Spatial registration of support vector machine models for multi-session and group real-time fMRI

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INTRODUCTION We are developing a support vector machine (SVM)-based real-time (rt)-fMRI system similar to the one described in [1], but with the additional capability of multi-session and group-based SVM models. This will be critical for handling movement between runs within a session, progressive training and testing across sessions, and the use of group models to affect rehabilitation/therapy for applications such as addiction and stroke by reinforcing desired compensatory or normative multi-voxel pattern targets built from databases of recovered individuals. This requires that the SVM model and the test data be spatially aligned, and here we investigate alignment strategies to verify the potential trade-off between classification accuracy and rt-fMRI computational demands. We investigate this tradeoff using two tasks that are unlikely to elicit learning effects across repeated runs or sessions, a bimanual button tapping task and a multi-source interference task. These tasks were also chosen to provide both high and modest (above chance) prediction accuracies, respectively. Finally, to evaluate group models, we tested a nine-subject model based on data collected across two 3T scanner platforms.

APPROACH Let $\vec{x}^{trn}$ and $\vec{x}^{tst}$ be an fMRI training and testing volume, respectively. A linear SVM model is defined by a linear decision boundary $\vec{w}$ and an offset term w_0 such that the classifier decision function $D(\vec{x}^{tst}) = (\vec{w} \cdot \vec{x}^{tst}) + w_0$. The boundary, $\vec{w}$, is defined as $\sum_{t=1}^{T} \alpha_t \vec{x}_t^{trn}$, where α_t are the weights of the sum of all T training time points. Note that $\vec{w}$ has the same coordinates as the training data and that therefore the decision function $D(\vec{x}^{tst})$ assumes that the test data and the SVM model are spatially aligned. Here we examine the following approaches: 1) aligning the training data to the test data and training the classifier to determine the SVM model in the test space; 2) training a model in the original space and aligning the model ($\vec{w}$) to the test data space; 3) performing the same alignment as in 2, but replacing α_t with that determined in 1; and 4) normalizing all data to a common Talairach [2] space. The rationale for strategy 3 is that alignment will incur some interpolation errors, which could affect both the training data and their weighting.

METHODS
Data collection: Ten volunteers participated in two imaging sessions, separated by at least 24 hours, at 3 T (5 on a Siemens Trio, 4 a Siemens Allegra, and 1 on both platforms) with a T1-weighted scan and four BOLD fMRI runs (TR = 2000 ms, TE = 30 ms, 34 slices). fMRI runs alternated between a bimanual button-tapping task, self-paced at a 1:1 ratio and an executive control multi-source interference task (MSIT) [3]. Button presses were recorded to verify the subject's task performance.
Analysis: Analysis was performed using AFNI [4]. Each run was motion corrected and spatially smoothed (4 mm). SVM classification was performed using the AFNI plugin, 3dsvm [5]. Training was performed using a single run as training data and by concatenating the two session runs for each task to generate a larger training dataset. Leave-one-subject-out group datasets were built by concatenating the normalized data for nine of the ten subject datasets.

RESULTS Prediction accuracy results are shown in Table 1. The mean inter-session distance was 15.12 mm. Prediction accuracies for the tapping task are higher than for the MSIT, as expected. Concatenating the two runs within a session gives higher prediction accuracies than building the SVM model on a single run. Beyond these differences, all alignment strategies did not differ in prediction accuracy. The slight drop in accuracy in the control condition (predicting within a run) can be recovered by using more training data (using concatenation to combine two runs). The α values for models estimated in the native space were highly correlated with those estimated in the test data space (Tapping = 0.996; MSIT = 0.997). The group result led to a mean prediction accuracy of 94.77±4.56%.

	Percent prediction accuracies									
	Align training data to test space and retrain		Align model to test data space		Align model to test data (replaced alphas)		Talairach		Control (intra run)	
training data	Tapping	MSIT	Tapping	MSIT	Tapping	MSIT	Tapping	MSIT	Tapping	MSIT
single run	90.83±7.23	69.44±9.05	90.71±7.61	69.48±9.11	90.79±7.39	69.46±9.00	91.12±7.17	69.26±8.93	93.33±7.40	72.01±8.37
2 runs combined	93.96±5.84	73.21±8.54	93.98±6.10	73.59±8.28	94.01±5.67	73.31±8.62				

Table 1. Prediction accuracies for SVM models of bimanual button tapping and an executive control task.

DISCUSSION AND CONCLUSION These results imply that 1) alignment across scanning sessions is comparable to alignment within a scanning session and 2) there are no deleterious interpolation error effects from transforming the SVM model to the test space compared to transforming the training data and re-estimating the SVM model. This demonstrates the feasibility of a model-to-scan alignment system for the real-time fMRI in which the least demanding computational approach does not lead to a compromise of classification accuracy. In other words, one practical approach would be to train the SVM prior to the real-time session, find alignment parameters during the session, and apply the transformation only once (to the model). This is preferable to retraining or to having to apply a transformation to the model space to every time-point as test data are acquired. This work also demonstrates the feasibility of using group SVM models in real-time experiments.

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