

Class-wise contributions to spatio-temporal SVM classification of fMRI data

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Introduction: Nowadays most fMRI studies are analysed using mass-univariate GLM fitting approaches [1]. These require that a model of the task-related BOLD response be known beforehand. However, since most brain function is assumed to be the product of distributed processes involving a network of cortical areas, one may question whether one model for the task related BOLD response could be sufficient to encompass the complex temporal dynamics of all brain areas. Recently Mourao-Miranda et al. proposed a method for model-free detection of task-related BOLD responses which are discriminating between two tasks, i.e. spatio-temporal support vector machine (spatt-SVM) [2]. Accordingly, task-related transient responses will be detected with the same efficiency as sustained responses [2&3].

However, the resulting “discriminating” brain maps are hard to interpret. They have to be displayed unthresholded, because univariate tests are not suited to determine a threshold for multivariate maps [3]. Additionally, the sign of the task-wise contributions to the discrimination map cannot be determined. A positive/negative value in the discrimination map corresponds to higher/lower activity during Task 1 compared to Task 2, but does not reveal if e.g. one task had positive signal change while the other task had a negative signal change. Furthermore, if some areas are responding similarly to the different classes(tasks), they will only appear very weakly or not at all in the discrimination map.

This project is set to devise methods for constructing functional brain maps from the results of spatio-temporal SVM which lend themselves more readily to interpretations of information content and class(task)-wise similarities versus class(task)-wise distinctions in terms of “activations/deactivations” (in order to achieve comparability with GLM results). In this abstract we will concentrate on the relationship between the discrimination map and the class exemplars, to construct “class contribution” maps, which can reveal class(task)-wise signal features. These are applied to fMRI data from a galvanic vestibular stimulation (GVS) experiment using unilateral direct current stimulation, since electrophysiologic [4], behavioural [5] and fMRI [6] experiments suggest that brain responses would differ in their temporal characteristics for the different parts of the vestibular network.

Theory and Methods: SVMs achieve classification by finding a hyperplane which separates the data according to their class labels (+1&-1), while fulfilling the constraint that the distance to the nearest class exemplars (i.e. the support vectors) is maximal. The solution is formulated in terms of the normal vector defining the separating hyperplane, called the weight vector. Therefore the weight vector is the direction along which the classes differ most, i.e. the “discriminating” brain map [2&3]. The weight vector w is a weighted sum of the support vectors belonging to the different classes(tasks) and can thus be separated into contributions from each class (i.e. “class contribution” maps C1C and C2C, can be constructed).

$$w = \sum_i c_i \alpha_i x_i = \sum_{\{c_j=+1\}} \alpha_j x_j - \sum_{\{c_k=-1\}} \alpha_k x_k = \text{C1C} - \text{C2C}$$

The α are the Lagrange multipliers determined by the SVM algorithm, c_i are class indices (+1/-1) and the x_i are the N class examples used for training. Spatio-temporal classification is achieved by defining the training and test examples x_i as spatio-temporal fMRI observations [2]. Therefore an example x_i is a vector containing all voxels (selected from the preprocessed brain images by a mask) with all their timepoints over a task/stimulation block. In this work, we use spatio-temporal SVM as implemented in the PROBID toolbox (<http://www.brainmap.co.uk/>) and produce the “class contribution” maps from the estimated parameters and the training examples. Whole-brain echo-planar images (TR= 2800ms) of 7 right handed healthy subjects were acquired using a 3T GE-SignaHD-Excite Scanner, while unilateral GVS with direct current was applied (block-design, rest periods in between changes of left and right stimulation site). The cathodes were placed on the mastoid of each side and the anodes near C7. The current amplitudes were determined by asking each subject to report when he felt an illusory head movement, while keeping skin irritation minimal. Preprocessing was done with SPM 5 (realign, normalize, smooth (8mm)³ FWHM) and PROBID (linear detrend and z-scoring of voxel timecourses). Voxels were selected using a mask covering the vestibular network, i.e. insular cortex, thalamus, inferior parietal lobule, middle temporal gyrus, brodmann area 8, superior frontal gyrus and the cerebellar vermis. Given this mask, the algorithm can reveal the spatio-temporal response of this network to GVS stimulation of the right side versus the left side, without assuming a model for the task(stimulation)-related BOLD response.

Results and Discussion:

The classifiers performance was found to be 85% at a significance level of $p < 0.001$. Figure 1 shows the discrimination map (a) and the respective class contribution maps C1C and C2C (b&c) over the whole stimulation block (6TRs). The peak of the insular cortex and the thalamus seem to appear in the same time window (T2), after a delay of 1 TR from the stimulus onset. The response of the temporal lobe seems to reach its peak after the response of the insula and thalamus (in time window T3). The class contribution maps suggest that the responses are positive for both classes (stimulations) and that most areas respond similarly for both classes (stimulations).

Conclusion and future work:

The current results support the general conclusion of previous studies [3&4], that this classification approach can reveal (task-related) responses without assuming a model for the spatio-temporal characteristics of the network of brain areas involved in stimulus processing. The proposed class contribution maps reveal class(task)-wise contributions to the discrimination map, allowing interpretations regarding areas which are responding similarly versus distinctly to the tasks. Further studies are necessary to extend this work to produce “importance maps” which can reveal the information content of areas contributing to the classification performance.

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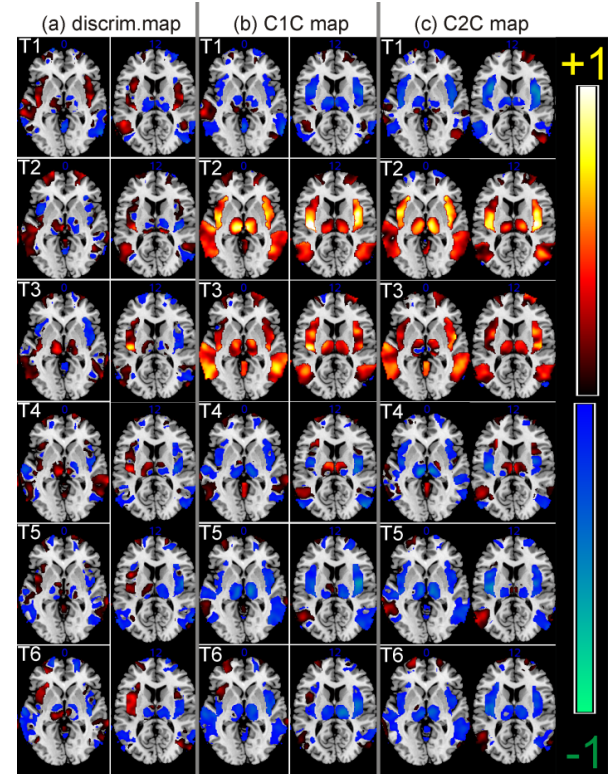


Fig. 1: Axial slices at MNI coordinates $z=0$ and $z=12$ of (a) discrimination map, (b) class 1 (GVS R) contribution map and (c) class 2 (GVS L) contribution map for the whole stimulation block of 6 TRs. All maps are scaled relative to the discrimination map (a), to have the same colorbar.

References:

- [1] Friston et al., 1995; Hum.BrainMapp. 2.
- [2] Mourao-Miranda et al., 2007; NeuroImage 36.
- [3] Mourao-Miranda et al., 2009; J Cognitive Neurosci 21.
- [4] Goldberg et al., 1984; JNeurophysiol 51.
- [5] Fitzpatrick and Day, 2004; JApplPhysiol 96.
- [6] Stephan et al., 2009; AnnNYAcadSci 1164