How to deal with brain deactivations in the joint detection-estimation framework?

Abstract No:

1509

Authors:

Laurent RISSER[1], Thomas VINCENT[2], Florence FORBES[3], Jérôme IDIER[4], Philippe CIUCIU[2]

Institutions:

[1]Institute for Mathematical Sciences, Imperial College, London, United Kingdom, [2]CEA - NeuroSpin, Gif sur Yvette, France, [3]INRIA Rhône Alpes, Montbonnot, France, [4]IRCCyN/CNRS, Nantes, France

Introduction:

The Joint Detection-Estimation framework has been proposed in [1-3] as a generalization of regression methods for the analysis of fMRI data. It enables the detection of brain activation elicited by stimuli along an experimental paradigm. Also at the subject level, it makes the analysis of brain dynamics feasible through the estimation of regional Hemodynamic Response Functions. Up to now, the JDE framework has been developed to discriminate activating voxels from non-activating ones. Here, we extend this paradigm to also account for putative deactivations that may appear for instance in pathologies (epilepsy). To this end, for any brain region we introduce spatially adaptive 3-class mixture models and 3D Potts field to embody the spatial correlation over the hidden states of the voxels. The regularization is spatially adaptive and varies across experimental conditions. We finally illustrate the interest of this novel approach on synthetic and real unsmoothed fMRI data.

Methods:

The JDE procedure proposed in [1,2] relies on a prior parcellation of the brain into P functionally homogeneous and connected parcels [3], where typically P ≈ 500 to cover the whole brain. Every parcel is characterized by a specific model of the BOLD signal, which has to be fitted against the acquired fMRI time series in the corresponding parcel in order to estimate the HRF shape. As outlined in Fig. 1 the parcel-based BOLD signal remains bilinear regarding the unknown HRF and the voxelwise and stimulus-dependent magnitudes, also called Neural Response Levels (NRLs). The main originality in the present contribution lies in the prior model involving the NRLs, which is composed of stimulus-specific 3-class Spatial Mixture Models (SMM). The three components enable the discrimination of deactivating, non-activating and activating voxels in response to the corresponding stimulus. The spatial regularization is embodied in a hidden Potts field and allows us to recover activation clusters instead of isolated spots by enabling edge-preserving filtering. This regularization is also spatially adaptive meaning that its amount varies from one parcel to another given our ability to automatically tune all regularization parameters. The generalization to Potts fields of our min-max extrapolation scheme [4] for Partition Function (PF) estimation has made this automatic setting possible. This allows us to estimate all PFs very accurately prior to the Gibbs sampling loop in which the parameters of interest (HRF, NRLs) as well as hyper-parameters are estimated in the posterior mean sense from unsmoothed fMRI time series. Indeed, it has been shown in [5] that our PF estimation scheme is more stable than concurrent techniques based on mean-field approximations.

Results:

We applied the JDE procedure to synthetic fMRI time series, which have been generated at low signal-to-noise ratio considering true activation maps that do not derive from the Potts model. The underlying paradigm consisted of two stimulus types (M=2) whose activation patterns are shown in Fig. 2(a)-(d), respectively. Fig. 2(b)-(e) illustrates that a wrong choice of β-value~(β=0.2) in the supervised SMM (SSMM) induces a misspecification between the activating and deactivating voxels for the first experimental condition (m=1) and between deactivating and non-activating voxels as the background is almost classified into deactivating and the non-activating class is almost empty. For m=2, the situation is better but still noisy under SSMM. The situation is properly regularized by resorting to unsupervised SMM (USMM): Fig. 2(c-f) yield estimated labels matching exactly the true ones for m=1,2.
These results are enforced by the estimates of the prior mixture components shown in Fig. 3 for the two conditions. In the SSMM case, we observed a degeneracy regarding the activating class for m=1 (Fig. 3(a)), since the three Gaussian densities are superimposed. For m=2, the mixture parameters of the SSMM are also problematic while less degenerated. Since we obtained μ_{-1}≈μ_0 for m=2, this directly impacts the posterior classification towards the presence of false negatives. On the other hand, Fig. 3(b)-(d) illustrate a better distinction between the three components in the prior mixtures for m=1,2. For both conditions, we noticed that the distributions do not overlap (Fig. 3(b)) with the USMM setting. Hence, we found an exact posterior classification. Fig. 4 illustrates the behavior of the SSMM when varying the β-value. A wrong tuning yields a significant decrease in the classification rate of non-activating (blue) and deactivating labels (red) for β<0.8 et β>1.2. The USMM provides β=0.92 (see ◊) which is in this optimal range [0.8-1.5] and yields optimal classifications.

Conclusions:

We extended a joint detection-estimation of brain activity framework which enables the processing of unsmoothed fMRI data, described in [2,3]. The latter approach considers two possible states at each voxel: activating or non-activating. Here, we generalize the model to consider de-activation, in order to take into account putative negative BOLD effects. The spatial regularization then required 3-colors Potts fields. In order to make it spatially adaptive, the JDE technique calls for a reliable and fast estimation of 3D Potts field PFs. The JDE approach is actually performed independently in a large number of parcels of different shape, each parcel requiring a specific PF estimation. We extended the algorithm proposed in [3] to the 3-colors Potts fields PF approximation. The validation on synthetic fMRI data showed promising results in terms of statistical sensitivity. Ongoing work will be devoted to the processing of real fMRI datasets for which we expect de-activations.

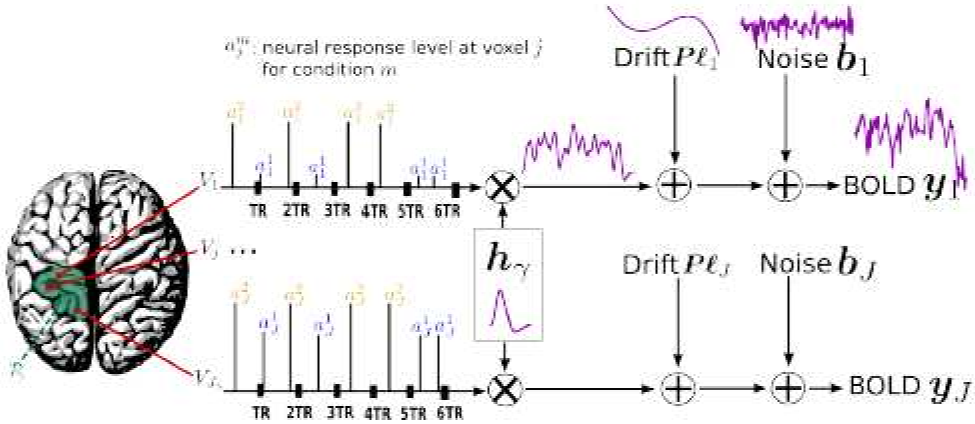

Fig. Parcel-based regional BOLD model. The size of each parcel $\mathcal{P}_\gamma$ varies typically between by a few tens and a few hundreds of voxels: $80 \leqslant J_\gamma \leqslant 350$. The number M of experimental conditions involved in the model usually varies from 1 to 5. In our example, $M = 2$, the NRLs (a_j^1, a_j^2) corresponding to the first and the second conditions are surrounded by circles and squares, respectively. Note that our model accounts for asynchronous paradigms in which the onsets do not necessarily match acquisition time points. As illustrated, the NRLs take different values from one voxel to another. The HRF h_γ can be sampled at a period of 1s and estimated on a range of 20 to 25s (*e.g.*, $D = 25$). Most often, the LFD coefficients ℓ_j are estimated on a few components ($Q = 4$).

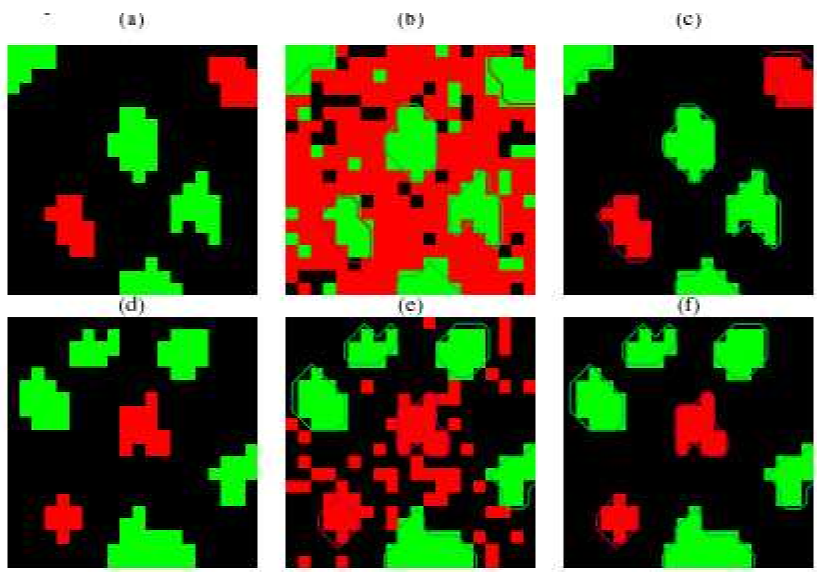

Fig. Estimated labels in the Maximum A Posteriori sense. Top row: $(\hat{q}^1)^{MAP}$. Bottom row: $(\hat{q}^2)^{MAP}$. (a)-(c): Label maps obtained using the supervised SMM (SSMM) for $m = 1$ and $m = 2$, respectively with $\beta^{(1)} = \beta^{(2)} = 0.2$. (b)-(d): Label maps obtained using the unsupervised SMM (USMM) approach. Deactivating, non-activating and activating voxels are color coded in red, blue and green, respectively.

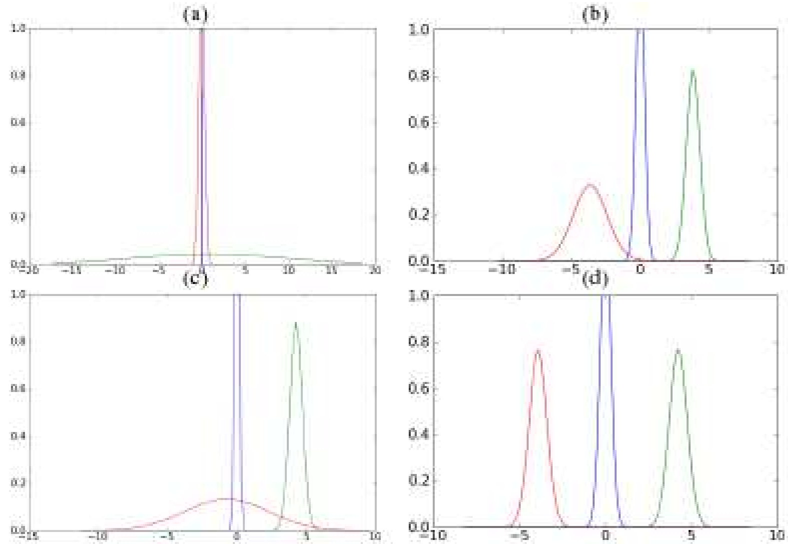

Fig Estimated components of the three-class Gaussian prior mixture. Top row: first experimental condition ($m = 1$). Bottom row: second experimental condition ($m = 2$). (a)-(c): Mixture components yielded by the SSMM approach for $m = 1$ and $m = 2$, with $\beta^{(1)} = \beta^{(2)} = 0.2$; (b)-(d): Mixture components given by the USMM approach. Deactivating, non-activating and activating voxels are color coded in red, blue and green, respectively.

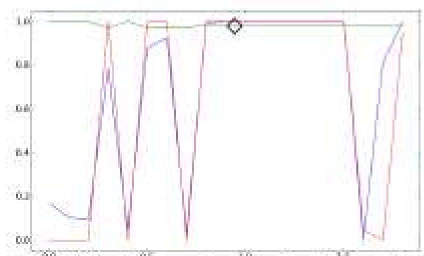

Fig. Rate of right classification of $(\hat{q}^1)^{MAP}$ and $(\hat{q}^2)^{MAP}$ in the supervised case for different fixed β-values. Activating, non-activating and deactivating classes are color coded in red, blue and green, respectively.

References:

MAKNI, S. (2008), 'A fully Bayesian approach to the parcel-based detection-estimation of brain activitation in fMRI detection-estimation of brain activity in fMRI', *NeuroImage*, vol. 41, no. 3, pp. 941-969.
VINCENT, T. (2010), 'Spatially adaptive mixture modeling for analysis of {within-subject Spatially adaptive mixture modeling for analysis of within-subject fMRI time series', *IEEE Trans on Medical Imaging*, vol. 29, no. in press.
THIRION, B. (2006), 'Dealing with the shortcomings of spatial normalization: Multi-subject parcellation of fMRI datasets', *Human Brain Mapping*, vol. 27, no. 8, pp. 678-693.
RISSER, L. (2009), 'Robust extrapolation scheme for fast estimation of 3D Ising field partition functions. Application to within-subject fMRI data analysis', *MICCAI'09*, vol. LNCS 5761, pp. 975-983.
RISSER, L. (2010), 'Min-max extrapolation scheme for fast estimation of 3D Potts field partition functions. Application to the joint detection-estimation of brain activity in fMRI', *submitted to Journal of Signal Processing Systems*.

Categories

- Bayesian Modeling (Modeling and Analysis)
- Bold fMRI (Modeling and Analysis)