A Comparison of SVM and RVM for Real-Time fMRI Applications

D. A. Perez[1], R. C. Craddock[2], G. A. James[1], and X. P. Hu[1]
[1]The Wallace H. Coulter Department of Biomedical Engineering, Georgia Institute of Technology/Emory University, Atlanta, GA, United States, [2]School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, United States

Introduction: Multivariate pattern analysis (MVPA) of fMRI data has been growing in popularity due to its sensitivity to networks of brain activation [1]. Another benefit of MVPA is that it is performed in a predictive modeling framework which is natural for implementing brain state prediction and real-time fMRI applications such as brain computer interfaces [2]. Support vector machines (SVM) have been particularly popular for MVPA owing to their high prediction accuracy even with noisy datasets [3]. Recent work has proposed the use of relevance vector machines (RVM) as an alternative to SVM [4]. RVMs are particularly attractive in time sensitive applications such as real-time fMRI since they tend to perform training and classification faster than SVMs. Despite the use of both methods in fMRI research, little has been done to compare the performance of these two techniques. This study compares RVM to SVM in terms of time and accuracy to determine which is better suited to real-time applications.

Methods: SVM was implemented using the SVM routines of MATLAB's bioinformatics toolbox (Mathworks, Natick RI). RVM was implemented using the Spider machine learning toolbox for MATLAB (http://www.kyb.tuebingen.mpg.de/bs/people/spider/main.html). Two right-handed volunteers viewed alternating 30 second blocks of a visual stimulus (an 8 Hz flashing checkerboard) and a fixation stimulus (a static fixation cross), presented with Presentation software. Two six-minute fMRI scans were acquired using a Siemens Magnetom Trio 3T MRI scanner (FOV=192mm, TR/TE/FA=2s/28ms/90^o, resolution=3x3mm, 34 3mm-axial slices). Data preprocessing was performed with AFNI and in-house Matlab scripts. Images were corrected for slice timing and motion. A mask encompassing the whole brain was constructed and applied to the datasets. The datasets were next detrended and standardized using z-score. Then, the datasets from the two scans were concatenated into one dataset consisting of a total of 360 images. Leave-one out cross validation was performed by designating one epoch (30 images) as the testing data and the rest as training data (330 images). This was done for each epoch which resulted in a total of 12 combinations of training/testing data for each subject. For each algorithm, a linear kernel was utilized as well as a parameter of C=1 for SVM and ζ=1 for RVM. The latter parameters were chosen as such since there was no significant difference in classification error between a range of different values of C and ζ. Training duration, decision time, classification accuracy, and number of support or relevance vectors were all recorded for each execution of the algorithm. These averaged results were then compared to results obtained after a simple feature selection. Filter feature selection (FS) was implemented by first smoothing the dataset and applying a general linear modeling (GLM) using a hemodynamic model of the visual task as the regressor of interest. GLM results were thresholded (q=0.005), voxels passing this threshold were retained for further analysis by SVM and RVM. For each case (SVM no FS, SVM w/ FS, RVM no FS, RVM w/ FS), a feature space weighting (FSW) map was constructed using either the support vectors from SVM or relevance vectors from RVM. . The top 10 percent of voxels from each FSW map were retained and visualized overlaid on an anatomical image.

Table 1: Functional Performance of SVM and RVM

Metrics	Training without Feature Selection		Training with Feature Selection	
Algorithm	SVM	RVM	SVM	RVM
Training time (sec)	17.252	3.250	16.787	2.361
Decision time (sec)	0.156	0.073	0.059	0.028
Classification Accuracy (%)	81.94	80.56	85.28	86.39
Number of Vectors (out of 330)	216.67	16.00	193.25	13.17

Results/Discussion: The results of applying SVM and RVM to the subject data are listed in Table 1. Both algorithms were able to obtain better than random prediction accuracies (i.e., >50%). Feature selection offers an improvement in speed and accuracy for both SVM and RVM. RVM was substantially faster for both training the classifier and classification time. RVMs faster classification time can be attributed to the fewer number of vectors used to define the decision boundary. The algorithms obtained similar prediction accuracy. Figure 1 illustrates those voxels determined most relevant for classification by SVM and RVM both with and without feature selection. The corresponding color bar indicates the strength of weight the two labels used. The top half of the bar corresponds to the visual state while the lower half corresponds with the rest state. Both methods correctly identified the visual cortex as most relevant to the classification task. There are small differences between the results of SVM and RVM which can be attributed to the differences between support vectors and relevance vectors. Support vectors are those vectors closest to the decision boundary, whereas relevance vectors are those that are farthest from the decision boundary [5].

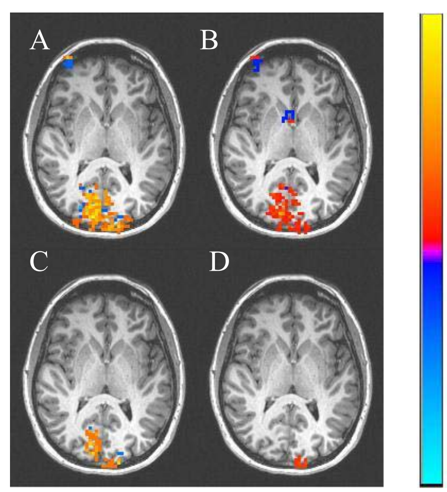

Figure 1. FSW Maps for SVM and RVM. (A) SVM with no FS, (B) RVM with no FS, (C) SVM with FS, (D) RVM with FS

Conclusion: Relevance vector machines obtained the same prediction accuracy as SVM but with a sparser model and faster training and classification time. This result proves that RVM is a preferable alternative to SVM in time sensitive applications such as real-time fMRI. The voxels identified as most relevant by both methods are nearly identical, illustrating that the two methods are using the same information for classification, but that RVM is capable of performing the task much faster.

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