Real Time fRMI: Machine Learning or ROIs?

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Introduction:
Real time fMRI has multiple potential applications, including providing means for a non-invasive brain computer interface, and training subjects to control their own brain activation as a means of modulating cognitive function or disease (1). The first applications of this technology used voxel intensity averaging over regions of interest, but recent research has introduced the concept of instead using machine learning classifiers to discriminate between different cognitive states (2). Little work has been done directly comparing these methods of data reduction; we offer a comparative overview of performance of these techniques.

Methods:

Data Acquisition:
16 healthy volunteers were scanned in a 3T Bruker system using echo-planar functional images (TR=1.1s, TE=27.5ms, 21 interleaved axial slices, 4mm thickness, 1mm slice-gap, 200mm FOV, 64x64 matrix). Subjects were asked to follow a task 1 / task 2 / rest paradigm for 30s blocks of each, with a selection of 4 imagery tasks: playing tennis, navigating around their house, visualizing faces and singing ‘jingle bells’ whilst remaining motionless. Between 7 and 10 task / task / rest blocks of each type were acquired from each subject. Each dataset was split into two subsets: a training set (the first two blocks of task / task / rest data) and a test set (the remaining blocks).

Region of Interest Approach:
Average intensity values over a predetermined ROI were calculated, and a decision boundary constructed from the training data. Four possible ROIs were sampled, 1) whole imaging volume, 2) masked brain only voxels (using an ad hoc threshold of 0.8 x mean intensity) 3) all ROIs found to activate in a task as taken from a block design analysis of this dataset (3), 4) Supplementary motor and premotor areas common to all tasks, also taken from (3). Using the concept of an ‘answer block’ to avoid problems of drift (comparing classifier outputs over subsequent blocks) we then predicted whether each block transition was from task to rest or rest to task, and recorded accuracy.

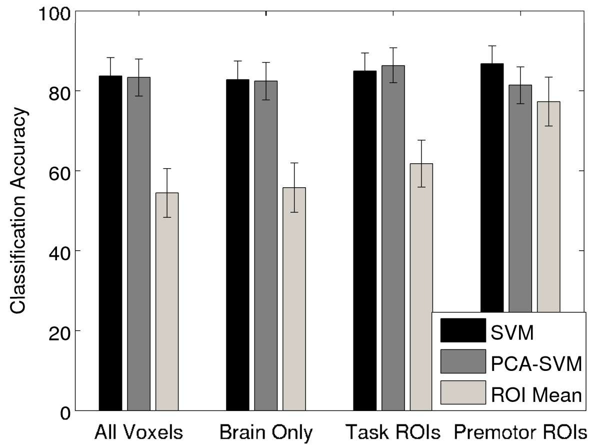

Fig. 1: Classification accuracy for machine learning (SVM), machine learning with preliminary PCA (PCA-SVM) or classification by averaging over an ROI (mean) for four different ROIs (see methods).

Machine Learning: Using the same ROIs as above to provide input variables, a support vector machines classifier was trained on voxel intensities to discriminate between task and rest neural states. As above, predictions used ‘answer blocks’ to determine the nature of each transition, and accuracy was recorded. As a separate experiment, we repeated the same with the additional data reduction step of principal components analysis before support vector machine learning.

Optimal Block Length:
As an additional study, we removed scans from the end of each task / rest state to study how accuracy correlated to block length used. By removing scans from the end of each recorded state we approximated the effects of using shorter blocks to those recorded, and sampled accuracy with block lengths of 2, 6, 10, 14, 18, 22 and 26 scans each. This was conducted for both the averaging over region of interest and machine learning predictor cases.

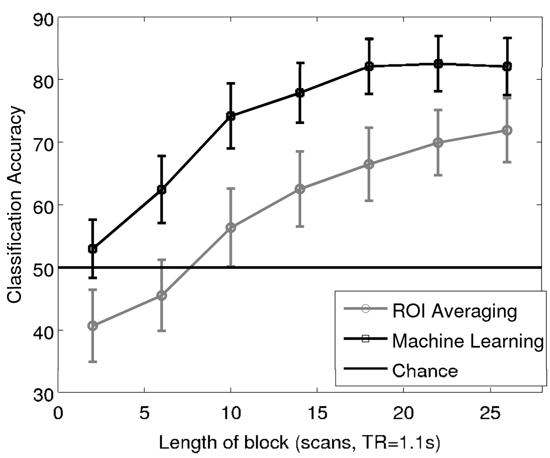

Fig. 2: Classification accuracy as a function of block length for both machine learning and ROI averaging techniques.

Results:
Support vector machines outperformed simple averaging over regions of interest in every region of interest chosen. Using principal components analysis prior to machine learning did not improve performance. Further to this, machine learning performance was unaffected by the region of interest selected, whereas ROI averaging was extremely sensitive to region selection.
Performance of both types of state prediction decreased with decreasing block length, though machine learning accuracy did not decrease until blocks of length less than 18 scans were used.

Discussion and conclusions:
From our results it is clear that support vector machines outperform simple averaging over regions of interest in discrimination between task and rest for real time fMRI. Support vector machine accuracy is also unaffected by region selection, avoiding the need for localization of ROIs at the start of an experiment, in effect automatically selecting predictive regions during its training phase. However, it should be noted that machine learning tools do still require a supervised learning phase to calculate the discriminant function between two neural states.
Using machine learning tools, accuracy is maintained down to a block length of 18 scans, and is reduced to chance levels for blocks of length less than 6 scans. For averaging over regions of interest, there is a decline in performance associated with any reduction in block length.

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References:
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