Improved pattern classification in functional MRI using neuro-anatomically selective boosting

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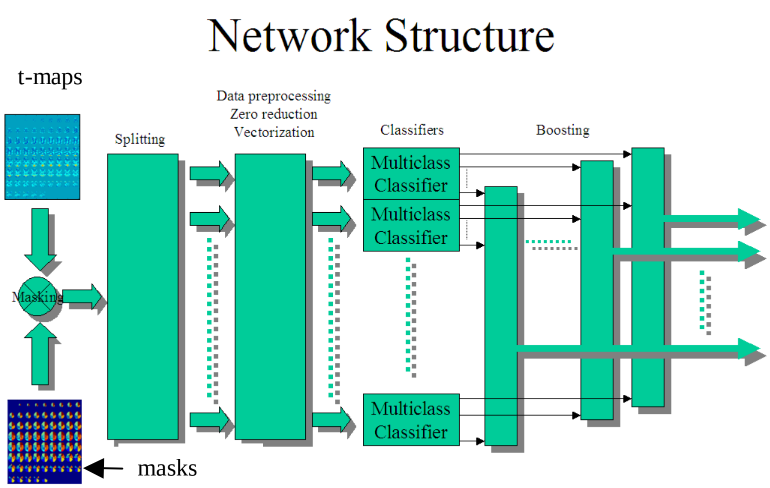
Introduction

Pattern classification in functional MRI is a novel methodology to automatically interpret activation patterns [1]. Automatic and reliable classification of patterns is challenging due to the high dimensionality of fMRI data and the small number of available data sets. Pattern classification across groups of subjects and different scanner field strengths has not been described so far, in part due to inter-individual differences in functional brain anatomy, and time course, amplitude and extent of brain activation, and field strength effects.

In this study we address the problem of multi-class classification of 4 different activation patterns across groups of subjects at two different field strengths, which challenge the performance of standard classifiers. We assessed robustness of training and testing with different subjects and field strengths.

Methods

Subjects and paradigm: Ten healthy subjects were studied using a 1.5 Tesla Siemens Sonata scanner and eight healthy subjects using a 4.0 Tesla Bruker Medspec Scanner. The paradigm consists of four randomly sequenced blocked tasks (8 sec each): visual (8 Hz checkerboard stimulation), motor (2 Hz right index finger tapping), auditory (syllable discrimination) and cognitive (mental calculation), interleaved with baseline blocks, extending over a total of 132 sec. Functional MRI data were acquired using single-shot echo-planar imaging. Statistical parametric mapping using SPM99 was performed to generate t-maps that represent brain activation changes. Preprocessing steps included motion correction, slice-time correction, spatial normalization and spatial smoothing. Statistical analysis using a design matrix with 4 conditions (motor, visual, auditory, cognitive) was performed with corrected amplitude threshold ($p = 0.05$).



Structure of the classifier: The resulting t-maps are masked to obtain 14 sub-maps corresponding to left and right parts of subcortical, brainstem, cerebellum, frontal, parietal, temporal and occipital areas. An array of 14 multi-class nonlinear Support Vector Machines [2] is used to classify each sub-map separately. An optimal combination of the outputs of the different classifiers using a modification of standard boosting techniques [3] that selects those regions which contain useful information for classification (see figure). This new boosting strategy is a spatially distributed algorithm that has two main advantages over the use of a single classifier: the segmentation of the activation maps leads to reduced complexity in each classifier. This improves generalization and reduces the computational cost, which increases linearly with the number of classifiers and quadratically with the number of voxels submitted to each classifier. The optimal combination of classifiers removes contributions from areas that do not contain relevant activation, thus reducing the effect of noise on the generalization ability of the classifier.

Results:

The performance of the boosting algorithm was compared to that of other conventional techniques [1] using two different approaches:

(1) The leave-one out technique was used to compare between individual subjects at single field strength, and across field strengths. Ten different subjects scanned at 1.5 Tesla were selected. Training is performed with 9 subjects, leaving one out for testing. Results in 2-class and 4-class classification show 100% of accuracy, dramatically outperforming classical single classifier techniques, that give 15% in binary classification and 60% in 4-class classification. A second analysis was carried out using 188 images coming from 18 subjects scanned in the 1.5 Tesla and 4 Tesla. Using the leave-one-out technique, we measure a 97.3% of accuracy in 4 class classification. Only 5 images were misclassified. Experiments with standard approaches give accuracy up to 80%, which is better than before due to the increased information contained in the data

(2) Data sets were divided into training sets and classifications sets to compare between different field strengths. First, we used the activation maps from 8 subjects scanned with the 4 Tesla scanner to train the boosted classifier network, and we perform the test using the 10 subjects scanned at 1.5 Tesla. Accuracy was again of 100%. Activation maps at 4 Tesla have higher signal to noise ratio (SNR), so classification performance is challenged by the lower SNR of the 1.5 Tesla data. In order to test for the robustness against overfitting due to noise, we trained the system with maps at 1.5 T and then tested it with maps at 4 T. Classification accuracy was 96.7%, also outperforming the accuracy of standard approaches.

Discussion:

Boosting was shown to considerably improve the generalization performance of classification. It also reduces computation time, which makes it attractive for real-time fMRI applications. Ongoing studies investigate the effect of changing the sizes and number of neuro-anatomically defined masks, and aim at classifying cognitive tasks that result in more similar activation patterns.

References

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