Motivation
Hemodynamic Response Function (HRF) describes the temporal dynamics of the brain region response during activations.
HRFs vary from region to region, from task to task and from subject to subject [1], in addition to age and disease [2].
Critical for understanding the relationship between activated brain areas.

Research Goal
Extract reliable region-specific HRFs from Functional Magnetic Resonance Imaging (fMRI) data with unknown drift.

What is Drift?
Drift is the low frequency trends in the fMRI time series caused by uncorrected head movement, instrumental instability, long memory neuronal oscillations, or vasomotion.

Why a new method for HRF estimation?

- Proposed parametric methods: Inability to capture a wide range of detectable HRFs (e.g. use of priors). Least-squares method shown in Figure 1.
- Mostly proposed non-parametric methods: Inability to integrate drift uncertainty leading to large number of assumptions.
- Recently proposed non-parametric method by [3]: Probabilistic treatment of the drift coefficient vector, but at a significantly higher computational cost.

Benefits of considering an unknown drift matrix.

Why this method?
- Very simple to implement and converges within a few iterations.
- Better estimation of the HRF without any assumption on the drift matrix.
- Well adapted to deal with regional HRF estimation in an efficient way without including a smoothing prior on the HRF.
- Improved convergence.

Approach
- Detect activated regions of the brain in response to certain tasks.
- Group the voxels into sub-regions.
- Iteratively estimate the drift matrix and the region wise HRF until convergence.

Model and notations
The normal linear regression model used to analyze the pre-processed fMRI data has the following form

\[ y_i = \beta_0 + \beta_1 x_i + \epsilon_i \sim N(\mu_i, \sigma_i^2 I) \]  

\( \alpha \) is a known \((N \times p)\) matrix : lagged stimulus covariates. 
\( \beta \) is the \((N \times d)\) drift matrix. 

(1) is a mixed-effects model, where \( \alpha_i \) describes the fixed effects and \( \beta_0 \) describes the random effects. 

Observe that data is modelled as: 
\[ y_i = \alpha_i + \beta_0 + \epsilon_i \sim N(\mu_i, \sigma_i^2 I) \] 

Iterative minimization of the Kullback Leibler divergence between the mixed-effects model and observed data model [4]. 
Closed form expressions are obtained for the HRF estimate \( \hat{\beta} \) and the drift matrix estimate.

Results
- Figure 3 shows the results on real fMRI data.
- Results on synthetic fMRI data show a smoother estimate with an improvement of order 10 in quadratic error when compared to least squares method. See Figure 2 to be compared with Figure 1 and Table 1.

Future Directions
- To accurately detect brain activations leading to an accurate region-specific hemodynamics.
- To work on connectivity and information flow within the brain for modelling the causal interactions among the brain regions.

Acknowledgements
- Strength of the proposed algorithm is assessed on real data described in C. Buchel et al 1997 and Hermann Hinrichs et al 2001, respectively.
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