SVM-based Classification of Motor Tasks on fMRI-BOLD Data

Gerald Brantner[1], Samir Menon[1], Georg Schorpp[2], and Oussama Khatib[1]

***Abstract*— In this study we demonstrate the feasibility of SVM classifiers on closely related motor tasks and use the results to gain insight into neural motor activity in general and the fMRI-BOLD response function in particular. Focusing on two classic motor paradigms—limb motions and manipulation forces—we found that motor BOLD responses for different limb motions are more discriminable than those for different manipulation force levels. We also found that reliable motor voxels, ranked by cross validation score (R^2) for a Haemodynamic Response Function (HRF) model, are more informative and exponentially increase classifier performance with rank. Finally, we found that BOLD response's late stage temporal dynamics in motor cortex are more informative than the early stage responses.**

I. Introduction and Methods

Three subjects (S1, S2, S3) performed a set of ten tasks (Figure 1) involving five different motions while holding a 0.05kg (light) or 0.5kg (heavy) object. Each task was repeated 12 times in random order. We use linear SVM with L2-regularization and compute prediction accuracies using 6-fold cross validation.

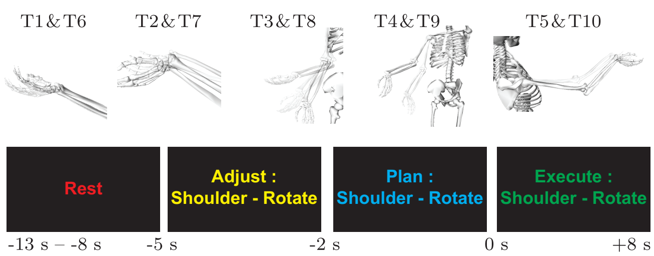

Fig. 1. **Motor Tasks.** Task T1 & T6: Wrist-Flex, T2 & T7: Wrist-Rotate, T3 & T8: Elbow-Flex, T4 & T9: Shoulder-Flex, T5 & T10: Shoulder-Rotate. T1 – T5: Light weight, T6 – T10: Heavy weight. **Experiment stimuli.** Rest: subject relaxes (duration randomized); Adjust: subject positions arm, grasps appropriate weigh, and assumes zero-position; Plan: subject holds zero-position; Execute: subject performs motion.

II. Results

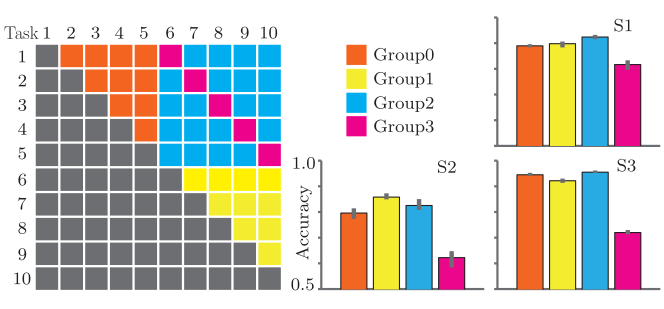

Fig. 2. **Confusion matrix.** Binary classifications were segregated into four groups. Group 0: All light–weight, Group 1: All heavy–weight, Group 2: Cross-motion and weight, Group 3: Light vs. heavy–weight with similar motion. **Classifier performance by group.** Median distribution of all binary pairs within each group. 50 out of the 500 most reliable voxels (high R^2) were selected at random. Group 3 displays significantly lower performance.

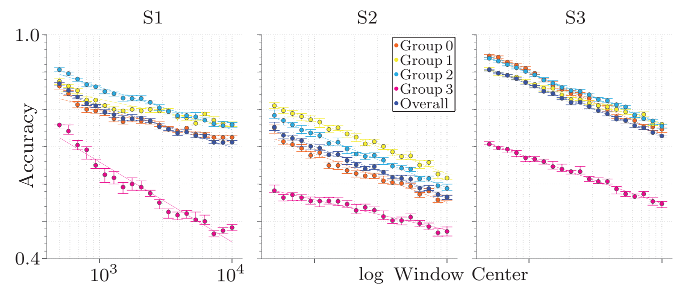

Fig. 3. **Accuracy vs. Reliability.** Tasks were classified using 50 random voxels drawn from a 1000-voxel-window for decreasing R^2. All subjects and task groups display exponential decrease in accuracy with voxel rank.

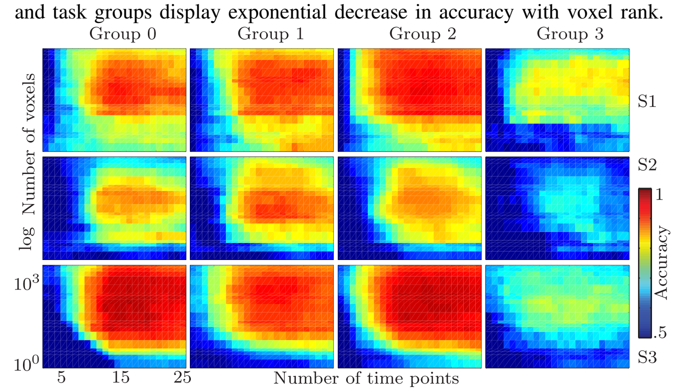

Fig. 4. **Grid search over feature space.** Uses a time interval starting at t=0, and voxel interval starting at highest R^2 rank. Peak accuracy requires approx. 0 to 12–14sec of time-series and a few hundred voxels.

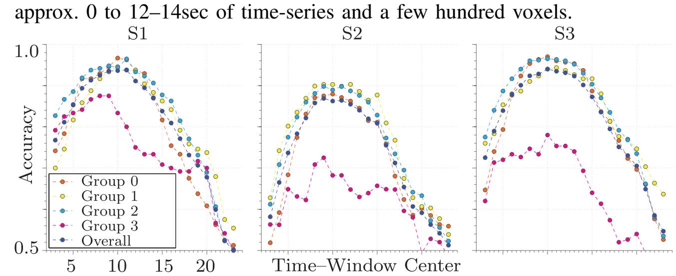

Fig. 5. **Optimal time window.** A 5-sec moving time window over BOLD responses suggest that 7.5–12.5sec (late-stage) dynamics capture inter-task differences.

Appendix

Scan protocol: Gradient echo EPI, $2.5\times2.5\times2.5mm^3$ voxels, 1.57s TR, 28ms TE, 72° flip angle. Preprocessing: Slice time and motion correction (SPM), spatial undistortion using fieldmaps, and denoising with GLMDenoise. Device: GE Discovery MR750. SVM implementation: LIBSVM v3.17.

[1]G. Brantner, S. Menon, and O. Khatib are with the Artificial Intelligence Laboratory, Department of Computer Science, Stanford University, Stanford, CA 94305, USA (geraldb@stanford.edu, smenon@stanford.edu, ok@cs.stanford.edu)

[2]G. Schorpp is with the Department of Management Science and Engineering, Stanford University, Stanford, CA 94305, USA (gschorpp@stanford.edu)