A Survey of Recent Statistical Methods for EEG-fMRI

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Abstract

Statistical analysis of EEG-FMRI in neuroscience have major challenges both from theoretical and practical aspects such as complex relationships, sparsity and smoothing. In this manner, many Functional Data Analysis methods are developed which considered function or curve as building blocks in models. But Functional data analysis have different frameworks with different basis functions. The aim is to review recent developments in statistical methods specially functional data analysis methods for EEG-FMRI.

Keywords: Sparsity, Smoothing, EEG-fMRI, Functional data analysis

Introduction

In this poster, we first review big data in the neuroscience, EEG-FMRI, for studying brain activities. Then according to intrinsic high dimensional datasets, we compare two most cited functional data analysis(FDA) frameworks, Jeffrey S. Morris [1]. Finally, we present a recent FDA method for EEG-fMRI, Xin Qi and Ruiyan Luo[2].

EEG-fMRI

Recently there are many researches in the neurosciences that capturing simultaneously Electroencephalography (EEG), with many electrodes around the head, and functional magnetic resonance imaging (fMRI). The first dataset consists of many electrical signals generated by nerve cells and the second dataset are activation levels of thousands voxels in the brain images. The researchers use preprocessing methods to get an organized and ready to use datasets. The figure a shows a process of capturing EEG-fMRI simultaneously while subject perform tasks.



Figure a

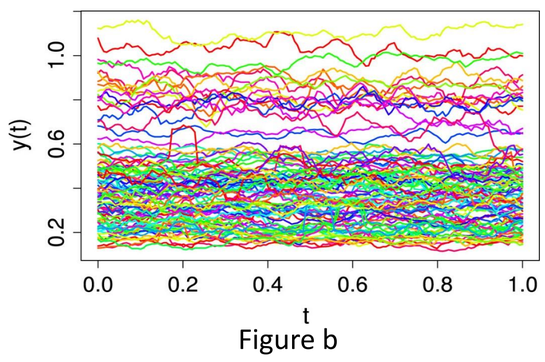


Figure b

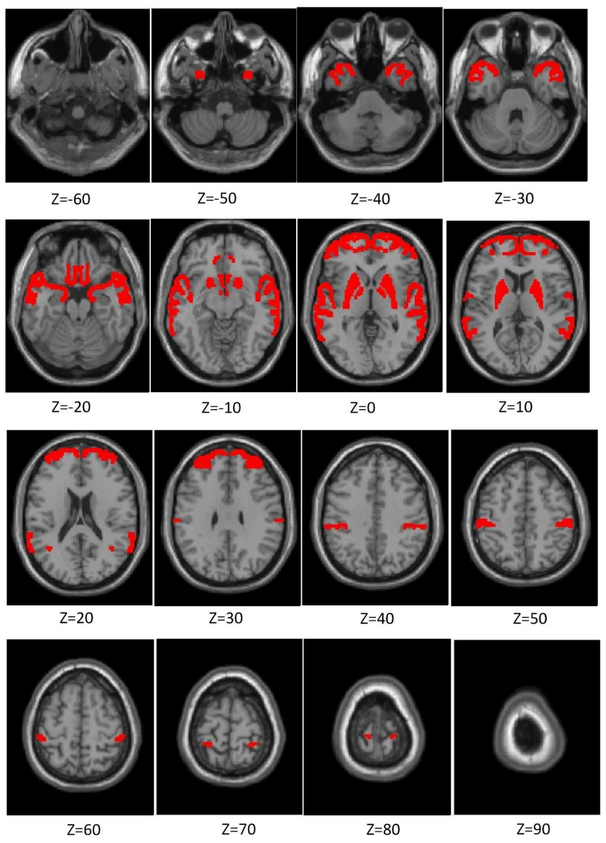


Figure c

Two General FDA Framework

The new statistical methods for analyzing high dimensional EEG-fMRI are the main topics of many articles. Among them, Functional Data Analysis (FDA) methods, the building blocks are functions or curves instead of points, gained a special attention. FDA has two main framework: Functional Linear Array Model (FLAM) Sarah Brockhaus et al.[3] and Functional Mixed Model Framework (FMM) ,Jeffrey S. Morris [1]. :

	Functional Linear Array Model (FLAM)	Functional Mixed Model (FMM)
Core regression model	Generalized additive model (GAM)	FMM
Basis Representations	Tensor product of basis functions	Basis Transform Modeling
Penalization	Quadratic penalties for each additive term	Basis Transform Modeling
R Packages	Generalized additive models (refund package in R) and component-wise gradient boosting (FDboost in R)	Bayesian wavelet-based functional mixed model (WFMM) and R-wrapper (wrapfmm)
Strengths	GAM, functional response regression, functional predictor regression, function-on-function regression, allow for fixed and random effects, any number of additive predictor terms.	Bayesian, functional response regression (main), functional predictor regression, function-on-function regression , allow for fixed and random effects, any number of additive predictor terms, higher order basis functions for 2D and 3D data, scalability to extremely large functional data sets.

Functional Linear Regression Model with Functional Responses

Time series of particular EEG *Defined in an interval [a,b](fig b)*

Time series curves of thousands of voxels in fMRI data. *Random functions defined in [0,1]*

$$\forall_{t\in[a,b]} \qquad y(t) = \mu(t) + \underbrace{\int_0^1 \boldsymbol{x}(s)^T \boldsymbol{\beta}(s,t)ds}_{} + \varepsilon(t)$$

Decomposition of $\boldsymbol{\beta}(s,t)$

$$S(t)$$ *Random functions with mean zero*

$\{\tilde{w}_k(t) : k \in \mathbb{N}\}$ Unit-norm orthogonal eigenfunctions of the covariance function.

$\{\sigma_k^2 : k \in \mathbb{N}\}$ Corresponding eigenvalues

Karhunen–Loève expansion of S(t)

$$S(t) = \sum_{k=1}^{\infty} \tilde{r}_k \tilde{w}_k(t) \qquad with \quad \tilde{r}_k = \int_a^b S(t)\,\tilde{w}_k(t)dt, \quad E(\tilde{r}_k^2) = \sigma_k^2$$

Define

$$\alpha_k(s) = \frac{1}{\sigma_k^2}\int_a^b \beta(s,t)w_k(t)dt$$

$$\boldsymbol{\beta}(s,t)$$

$$y(t) = \mu(t) + \int_0^1 \mathbf{x}(s)^T \left\{\sum_{k=1}^{K_0} \alpha_k(s)w_k(t)\right\} ds + \varepsilon(t).$$

Generalized Functional Eigenvalue Problem

$$max_{\alpha(s)} \frac{\int_0^1\int_0^1 \alpha(s)^T\hat{\Lambda}(s,\acute{s})\alpha(\acute{s})ds\acute{ds}}{\int_0^1\int_0^1 \alpha(s)^T\hat{\Sigma}(s,\acute{s})\alpha(\acute{s})ds\acute{ds} + P(\alpha)}$$

$$subject\ to \int_0^1\int_0^1 \alpha(s)^T\hat{\Sigma}(s,\acute{s})\alpha(\acute{s})ds\acute{ds} = 1, \int_0^1\int_0^1 \hat{\alpha}_{\acute{k}}(s)\hat{\Sigma}(s,\acute{s})\alpha(\acute{s})ds\acute{ds} = 0$$

Simultaneous Sparse-Smooth Penalty

$$P(\alpha) = \tau\left\{(1-\lambda)\left(\sum_{j=1}^{p}\|\alpha_j\|_{\eta}^2\right) + \lambda\left(\sum_{j=1}^{p}\|\alpha_j\|_{\eta}\right)^2\right\}$$

Application

The simultaneous EEG-fMRI dataset for 17 person in the Auditory and Visual Oddball project ,Walz et al. [4],were considered. The training dataset for model fitting was randomly selected, then mean squared prediction error (MSPE) ,relative MSPE and average R-squared for test dataset based on the fitted model was calculated. Among four modeling strategy including full method, without smooth penalty, without sparse penalty and without any penalty, the first one has better performance in all three measures. The figure c shows that 11 ROI (Region of interest) among 55 ROI with full model has nonzero coefficient.

Conclusion

The FLAM and FMM framework works well in a sparse sampling grid and very high dimensional grids, respectively. The proposed simultaneous sparse-smooth penalty term in the generalized functional eigenvalue problem increase prediction accuracy of the functional linear regression model with functional responses in EEG-fMRI.

References

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