Comparison of Feature Selection Methods for Classification of Temporal fMRI Volumes Using SVM

A. E. Ercan¹, E. Karahan², O. Ozvurt², and C. Ozturk²

¹Biomedical Engineering, TU Delft, Delft, Netherlands, ²Institute of Biomedical Engineering, Bogazici University, Istanbul, Turkey

Introduction

Recent functional magnetic resonance imaging (fMRI) studies include classification of the activation states of the brain following a specific task. Various classifiers have been used and compared in order to predict the "underlying state patterns" within temporal fMRI volumes, where each volume corresponds to a global brain snapshot at a different time instant during acquisition. Support Vector Machines (SVM) are shown to produce the highest classification accuracy in similar problems [1]. High dimensional feature space (number of voxels) of fMRI volumes has been a drawback for such classifications since large feature dimension is known to increase the classification error and the computation time [2]. To resolve this problem, number of features could be reduced by anatomically selecting brain ROI's which are expected to be active during a specific state, either through masking or by mathematically selecting more significant dimensions in the original data. Principle component analysis (PCA) is one of the unsupervised mathematical feature reduction methods which eliminate the covariant features from the data set [3]. In this study; for fMRI scans obtained from a bimanual finger tapping experiment, we combined the mathematical and anatomical feature selection methods and examined the effects of different feature reduction methods on the classification accuracy of a linear SVM classifier.

Methods

Data Acquisition

fMRI experiment is conducted with two healthy volunteers. The experiment is designed to trigger activation in motor cortex of subjects' brains as a response to the right or left hand movements. 3 Tesla Siemens (Trio) MR scanner is used for data acquisition. Each session began with anatomical scan of the subject (TR = 2s, TE = 3.94 ms, Slice Thickness = 0.75 mm, Matrix Size = 320 x 288) which is followed by functional scans (TR = 2.66 s, TE = 30 ms, Slice Thickness = 3 mm, Matrix Size = 64 x 64, Field of View = 19.2 cm, Number of Slices = 36) during which finger tapping paradigm was executed. The functional session lasted for a total scan time of 200 TR (~9 minutes), which consists of 5 times repetition of 40 TR blocks. For each block, the participants were asked to stand still (baseline) for a duration of 10 TR, perform left hand finger tapping for 10 TR (26.6 seconds), stand still for 10 TR and perform right hand finger tapping for 10 TR.

Two different masking methods are applied to the realigned functional scans in order to reduce the number of voxels anatomically: grey matter (GM) mask and region of interest (ROI) mask. Grey matter masks are created for each subject by selecting the voxels from Grey Matter Region of the subject's structural brain scans by making use of segmentation function in SPM8 (SPM-Statistical Parametric Mapping, http://www.fil.ion.ucl.ac.uk/spm/). ROI mask is created using wfu_pickatlas toolbox in SVM [4]. Broadmann 4 and 6 regions which correspond to the motor cortex region of the Talairach Brain are selected to create the ROI-based mask. The number of features, which corresponds to 145146 voxels in the original fMRI volumes, reduced to 14097 after applying GM mask and to 4576 voxels after applying ROI mask. Following the masking procedure, a further mathematical feature reduction is applied to the data set. Eigenvalues and eigenvectors of the covariance matrix are found using Singular Value Decomposition (SVD) and used for selecting the significant voxels with high variances through PCA. The obtained data is set to retain 95% of the variance. The number of features reduced to 59 for GM masked data and to 77 for ROI masked data. The rows of the data matrix corresponding to different TR times are then labeled according to the type of stimuli.

Classification

Spider toolbox (Spider, http://www.kyb.tuebingen.mpg.de/bs/people/spider/) for Matlab is used for implementation of SVM classifier. The classification is done on two-class data sets. The classes to be distinguished are specified to correspond to the type of stimuli (left hand, right hand or no movement). The data matrix is subdivided for distinguishing right hand movement versus rest classes, left hand movement versus rest classes, left hand movement versus right hand movement classes (100 fMRI temporal volumes), and movement versus rest classes (200 fMRI temporal volumes). Random permutation is applied for separating the data matrix into training and test data sets: 2/3 of the volumes from each class is used as training data set and the rest is used as the test data set. The feature space is divided into two regions, identifying two different classes, with a linear hyper plane established according to the supervised training data sets (120 points for movement vs. rest classification and 60 points for right/left-hand-movement vs. rest, or right vs. left hand movement classifications). The rest of the data is used as the unknown test set and classified according to the function obtained during training. The procedure concerning separation of data into training and test sets, followed by classification of the data, is repeated over 1000 times. Validation accuracy, which corresponds to the percent number of correct classes in the output, is calculated for each repetition as an evaluation parameter for the estimation success. The accuracies are then averaged over 1000.

Results and Discussion

Table 1 displays success rates obtained by the classification of functional volumes using a linear SVM classifier with/without application of PCA to GM and ROI masked data.

Two-Class Combinations	GM	GM with PCA	ROI	ROI with PCA
Movement vs. Rest	0.67 ± 0.01	0.63 ± 0.05	0.81 ± 0.01	0.71 ± 0.06
Left Hand Movement vs. Rest	0.78 ± 0.01	0.80 ± 0.02	0.90 ± 0.01	0.87 ± 0.02
Right Hand Movement vs. Rest	0.85 ± 0.02	0.80 ± 0.02	0.92 ± 0.01	0.93 ± 0.01
Right vs. Left Hand Movement	0.88 ± 0.04	0.86 <u>+</u> 0.05	0.88 ± 0.07	0.99 <u>+</u> 0.01
Average	0.80 + 0.04	0.77 + 0.05	0.88 + 0.02	0.88 + 0.05

Table 1. Accuracy of Classification for different two-class combinations after Grey Matter Masking with/without applying PCA and Region of Interest masking (ROI) of motor cortex with/without applying PCA.

ROI-based feature selection, which shows higher classification accuracy (~88% confidence) compared to GM-based feature selection (~80% confidence) for linear SVM classifier, is recommended for the classification problems with similar fMRI pradigms. The classification accuracy of right vs. left hand movement being higher than movement vs. rest one for all cases, reveals that to choose the two-class combination to be classified regarding the physiological effects of the fMRI paradigm significantly affects the accuracy values.

For all two-class combinations, the estimation successes obtained after applying PCA are observed to be acceptably close (within 90 to 95% confidence interval) to estimation accuracies obtained directly after masking, without further application of PCA. Since it retains the characteristic of masking methods while making the calculations easier and faster to compute, PCA is concluded to be a reliable method for reduction of feature space dimensionality. Indeed, applying PCA after anatomical feature selection is suggested before applying linear SVM. **Acknowledgements:** This work is supported by the Turkish State Planning Organization (DPT) under the Boğaziçi University TAM Project (2007K120610) and Life Sciences Research Center Project (2009K120520). **References:**[1]Mitchell et al., Machine Learning, 57, 145–175, 2004.[2] Sun et al., Pattern Recognition, vol. 37, pp. 2165-2176, 2004. [3]Tipping et al., J. Royal Statistical Soc., 61(3):611–622, 1999.[4] Maldjian et al., Neurolmage 2003. 19:1233-1239.