. A corollary is that failure to choose the optimal parameters might actually harm the quality of the data. To circumvent this problem, a parameter-free spatio-temporal filtering technique is introduced and applied to multi-epoch event-related data. The technique relies on cross-validation [1], which automatically determines which contiguous neighbors of a pixel of interest are similarly activated as the pixel itself. The similarly activated neighbors are then denoised by a wavelet shrinkage method based on a second cross-validation in the temporal domain [2-3]. Receiver-operating characteristic (ROC) analysis on simulated data shows that the new technique leads to improvement in the detectability of activated regions. The applicability of the new technique is also demonstrated on experimental data obtained based on a visually cued-motor paradigm.

METHODS

Identification of Close Neighbors: The first component of the technique is to use “leave-one-out” cross-validation to make the binary decision: given a pixel p and one of its 8 neighbors q , are they similarly activated? Denote the i th epoch time courses for pixel p and q as \bar{p}_i and \bar{q}_i , with i ranging from 1 to N . Also, fix a $j \in \{1, \dots, N\}$ and denote $\{\bar{p}_k : k \neq j\}$ as set 1 and $\{\bar{q}_i : i = 1, \dots, N\}$ as set 2. The average of set 1 can be viewed as a predictor for the ‘unseen’ epoch \bar{p}_j . Also, if p and q are similarly activated, then the pooled average of sets 1 and 2 can statistically yield an improved predictor for \bar{p}_j . Thus, the above idea reduces to the computation of the root mean squared (RMS) errors between the average of set 1 and \bar{p}_j (denoted as $\text{RMS}_{1,j}$), and between the pooled average and \bar{p}_j (denoted as $\text{RMS}_{2,j}$). $\text{RMS}_{1,j}$ and $\text{RMS}_{2,j}$ are then summed across all $j \in \{1, \dots, N\}$ and compared to determine whether neighbor q is similarly activated as pixel p (set $\text{sim}(p,q)$ as true if $\sum \text{RMS}_{2,j} > \sum \text{RMS}_{1,j}$). Notice that the algorithm described so far could yield relation that is not symmetric, i.e. $\text{sim}(p,q)$ does not necessarily imply $\text{sim}(q,p)$. To repair this defect, a more stringent condition is imposed: a given pair of contiguous pixels p and q are similarly activated if and only if both $\text{sim}(p,q)$ and $\text{sim}(q,p)$ are true.

Wavelet Denoising of Time Courses: In the second component of the technique, raw time courses are averaged across epochs on a pixel-by-pixel basis and are denoted as \hat{p} for pixel p . Now, given pixel p and its similarly activated neighbors q^a 's, where $a=1, \dots, M < 9$, time course \hat{p} is denoised by applying wavelet shrinkage on each of \hat{p} 's wavelet coefficients. The amount of shrinkage is determined by performing a second “leave-one-out” cross-validation as detailed in [2-3]. This involves computing the prediction error for each of \hat{p} 's wavelet coefficients using information from the individual epochs of pixels p and q^a 's, as a function of the shrinkage factors. The shrinkage factors that give the best prediction error are then used to filter \hat{p} .

Simulation: Simulated functional data were generated as follows: baseline data were obtained from a volunteer on a 1.5T whole body MR scanner. 256 T2*-weighted EPI images were collected in a resting period (TR/TE=300/55ms, matrix size=64×64, field

of view=20×20 cm²). Then, two epochs of artificial activation with signal pattern of a half sinusoid and pre-assigned contrast level (ranging from 1-2%) were superimposed on the predetermined “activated” areas. Finally, a region of interest encompassing the brain was delineated, and the pixels within the ROI were processed and analyzed.

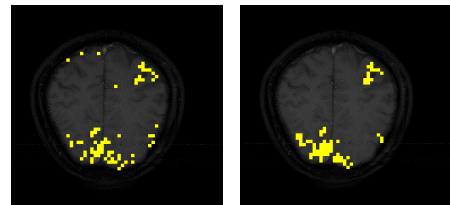
Experimental data: The task consists of rapid finger movement using the dominant hand when cued with flashing LED goggles. 256 T2*-weighted images (TR/TE=300/60ms, matrix size=64×64, field of view=22×22 cm²), constituting four epochs, were acquired on a single brain slice traversing the occipital and the motor cortices.

RESULTS AND DISCUSSION

Performance of the spatio-temporal filtering technique was assessed through ROC analysis. Specifically, the pre-filtered and filtered simulated data sets were submitted separately to Kohonen's self-organizing map (SOM), a neural network algorithm for data clustering [4]. Upon completion of an SOM analysis, nodes from the neuron map were ordered according to their correlation with the known signal pattern and successively included in the “activation” cluster. The false positive fractions and true positive fractions were calculated to generate the ROC curve. The area under the ROC curve was subsequently used as a measure of the detectability (with a theoretical maximum value equal to 1) of the activated regions for the data set under consideration. The simulations were repeated 5 times for each setting, and the detectability measures at various contrast levels are as follows:

Contrast level	1.00%	1.50%	2.00%
Pre-filtered data	0.752±0.013	0.864±0.011	0.931±0.006
Filtered data	0.852±0.012	0.926±0.004	0.968±0.004

It is clear that filtering leads to considerable improvement in detectability. Finally, the filtering technique was applied to the experimental data. Cross correlation analysis was applied to both the pre-filtered and the filtered data sets. By choosing the top 7% of pixels whose time courses are the most correlated with a prescribed model time course, the following activation maps were obtained:



The map on the right (for filtered data) shows clear activation in the visual and the motor cortices. The activation map on the left (for pre-filtered data) is more scattered.

CONCLUSION

Both the ROC analysis and visual inspection of the experimental data indicate that the filtering technique leads to improvement in the detectability of activated regions. Further, the technique is fully self-adaptive -- there is no parameter that needs manual tuning.

References:

1. Cherkassky, V. and F. Mulier. Learning from Data: Concepts, Theory and Methods. New York: John Wiley & Sons (1998)
2. Ngan, S.-C., LaConte, S.M., Hu, X., NeuroImage (submitted)
3. Nowak, R.D., IEEE Signal Process. Lett. 4:23-25.
4. Kohonen, T., Biol Cybern 43:59-69 (1982)

Work supported by NIH grants RR8079, RO1MH55346 and RO3MH59245.