A hybrid LDA+gCCA model for fMRI data classification and visualisation

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Introduction

- Linear predictive models are applied to functional MRI (fMRI) data to estimate linear boundaries that can discriminate scans acquired during different experimental task states.
- Linear predictive models can provide boundaries with significantly non-random predictive power and resulting discriminate SPMs.
- Maximizing the prediction enhances detection of the task-positive brain networks.
- Maximizing spatial reproducibility facilitates detection of temporally variable and spatially large-scale networks, e.g., the default mode network.
- We introduce a flexible hybrid model that optimises spatial pattern reliability by simultaneously enhancing the prediction power and reproducibility of linear predictive models.
- Based on the results on the simulated and real fMRI data, the proposed method better reflects the interactions of the task-positive, and default mode networks in an SPM.

Methods

- Spatial reproducibility maximization: To maximize the spatial reproducibility, we fit the gCCA model [Afshin-Pour, et al. 2012; http://www.nitrc.org/projects/gcca].
- Prediction maximization: To maximize the prediction of the brain conditions, we fit a linear discriminate model (LDA) to each subject’s fMRI data.
- Hybrid model: To maximize both prediction accuracy and spatial reproducibility of the estimated spatial maps (\(z_q\)), we linearly combine the gCCA and LDA optimization functions as follows:
  \[
  \rho = (1 - \beta_1) \cdot y + \beta_1 \cdot y_q \]
- \(y\) and \(q\) are hyper-parameters.
- The unknown weights \(a_q\) (1st SVD) are estimated such that \(\rho\) is maximized using a steepest descend method.

Selecting the parameters

- The optimum \(q, \beta\) are determined based on the prediction (p) and reproducibility (r) metrics.
- The p and r metrics may not be optimized at the same time.
- It has been suggested that the \((p, r)\) pair that minimizes the distance (\(\Delta\)) from \((p=1, r=1)\) is a useful single operating point:
  \[
  \Delta = \sqrt{(1-p)^2 + (1-r)^2}
  \]

Results: Simulated dataset

- (a): The activation pattern for the simulated dataset (Network A: Yellow-Red; Network B: Blue-Green)
- (b): The activation maps (p<0.05 uncorrected) extracted using GNB, LDA, Hybrid for: upper row, \(\Delta_{\text{real}}\); lower row, \(\Delta_{\text{real}}\).
- (c): The normalized area under ROC curves (False positives <0.1) quantifying the detection performance for the networks A and B, \(\beta_1\).
- (d): The scatter plot of \(p\) vs. \(\Delta\) vs. \(\beta_1\) (ROC performance) versus \(\Delta\) of the hybrid model for different sets of the parameters \(y\) and \(q\), where \(\beta_{\text{max}} = \Delta_{\text{opt}}\).

Results: Real fMRI dataset

- Top: The p-r curves obtained by changing the number of PCs per subject, \(q\), and \(y\).
- Bottom: \(\Delta\) vs. the number of PCs.

Results: Spatial patterns

- The discriminant spatial maps acquired using GNB, NPAIRS-LDA, and the Hybrid model for the RT vs FIX and PMT vs RT contrasts (p<0.001).

Materials

Real fMRI datasets (Grady et al., 2010):
- Subjects were responding to several visual stimuli during the scan by pressing a button.
- During the scans there were blocks of five task conditions: 1) fixation (FIX); 2) simple reaction time (RT); 3) perceptual matching (PMT); 4) attentional cueing (ATT) and 5) delayed match-to-sample (DMS).
- Four runs were acquired for each subject using a block design with eight alternating task-fixation conditions (FIX) per run (20 scans/task-period alternating with 10 scans/fixed-period, TR=2s) for the four tasks (ATT, DMS, PMT, RT) with two repetitions each.
- We have used the PMT vs RT, and RT vs FIX task contrasts, to demonstrate the utility of the hybrid model.
- In order to have equal numbers of scans for RT and fixation only the two fixation blocks (FIX) adjacent to RT blocks were used from each run of the experiment.
- Spatial smoothing was performed on the spatially registered data using a spatial Gaussian filter with full width half maximum (FWHM) = 7mm.

NPAIRS split-half resampling procedures

- Datasets = 1, …, M are randomly split into two sets (1,2).
- Each of the three models below was trained on each set, and used to produce two consensus eigenimages (\(\beta_1, \beta_2\)) calculated per model.
- The models were tested on the set not used to train them. Two prediction values were estimated, and the average calculated as the final prediction value (p) per model.
- For each model the reproducibility (r) was calculated as the correlation coefficient between the resultant images (\(\beta_1, \beta_2\)).
- A final z-score SPM is calculated using the robust consensus average across 100 splits within the NPAIRS framework.

The Hybrid Model:
- Dimension reduction is performed for each subject, and q components per subjects are kept. The hybrid model applied in the NPAIRS framework.

LDA:
- We also applied LDA (Strother et al., 2004) to extract 2 predictive eigenimages for the RT vs FIX blocks, and PMT vs RT blocks implemented in the NPAIRS software package with the number of PCs per split (NPAIRS-LDA code is available at http://code.google.com/p/planpairs/).

Gaussian Naïve Bayes (GNB):
- We also applied GNB (Mitchell et al., 2004) in the NPAIRS framework to estimate the split-half spatial maps, and their p and r values.

Conclusion

- The new model is implemented in the NPAIRS split-half resampling framework, which permits measuring the model’s reproducibility (r) and prediction accuracy (p).
- These two parameters allow the Hybrid model to produce a broader range of solutions in prediction and reproducibility space compared to an LDA model alone.
- The hybrid model better captures the interaction between the task-positive and default mode networks in an SPM.