Discriminating One Finger From Another: Support Vector Classification of Event Related fMRI

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INTRODUCTION Recently, there have been several examples of brain state classification with fMRI [1-3]. For block design data, which tend to be acquired at low sampling rates, there is a general correspondence between each acquired image and the stimulus, thus providing a direct class label for each TR. For event-related (ER) data, several images must be considered as belonging to the time evolution of the same class (i.e., event) of brain activity. Confounding the issue is that generally only a limited number of (unknown) brain locations are strongly "activated" by the particular stimulus paradigm. Thus our data situation is extreme in that we have many (mostly spurious) variables with relatively few repeated observations of those variables. In this study, we examine the issue of feature selection on a hyper-image dataset constructed by concatenating images within ER epochs as in [1]. Experimental data were collected to evaluate the appropriateness of two different feature selection strategies and to explore the limits of detection of brain state events using support vector machine classification (SVC) [4].

THEORY In multivariate discrimination settings feature selection is often a helpful and sometimes necessary preprocessing step. The basic principle is to select those variables that best distinguish observations as belonging to either class 0 or class 1. One common method is to use Fisher's discriminant ranking using $FDR_i=(\mu_{i,c=0} - \mu_{i,c=1})/(\sigma^2_{i,c=0} + \sigma^2_{i,c=1})$ where i ranges over the number of variables and μ and σ^2 are the mean and variance estimates for classes 1 and 0 for that variable. We also consider ranking variables represented as "curves" or time series using the adaptive Neyman test [4]. Define $z_p(t) = (\bar{v}_{p,c=0}(t) - \bar{v}_{p,c=1}(t))/(\sigma^2_{p,c=0}(t)/n_{c=0} + \sigma^2_{p,c=1}(t)/n_{c=1})$ as the standardized difference of the epochs (brain state 0 – brain state 1) for the pth voxel ($\bar{v}(t)$s are the average epoch time series and $\sigma(t)^2$s the estimated variance at each epoch time point). Then $T_p = (\sqrt{2m})^{-1}\sum_{f=1}^{m}((Z_p(f))^2 - 1)$ is calculated from the DFT of $z_p(t)$, denoted $Z_p(f)$, and the summation over the first m frequency bins. Given FDR_i or T_p we can rank individual space-time values or grouped epoch voxels respectively.

METHODS Paradigm: The scanning session consisted of 4 runs of left-or-right finger movement (LR) and 4 runs of right handed index-or-pinky movement (IP). Each run consisted of 36 (18 + 18) randomized 2 second events followed by 8 seconds of visual fixation. Periods were visually guided, using Presentation® (Ver. 0.76, www.neurobs.com). Imaging: fMRI data were collected on a 3T Siemens Trio, with 6 axial EPI slices (TR/TE = 500/34 msec, voxel=3.4 × 3.4 × 6 mm). Analysis: The fMRI runs were slice time corrected, registered to the first scan of the first run, and screened for motion in AFNI [5]. The 10 second window of scans (20 volumes) in each ER epoch was used to construct hyper-image data sets. For LR, each run was used as training data, testing with the remaining 3 runs. For IP leave-one-run-out was used, training with 3 runs (54 examples of each class) and testing with the remaining run. SVC was performed i) on the entire hyper-image dataset, ii) after ranking features with FDR_i and keeping 5% of the original features (fr-SVC), and iii) after ranking voxels with T_p and keeping 5% of the original voxels (vs-SVC).

Left vs. Right	Run 1	Run 2	Run 3	Run 4
SVC	0.54	0.66	0.75	0.74
fr-SVC	0.96	0.98	0.96	0.94
vs-SVC	0.99	0.99	1.00	0.99

Table 1. Ave prediction accuracy (LR). "Run 1" means using run 1 for training and all the other runs for testing.

Index vs. Pinky	Run 1	Run 2	Run 3	Run 4
SVC	0.58	0.64	0.58	0.53
fr-SVC	0.53	0.61	0.56	0.67
vs-SVC	0.58	0.67	0.72	0.78

Table 2. Ave prediction accuracy (IP). Leave-one-run-out was used: "Run 1" means train with 2,3, and 4 and test with 1.

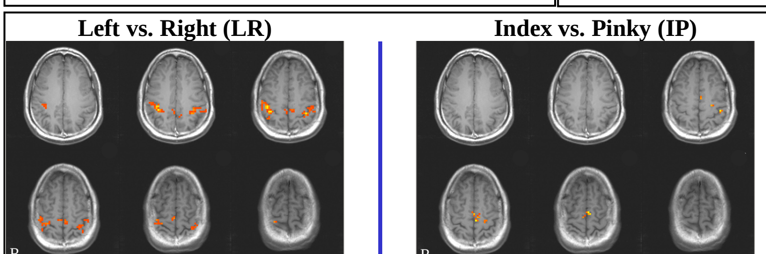

Figure 1. Voxel selection maps derived from models discriminating ER states for left vs. right finger movement (left) and right-handed index vs. pinky movement (right).

RESULTS AND DISCUSSION From Tables 1 and 2, we note SVC performed consistently above chance for both data sets. We observe an advantage to vs-SVC over fr-SVC, indicating the relative importance of the information content of the time evolution of activated voxels over the flexibility of selecting individual space-time variables. Indeed, for IP data, feature selection actually tended to decrease classification performance. The advantage of voxel selection is consistent with simulation results of ER data over a wide range of parameters (not shown). By its subtle nature, IP classification represented a challenge, requiring more training data than LR. On the other hand, strong stimuli such as a flashing checkerboard vs. bilateral finger movement with matched experimental conditions provided nearly perfect model performance with a single training run, without feature selection (not shown). The maps of voxels selected for vs-SVC are shown in Fig. 1. For LR we see a strong bilateral motor pattern, including the supplementary motor area (SMA). For IP we see primarily SMA with a small contribution from the left motor area.

CONCLUSION We have demonstrated the capability of SVC to classify ER-fMRI data to detect subtle brain state differences, and shown improvements in classification performance when feature selection treats voxel events as a functional unit.

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