

Combination of SVM and ROI Approaches for Real-Time fMRI Neurofeedback

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INTRODUCTION: Real-time functional magnetic resonance imaging (rtfMRI) [1] has led to a broad interest in neurofeedback as an approach to learn self-regulation of brain function. Common implementations of rtfMRI neurofeedback follow two distinct paths. The region-of-interest (ROI) approach focuses on activation within a small precisely defined brain region [2] while multivariate supervised learning techniques, such as support vector machines (SVM), use large-scale distributed patterns of brain activity [3]. Here we demonstrate that combination of the ROI and SVM based neurofeedback capabilities, in one rtfMRI system, benefits both methods and allows integrated training of functional self-regulation for localized brain region and large brain networks.

METHODS: The experiments were performed on General Electric Discovery MR750 3T MRI scanner with the standard 8-channel head coil array. A gradient echo EPI sequence with $FOV/slice=240/2.9\text{mm}$, $TR/TE=2000/30\text{ms}$, $SENSE=2$, 96×96 , $flip=90$, 34 axial slices, was employed for fMRI. A $T1$ -weighted MPRAGE sequence was used to provide an anatomical reference and to define an ROI (sphere with 7 mm radius in Talairach space centered at the left amygdala). A custom real-time fMRI system [4] utilizing AFNI [5] real-time features was used to provide neurofeedback. The study involved three healthy male participants. The experimental procedure included seven 9 min runs, and each run (except the Rest) consisted of 40 s long blocks with Rest, Happy, and Count conditions (Fig. 1). The SVM model was generated using 3dsvm function [3] in AFNI, which was applied to fMRI data from the Model run. To enable real-time SVM classification, we modified the AFNI real-time plugin to compute the SVM classifier as $[(\mathbf{x} \cdot \mathbf{w} + b) + 1]/2$, using \mathbf{w} and b from the SVM model. The Happy vs Rest classifier output was used to provide neurofeedback, presented as a red bar on the screen (Fig. 1) and updated every 2 s. The subject inside the scanner was asked to feel happy during the Happy condition by evoking happy memories so as to raise the level of the red bar. This work was originally intended as an SVM only study. We found, however, that, in order to generate a good SVM model, consistent with the subject neurofeedback in the Model run as well. Therefore, we combined the SVM and activation in the left amygdala ROI during the Practice and Model runs, and on the 5 was provided during the Rest and Count conditions, and during the entire Transfer run.

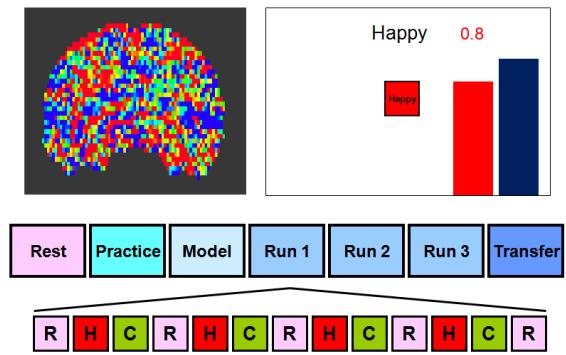


Fig. 1. *Left:* Whole-brain SVM weight volume \mathbf{w} for Happy vs Rest classification. *Right:* screen with neurofeedback bar (red) and target bar (blue). *Bottom:* experimental protocol.

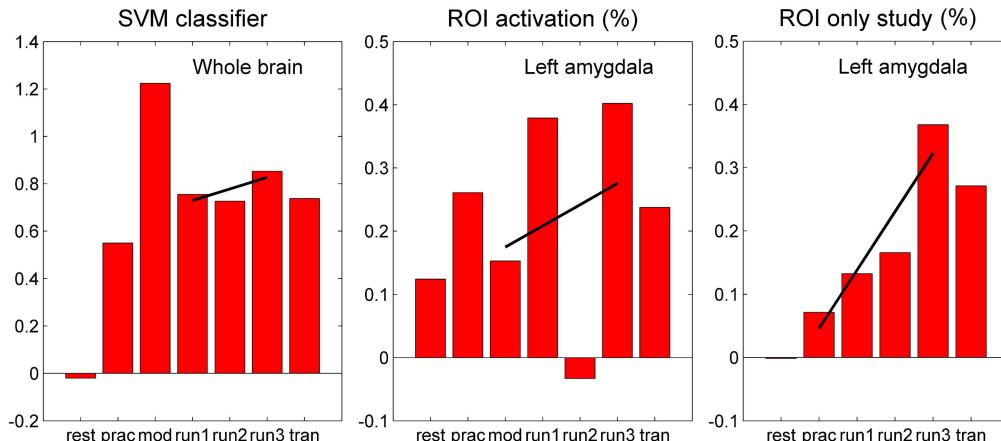


Fig. 2. *Left:* Average Happy vs. Rest SVM classifier output for each run based on the SVM model trained during the Model run. *Middle:* Average activation in the left amygdala ROI. *Right:* Average activation results (for 11 subjects) from a separate study that used the left amygdala ROI to provide neurofeedback.

RESULTS: The results for Happy conditions, averaged within each run and for all subjects, are exhibited in Fig. 2. An increase in both the SVM classifier values and the ROI activation levels across the training runs (Runs 1, 2, and 3) is observed. Clearly, the amygdala ROI results (Fig. 2, middle) show greater variability as compared to SVM results (Fig. 2, left), suggesting that high values of the SVM classifier do not necessarily predict high activation levels for the amygdala.

CONCLUSION: Our results show that SVM- and ROI-based approaches to rtfMRI neurofeedback complement each other and can be easily combined in the course of one fMRI session. Such combination enhances both approaches and makes it possible to integrate neurofeedback training of a specific brain region with training of a functional network involving this region.

REFERENCES: [1] R.W. Cox et al. *Magn. Reson. Med.* **33**, 230 (1995). [2] R.C. deCharms et al. *PNAS* **102**, 18626 (2005). [3] S.M. LaConte. *NeuroImage*, in press (2010). [4] J. Bodurka and P.A. Bandettini. *NeuroImage* **41** (Supp.1), S85 (2008). [5] R.W. Cox and J.S. Hyde. *NMR Biomed.* **10**, 171 (1997).