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Application of Spatiotemporal Gaussian Process Model for fMRI Data Analysis

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Abstract:

Statistical analysis is base on preparing brain maps. Their accuracy and reliability are essential. Adjusting models for considering spatiotemporal correlation that is embedded in fMRI data can increase accuracy, but it introduces a high computational cost. We applied a spatiotemporal Gaussian process model (STGP) for task-based fMRI data. This model modified common group-level-GLM for spatiotemporal correlation in a reasonably fast way that can solve the underestimation of parameter estimation variation and leads to a more accurate result with a less false positive rate. A simulation study was conducted to assess the accuracy of these models. Proposed model and group-level-GLM were fitted to a memory tfMRI data. The main activated area was the frontal brain lobe, as mentioned in previous studies. Z-score was computed for all voxels, and functional and activation maps for both models were calculated. The STGP model increased the absolute maximum Z-score by about 18 and 13 units compared to the group-level GLM. In the simulation study, the STGP model resulted in more accurate results (higher accuracy; lower: FPR) compared to the GLM. The STGP model was applied to denote group-level GLM for valid inference. This model resulted in a higher Z-score and more accurate results for experimental and simulated data.

Keywords: fMRI data analysis, Brain mapping, Spatiotemporal Gaussian Process model, Spatiotemporal correlation

Mathematics Subject Classification (2010): 60G20, 60H22.

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1 Introduction

Functional magnetic resonance imaging (fMRI) is a neuroimaging technique for brain mapping or association between mental function and its spatial location in brain anatomical structure (Bollmann, 2018; Hansen, 2020). As fMRI experiments make a sequence of three-dimensional images at each time point during scanning time, spatiotemporal correlations are absolutely embedded in acquired 4D data (Bollmann, 2018; Nader, 2019; Zhang, 2016).

Software packages for analysis of fMRI data commonly take advantage of General Linear Models (GLM) to analyze fMRI data. These models do not consider the spatiotemporal correlation structure of fMRI data (Wald and Polimeni, 2017). Ignoring this noise or residual correlation structure may lead to an underestimation of parameters' variability and consequently increases the false-positive rate (FPR), even up to 70%, especially in the group-level analysis (Bollmann, 2018; Cox, 2017; Eklund, 2015; Li, 2009; Wald and Polimeni, 2017). Moreover, it may restrict the reliability and accuracy of brain activation findings (Bollmann, 2018).

In this work, we applied the spatiotemporal Gaussian process (STGP) model for task-related memory fMRI data. Due to its ability to handle more massive spatiotemporal data, we used the model to analyze fMRI data. The STGP is a computationally efficient framework for approximating unstructured huge spatiotemporal covariance in group fMRI data analysis. It is expected to have a more accurate activation map due to its residual structure adjusting for the spatiotemporal correlation that increases accuracy and decreases FPR. A simulation study was conducted to evaluate the model's accuracy, precision compared with an ordinary GLM.

2 Methods

There were ten volunteers, including seven men and three women aged 19-32 years old, all right-handed with no history of medical, neurological, or psychiatric illness in this study. The stimulation task was done via a block design: 30 seconds rest and 30 seconds memory task. During the task time, the participants viewed 15 non-repeated random pictures of famous locations, people, or objects (Lewis-Peacock, 2008). We preprocessed the data by implementing the FSL software pack age.

The model-based analysis of data was conducted using the Spatiotemporal Gaussian Process (STGP) model to find the task-related brain activation. We consider recorded BOLD signal $Y_i(s,t)$ for each participant, at each three-dimensional voxel (spatial location) during scanning time:

$$Y_i(s,t) = X_i(s,t)\beta_i(s,t) + \Theta_i(s,t) + \varepsilon_i(s,t) \tag{2.1}$$

Where $X_i(s,t)$ is task-related design matrix (the stimulus matrix convoluted by Hemodynamic Response Function(HRF)), and $\beta_i(s,t)$ is regression coefficient. $\Theta_i(s,t)$ is spatiotemporal random function and $\varepsilon_i(s,t)$ is the measurement error. Two last items regarded as mutually independent and identically distributed as Gaussian process $GP(0, \Sigma_\Theta)$ and $GP(0, \Sigma_\varepsilon)$ respectively. In the first step, residuals were calculated to estimate Θ_i at the first step, by subtraction ordinary regression estimation from observations. $m_i(s,t) = Y_i(s,t) - X_i(s,t)\hat{\beta}_1(s,t)$,so:

$$\hat{\Theta}_1(s,t) \quad = \quad \sum_{m=1}^{s}\sum_{j=1}^{T}\{m_i(s_m,t_{ij}) - \beta_0 - \beta_1^T((s_m - s)^T, t_{ij} - t)^T\}^2 k_h(s_m - s)k(\frac{(t_{ij} - t)}{h_1})/h_1 \tag{2.2}$$

Where k_h is a univariate kernel function. FPCA is used to estimate spatiotemporal structure huge covariance matrix, on average of $\hat{\Theta}_1$ Products.

$$\hat{\Sigma}_\Theta((s,t),(s',t')) = n^{-1}\sum_{i=1}^{n}\hat{\Theta}_i(s,t)\hat{\Theta}_i(s',t') \tag{2.3}$$

First, K ordered eigenvalues and eigenfunction of this matrix that their sum be at least 70% of the total. Measurement error estimation calculated as:

$$\hat{\varepsilon}_i(s,t) = Y_i(s,t) - X_i(s,t)\hat{\beta}_1(s,t) - \hat{\Theta}_i, \tag{2.4}$$

Adjusted total covariance, parameter estimation, and Z-score were calculated, and a brain activation map was prepared.

A simulation study was conducted to evaluate the STGP model and compare its properties with the Group-Level GLM. Imaging data with an $S = 10 \times 10 \times 10$ set of voxels were generated for $n = 50$ subjects at $T = 100$ time points. The GLM, STGP were fitted to each simulated dataset. Then, we assessed the models using measures of accuracy (the percentage of voxels whose status in terms of activation or inactivity is correctly estimated by the model), false-positive rate, FPR (the ratio of active voxels that are incorrectly detected by the model as active voxels to the total number of active voxels).

3 Results

The STGP model and ordinary group-level GLM were fitted to tfMRI (memory task) data, and their performances were compared.

For both models, all preprocessing steps were performed the same way.

First level and group-level GLM analyses were implemented scores $(\hat{\beta}/SE(\hat{\beta})))$ were computed for all subjects and group-level for both models.

4 Discussion and Conclusion

This research aimed to assess the efficiency and accuracy of the STGP model compared to two common scenarios of fMRI data analysis, i.e., the GLM and Bayesian approaches. As statistical analysis is the basis of reported brain activation (Z-score) maps, it is obvious that inaccurate analysis can lead to imprecise brain maps (Wald and Polimeni, 2017). fMRI data are acquired in three-dimensional space during the scanning time, so when the spatiotemporal correlation is embedded, it makes it four-dimensional. Ignoring this correlation may lead to underestimating the variability and an increased false-positive rate (Bollmann, 2018). Main activated areas were the same at both models, occipital and frontal lobes that were expected based on previous work on this data (Lewis-Peacock, 2008). Besides, it was confirmed by previous work for memory task-based stimuli (Eriksson, 2015; Funahashi, 2017; Lara, 2015; Lewis-Peacock, 2008).

In this study, the STGP model increased the absolute maximum Z-score by about 18 and 13 units compared to the group-level GLM. An increasing Z-score showed more robust activation and suppressed activated areas in comparison with the GLM; this may be due to false activation removal. Activated voxels in the whole brain were observed to be ten percent less in the STGP model, especially the sporadic voxels in the GLM. This may be because the spatiotemporal correlation increases precision and accuracy while reduced diffused unrelated activated voxels, which were practically considered as noise in the computations. In the simulation study, the STGP model resulted in more accurate results (higher accuracy; lower: FPR) compared to the GLM, presumably due to the spatiotemporal correlation adjustment (Table 1).

Table 1: . The model comparison indexes for GLM, and STGP Model based on the simulation study.

Models	Accuracy (%)	FPR (%)
Group-Level-GLM	86.7	4.35
STGP Model	99.5	0.41

To conclude, the STGP model, which considers spatiotemporal dependencies in a single subject and group level fMRI data, resulted in more accurate and precise maps in real and simulated data. There is a tradeoff between accuracy, precision, and computational cost. The STGP is not as fast as GLM but provides less FPR and more accurate group-level voxel-wise task-based fMRI maps.

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