Nonlinear kernel-based fMRI activation detection

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Introduction:

Kernel Canonical Correlation Analysis (KCCA) is an efficient way to detect brain activation globally with less computational complexity. However, the current KCCA is limited to the linear kernel, and the performance for other more general types of kernels is not completely understood due to a lack of inverse mapping i.e. Back Construction (BC) methods. This study aims to expand the current KCCA method to arbitrary nonlinear kernels.
The general linear model (GLM) is commonly used in task fMRI data analysis. Several related methods such as an isotropic GLM with Gaussian Smoothing (GS) [1], Canonical Correlation Analysis (CCA) and Linear KCCA [2-5] have been used to obtain activation maps. Beyond linear methods, nonlinear kernel-based methods, such as the Support Vector Machine (SVM), are very powerful in data classification and prediction [6], but there is no method available to define an inverse mapping from the feature space to the original space for obtaining an activation map. In this study, we proposed a general type of BC technique which allows us to get the activation pattern for any type of linear or nonlinear kernel mapping. The new method was applied to real fMRI data for activation analysis.

Methods:

Structural and functional MRI data were obtained from the Human Connectome Project (HCP) database [7], which contains 3T MRI imaging data from 87 males aged 26-30 old. We focus on the working memory task fMRI study. fMRI data were acquired with 405 timeframes with multiband factor 8, TR/TE=720/33.1ms; FA=52 degrees; 72 slices; spatial resolution=2mm^3 with size=104 × 90. The data were minimally preprocessed (realignment, slice-timing correction, normalization to MNI, linear detrending). No spatial smoothing was performed. The task itself represents an event-related task design consisting of targets, non-targets, and lures contrasts. Figure 1 shows a flow chart of our data analysis. fMRI signal Y is transformed to feature space $\tilde{Y}$ by $\tilde{Y}=YA\in R^{(t\times p)}$, $A\in R^{(q\times p)}$ where A is the spatial transformation matrix, then map to the kernel space K_Y by an arbitrary kernel function. For the design matrix X, we define the contrast vector c=[1,-1,0] and map X to X_{eff} [8]. Then, map the X_{eff} to kernel space by $K_X=X_{eff} X'_{eff}$. Using KCCA, the solution vectors v_X and v_Y are found to maximize the canonical correlation $corr(K_X v_X,K_Y v_Y)$ in the feature space with penalty term γ to avoid overfitting [9]. To transform back to the ordinary space, we propose a BC method by $r=|\sum_t(\partial [(K_Y v_Y)]_t)/(\partial Y_t)|\in R^q$ where the (voxel-specific) correlation vector r measures the importance of each voxel's contributing to the signal in kernel space.

Results:

In Figure 2 (a1)-(e1), we show the activation pattern for one selected subject, with the color indicating the top 10% of voxels with high r value. In Figure 2 (a2)-(e2), we plot the same results using Gray Matter (GM) as a background. The GM is computed using spm package with segmentation probability p>0.5. The Hyperbolic tangent kernel avoids most activations arising outside the GM. To further characterize the overlapping, we treat the GM as the ground truth, using different thresholds to compute the true positive (activation appears on the GM) and false positive (activation not on the GM), with the ROC curve as shown in Figure 2 (f). Then using the 5mm GS as the reference, we define the subject-specific parameter $\alpha=(AUC)_{Kernel}/(AUC)_{GS}$ as a ratio measuring how many increasements compared with the GS. The distribution of α among all subjects are shown in Figure 2 (a3)-(e3), with the mean and average shown in Figure 2 (g). On average the Hyperbolic tangent kernel has highest α value among all other kernels.

Conclusions:

The key findings of this study are: 1) BC is an efficient method to compute activation maps for general types of kernel representations. 2) Hyperbolic tangent kernel can get activation in an optimum location compared with other kernels.
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Learning and Memory:

Working Memory [2]

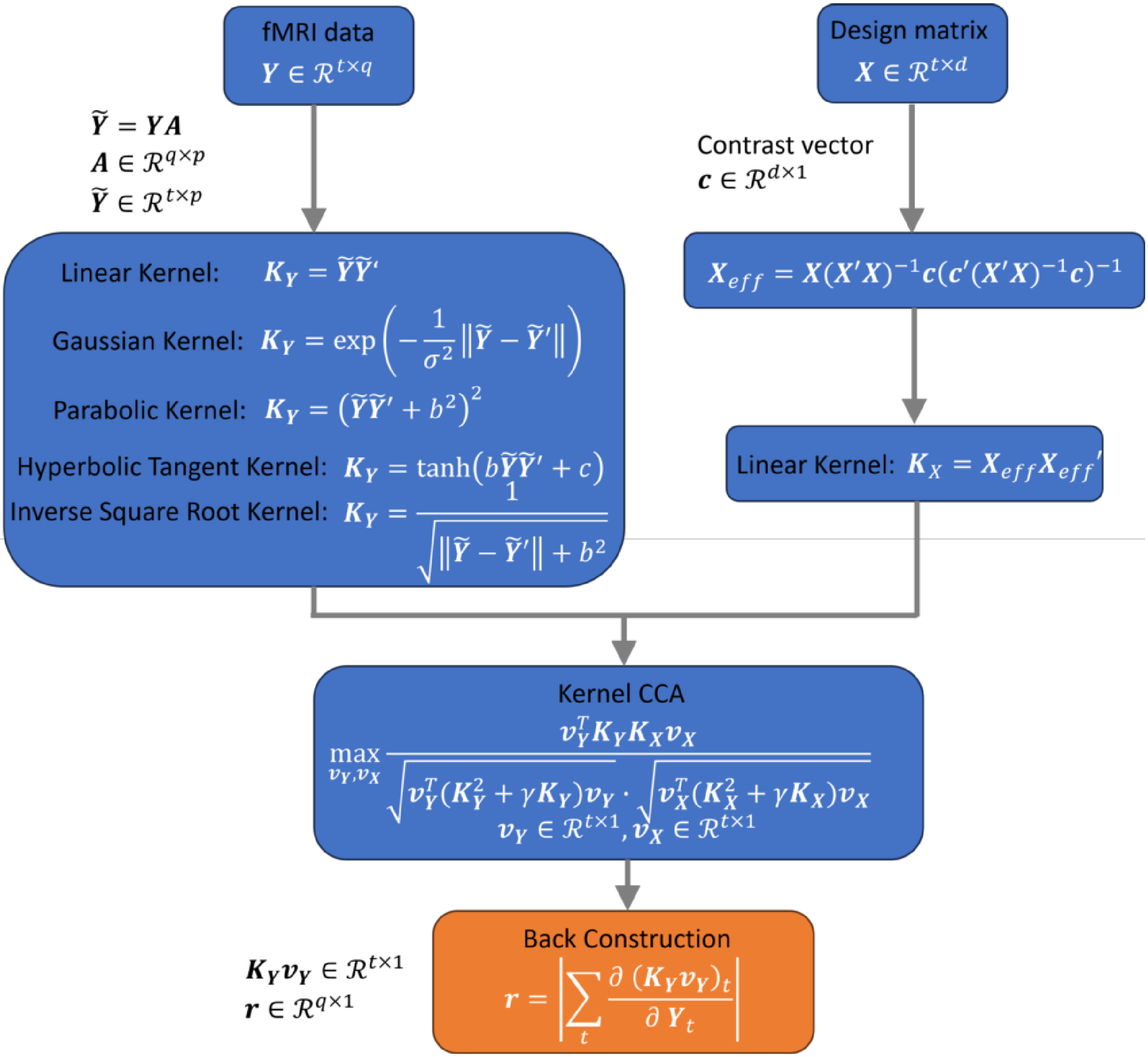
Modeling and Analysis Methods:

Activation (eg. BOLD task-fMRI) [1]

Keywords:

Data analysis
FUNCTIONAL MRI
Other - Activation

[1|2]Indicates the priority used for review



·Figure 1: A schematic diagram of regularized kernel canonical correlation analysis for task fMRI activation analysis.

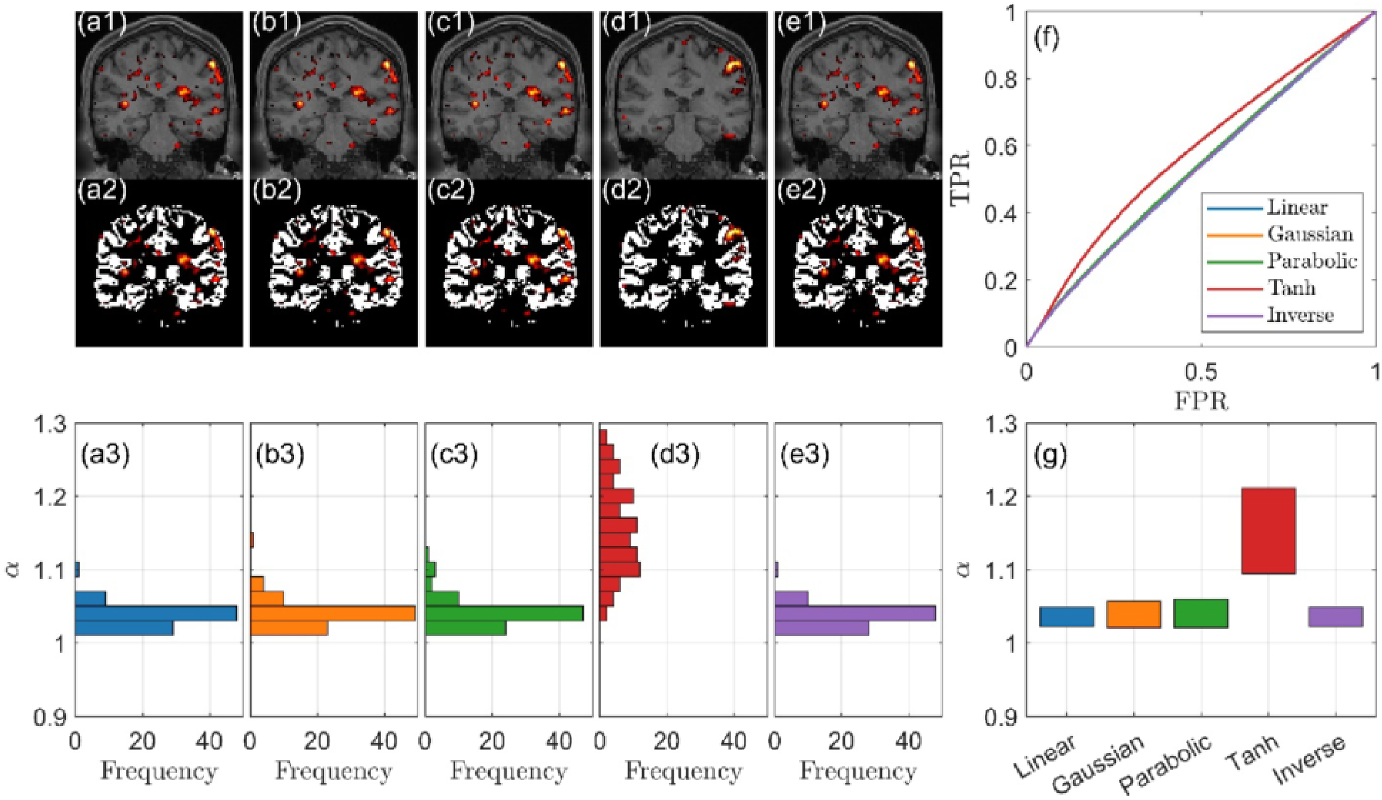


Figure 2: (a1)-(e1), activation pattern obtained from Linear kernel, Gaussian kernel, Parabolic kernel, Hyperbolic tangent kernel and Inverse square root kernel respectively. The color indicates the top 10% of voxels with high r value. The background is the T1 image at the corresponding location. (a2)-(e2) The same activation pattern but using the gray matter as background. The activation pattern obtained from the Hyperbolic tangent kernel has maximum overlapping on the gray matter. (f) ROC curves computed from five different kernels which are used to characterize the overlapping between the activation and the gray matter. (a3)-(e3) histogram for α computed from Linear kernel, Gaussian kernel, Parabolic kernel, Hyperbolic tangent kernel and Inverse square root kernel respectively. (g) Mean and variance for α based on 87 subjects.

Abstract Information

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Functional MRI
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For human MRI, what field strength scanner do you use?

3.0T

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SPM

Provide references using author date format

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