Automatic Model Selection Scheme for GLM-based Functional MRI Analysis

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Introduction

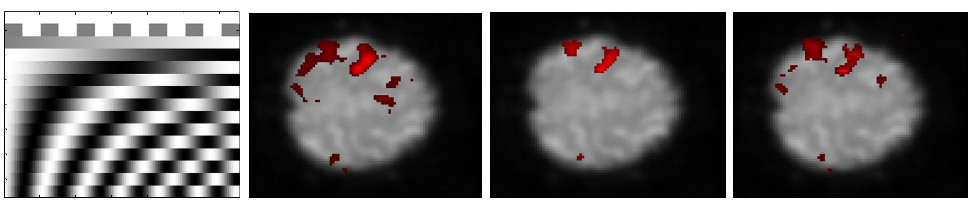
With its ability to model multiple experimental and confounding effects simultaneously, the general linear model (GLM) has been used to analyze functional MRI time series extensively. The first step of the analysis is model specification or specification of the design matrix, then followed by the estimation of model parameters. Assuming that the model fits, a given hypothesis is then assessed using the estimated model parameters. If it doesn't, then the model assumptions do not hold and the subsequent inference may not be valid. Obtaining an appropriate and parsimonious model for a given fMRI data is therefore critical. In this work, an automatic model selection scheme based on an information theoretic approach is applied in fMRI analysis. The approach is based on an orthogonalization procedure[1] previously proposed for the real-time estimation of GLM coefficients. The built-in model selection scheme of the algorithm provides a voxel-by-voxel basis of tuning the design matrix, thus avoiding ill-fitted models.

Methods

In the GLM framework, fMRI data is modeled as a linear combination of L explanatory functions (design matrix) plus an error term. Following [1], orthogonal basis functions are obtained from the explanatory functions using the usual Gram-Schmidt orthogonalization procedure. The coefficients associated with the orthogonal functions are then estimated. Since the square of the coefficient determines the contribution of a given orthogonal term in reducing the mean square error[1], this quantity could be used to select only the significant among the candidate terms. The number of terms that will be included in the final model is determined using Akaike's information criterion[2] (AIC). The approach is illustrated using an fMRI data set acquired using a gradient recalled EPI technique with the following imaging parameters: TR = 3s, FOV = 220mm, slice thickness = 3mm, gap 1mm, matrix dimension is 64 x 64, 30 slices per volume. The experiment was designed in a block manner with 13 task blocks. In the task blocks, the subject performed a finger-tapping task with a frequency of 1 Hz in synchrony with a flashing visual cue (2^{nd}, 6^{th}, and 10^{th} blocks) or an auditory cue (4^{th}, 8^{th}, and 12^{th} blocks). The difference in the obtained activation map as a function of the number of basis functions included in the analysis was investigated using 1) the entire design matrix shown in Fig. 1a), 2) only the first three rows, and 3) with automatic model selection applied voxel-by-voxel.

Results

Figure 1 (b)-(d), shows the activation maps of a representative axial slice containing the motor cortex obtained using different numbers of basis functions. Figure 1b shows the activation map when using only the first three rows of the design matrix (Fig 1a), while Fig 1c is the activation map using the entire design matrix. A significant decrease in the number of detected active voxels can be observed when all 15 basis functions are included (Fig 1c) as compared to using only the first three basis functions (Fig 1b). A comparison between the two maps clearly shows the dependence of the map to the number of basis functions used. Moreover, only voxels that are strongly activated were detected in Fig 1c. The results of AIC analysis showed that the number of significant terms varies from voxel to voxel indicating that different models are appropriate for different voxels. Thus, a voxel-by-voxel tuning of the design matrix becomes important. The activation map obtained using the proposed automatic model selection scheme applied voxel-by-voxel is shown in Fig 1d.



(a) (b) (c) (d)

Fig. 1a) Full design matrix modeling (top to bottom) baseline level, task design, linear drift, and several high pass filters. Activation maps of a representative slice containing the motor cortex obtained using b) only the first 3 rows of a), c) the entire design matrix, and d) with automatic model selection applied voxel-by-voxel.

Discussion

Implicit in any modeling is the assumption that the used model fits; otherwise, the subsequent statistical assessment based on the estimated model parameters may not be valid. In GLM-based analysis of fMRI time series, it is a common practice to use the same design matrix for all voxels analyzed. However, it is quite possible that different models will be appropriate for different voxels. Thus, one should account all possible effects of interest and confounds relevant at any voxel in the design matrix. This approach however has the danger of over-fitting the model with the extra parameters contributing to the reduction of the effective degrees of freedom of the residuals, which affects the detection of voxels that are not strongly activated (e.g., Fig. 1c). The presented approach brings automatic model selection to the voxel level instead of the entire image. Model over-specification at each voxel is avoided by including only significant terms in the design matrix. The number of terms to be included is determined by an information criterion approach (AIC) and does not require multiple comparisons of hierarchical models. Since the selection is built into the estimation process, the scheme can be performed simultaneously with the estimation process minimizing the required computations.

References

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