

## Chapter 3.10

# Classification of Multiple Interleaved Human Brain Tasks in Functional Magnetic Resonance Imaging

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### ABSTRACT

Pattern recognition in functional magnetic resonance imaging (fMRI) is a novel technique that may lead to a quantity of discovery tools in neuroscience. It is intended to automatically identify differences in distributed neural substrates resulting from cognitive tasks. Previous works in fMRI classification revealed that information is organized in coarse areas in the neural tissues rather than in small neural microstructures. This

fact opens a field of study of the functional areas of the brain from the multivariate analysis of the rather coarse images provided by fMRI. Nevertheless, reliable pattern classification is challenging due to the high dimensionality of fMRI data, the small number of available data sets, interindividual differences, and dependence on the acquisition methodology. The application of kernel methods and, in particular, SVMs, to pattern recognition of fMRI is a reasonable approach to deal with these difficulties and has given reasonable results in

accuracy and generalization ability. Some of the most relevant fMRI classification studies using SVMs are analyzed in this chapter. All of them were applied in individual subjects using ad hoc techniques to isolate small brain areas in order to reduce the dimensionality of the problem. Some of them included blind techniques for feature selection; others used the previous knowledge of the human brain to isolate the areas in which the information is presumed to lie. Nevertheless, these methods do not explicitly address the dimensionality, small data sets, or cross-subject classification issues. We present an approach to improve multiclass classification across groups of subjects, field strengths, and fMRI methods. We use an approach based on the segmentation of the brain in functional areas using a neuroanatomical atlas, and each map is classified separately using local classifiers. A single multiclass output is applied using an Adaboost aggregation of the classifier's outputs. This Adaboost combined the region-specific classifiers to achieve improved classification accuracy with respect to conventional techniques without previous ad hoc area or voxel selection.

## INTRODUCTION

Brain activation changes in response to even simple sensory input, and motor tasks encompass a widely distributed network of functional brain areas. Information embedded in the spatial shape and extent of these activation patterns, and differences in voxel-to-voxel time courses, are not easily quantified with conventional analysis tools, such as statistical parametric mapping (SPM; Kiebel & Friston, 2004a, 2004b). Pattern classification in functional magnetic resonance imaging (fMRI) is a novel approach that promises to characterize subtle differences in activation patterns between different tasks. Roughly speaking, fMRI uses MRI techniques to detect regional changes in blood flow, volume, or oxygenation in response

to task activation. The most popular technique uses blood oxygenation level dependent (BOLD) contrast, which is based on the different magnetic properties of the oxygenated and deoxygenated blood. Oxygenated blood presents diamagnetic properties while deoxygenated blood presents paramagnetic properties. These differences in susceptibility produce small differences in MR image intensity. Rapid image techniques together with statistical tools are used to generate fMRI images from sets of raw time-series data scans. The most general framework to obtain fMRI activation maps is the general linear model (GLM; Friston, Holmes, Worsley, Poline, Frith, & Frackowiak, 1995). The aim of this model is to explain the variation of the time course in terms of a linear combination of explanatory variables and an error term. The GLM can be written as  $\mathbf{X}=\mathbf{G}\beta+\mathbf{e}$ , where  $\mathbf{X}$  is a matrix containing the acquired data. It has a column for each voxel (a voxel, or volume pixel, is a three-dimensional pixel, or a quantity of 3-D data), and a row for each scan.  $\mathbf{G}$  is the so-called design matrix, and it has one row per time point in the original data, and one column for every explanatory variable in the model. In an fMRI experiment,  $\mathbf{G}$  contains indicators of the level of a certain activity reflecting the experimental design (e.g., zeros and ones for a required activation) or other kinds of information not related to the experiments (covariates of global cerebral blood flow, drift, respiration, etc.). Matrix  $\beta$  is the parameter matrix and  $\mathbf{e}$  is the vector of error terms. In order to obtain  $\beta$ , least squares are applied. Provided that one can split matrices  $\mathbf{G}$  and  $\beta$  into four parts containing indicators and covariates of interesting and confounding effects, a range of statistical analyses can be performed on the GLM. The student t-test (t-map) can be viewed as a particular case of the GLM, and it is one of the most used techniques in fMRI. Student t-tests and other statistical analyses can be viewed as particular cases of the GLM.

The automatic and reliable classification of patterns is challenging due to the high dimen-

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