CS229 Project: Classification of Motor Tasks Based on Functional Neuroimaging

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Brain-machine interfaces (BMIs) aim to establish a new way of communication between humans and computers. Especially paralyzed individuals could greatly benefit from BMIs. Currently, most successful systems rely on the implantation of electrodes on the motor cortex, but due to its invasive nature, this technique prohibits extensive research on human subjects. For this reason, a new approach is needed. As functional magnetic resonance imaging (fMRI) is human-safe, research using this method can be performed at a higher scale. Because brain structure and activity varies among individuals, machine learning is an essential tool to calibrate and train these interfaces. In this project we developed binary and multi-class classifiers, labeling a set of 10 performed motor tasks based on recorded fMRI brain signals. Our binary classifier achieved an average accuracy of 93% across all pairwise tasks and our multi-class classifier yielded an accuracy of 68%. We demonstrated that combining fMRI and machine learning is a viable path for research on BMIs.

Key words: Machine Learning, Functional Magnetic Resonance Imaging (fMRI), Brain-Machine Interface

1. Introduction

Brain signals of human and non-human primates have previously been translated to control mouse cursors [1, 2, 3], keyboard inputs [4], and to guide a robotic hand [5, 6]. Most successful systems rely on electrodes that are implanted in the brain. Electrodes, however, are invasive, which prevents the use on human subjects. Functional magnetic resonance imaging (fMRI) is a very promising alternative [7] because it is (1) non-invasive, (2) does not rely on ionizing radiation, and (3) has high spatial and temporal resolution, which makes it a safe method for research using human subjects. In this research we connect motor tasks with neural activity, in order to classify a subject's motor states based on observed brain signals using fMRI.

2. Data Collection and Preprocessing

We used data from a study conducted at the Stanford Center for Cognitive and Neurobiological Imaging (CNI) by GB (author), SM, and CA (Acknowledgements). The experiment required the test subject to perform a set of ten different tasks (Table 1). The subject repeated each task 12

Task #	Description	Task #	Description
1	Wrist - Up Down	6	Wrist - Up Down Weighted
2	Wrist - Rotate	7	Wrist - Rotate Weighted
3	Elbow - Up Down	8	Elbow - Up Down Weighted
4	Shoulder - Up Down	9	Shoulder - Up Down Weighted
5	Shoulder - Rotate	10	Shoulder - Rotate Weighted

Table 1 Set of Tasks

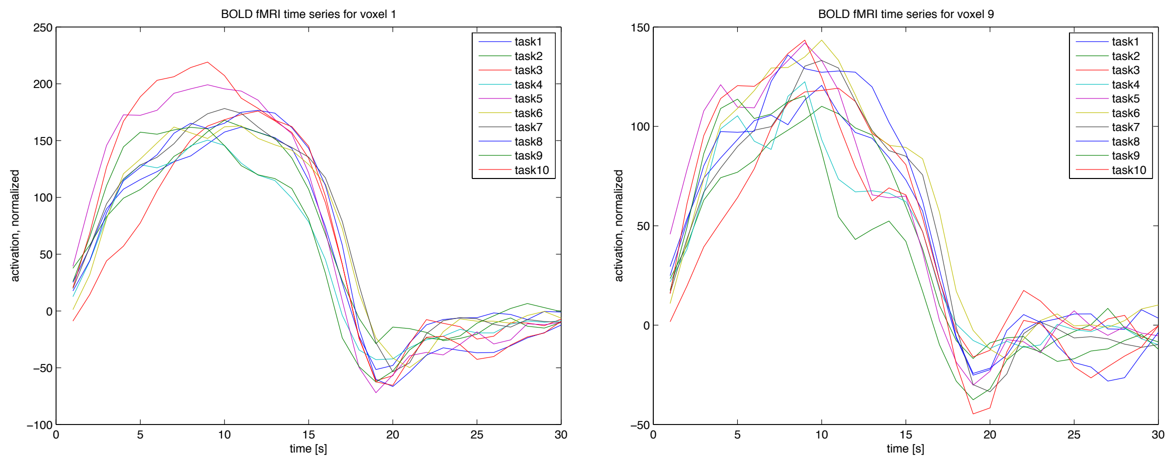

Figure 1 Sample fMRI BOLD signal for 2 voxels and varying tasks

times and the tasks were randomly ordered. The fMRI scanner partitions the brain into 120,000 voxels (cubes of volume $2.5mm^3$). For each of these voxels we simultaneously recorded the fMRI BOLD [8] signal, which measures oxygen consumption due to activation at a temporal resolution of one second (Figure 1). The raw signals were preprocessed using a standard pipeline.

3. Support Vector Machines

In this section we describe the implementation of our classifier based on Support Vector Machines. We employed MATLAB's integrated *svmtrain* and *svmclassify* functions. By default, the training function normalizes the data so that it is centered at its mean and has unit standard deviation. We found that a linear kernel performs very well for this problem and we chose Sequential Minimal Optimization (SMO) as an optimization method.

3.1 Initial Feature Selection

We faced two problems while classifying motor states with fMRI data: First, the feature size is very large, due to the large number of voxels, and second, the number of samples is much lower than the number of features. The low number of samples is a result of the time constraints and operational cost associated with the MR scanner. We performed preliminary tests and found that the most successful features are the concatenated time series of a subset of the recorded voxels (Figure 2). We used a two-stage selection process:

1. Filter by region of interest (ROI): For the scans, we only selected voxels that are part of the brain's motor cortex.

2. The voxels were ranked by an FIR model's reliability at capturing variance in BOLD signal responses to tasks. The top 5000 voxels were selected.

3.2 Binary SVM

We first used a binary SVM to pair-wise classify all combinations of tasks. For each pair we use 24 data points, 12 for each task. The parameters for the algorithm are the number of voxels considered as well as the length of the input signal. The algorithm uses leave-one-out cross validation for every pair and computes the overall mean accuracy, which reaches 93%. Figure (3) shows the individual classification accuracy across all pairs. We can see that the accuracy is decreased for similar tasks, especially for a task and its weighted counterpart, (green ellipsoids). This is expected and further validates this approach.

3.3 Multi Class SVM - One vs One

Next we developed a multi-class SVM algorithm that classifies across all 10 tasks at the same time. We found that one-vs-one yields the best results compared to other methods, such as one-vs-all (Section 4.2). For each test point, this algorithm applies binary classification over all possible

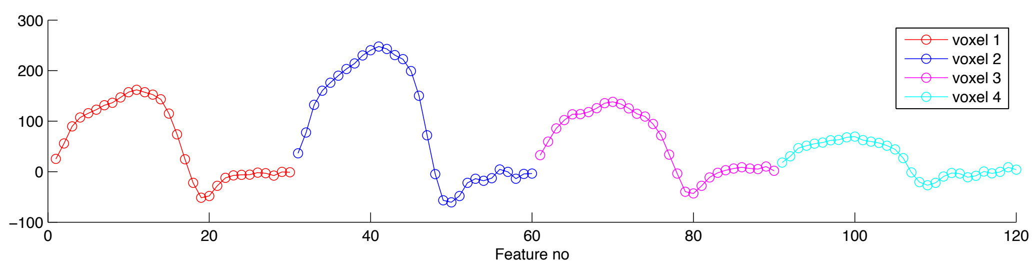

Figure 2 Illustration of a data point

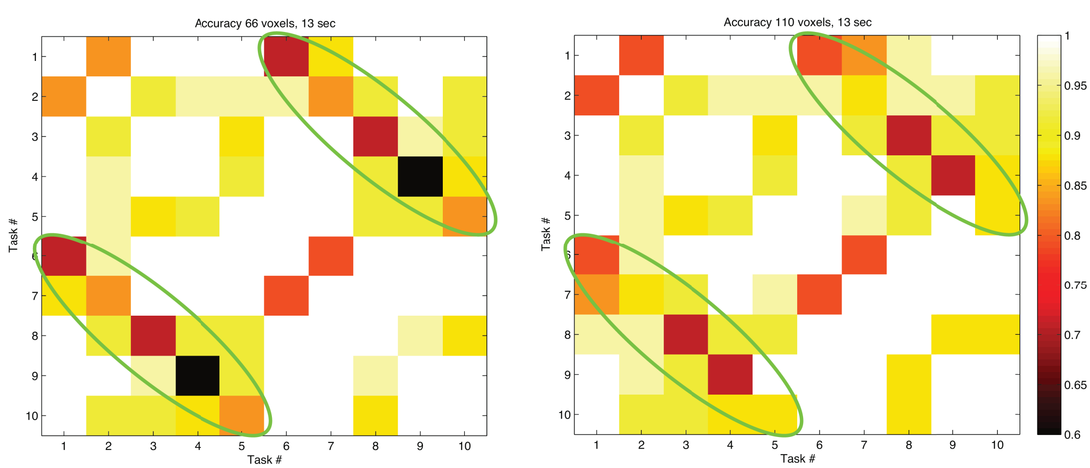

Figure 3 Confusion Matrix for 66 / 110 voxels and 13 sec duration

combinations and assigns a point to the winning class. Eventually the test point is classified to the class scoring the most points. This method in its standard implementation, however, does not account for ties. Our enhanced method instead applies another (binary / multi class) classification between the tied task types to make the final decision.

3.4 Heuristic Feature Selection Enhancement

After implementing both the binary and multi class SVM we found that using all available data, i.e. 5000 voxels over a 30 sec time window, does not lead to the best predictions. Instead, considering only the 60-120 most significant voxels over the first 10-15 seconds of the task execution leads to much better and more robust results (Figures 4 and 5). The graphs illustrate that the SVMs are more sensitive to choosing the right time window than to choosing the number of voxels.

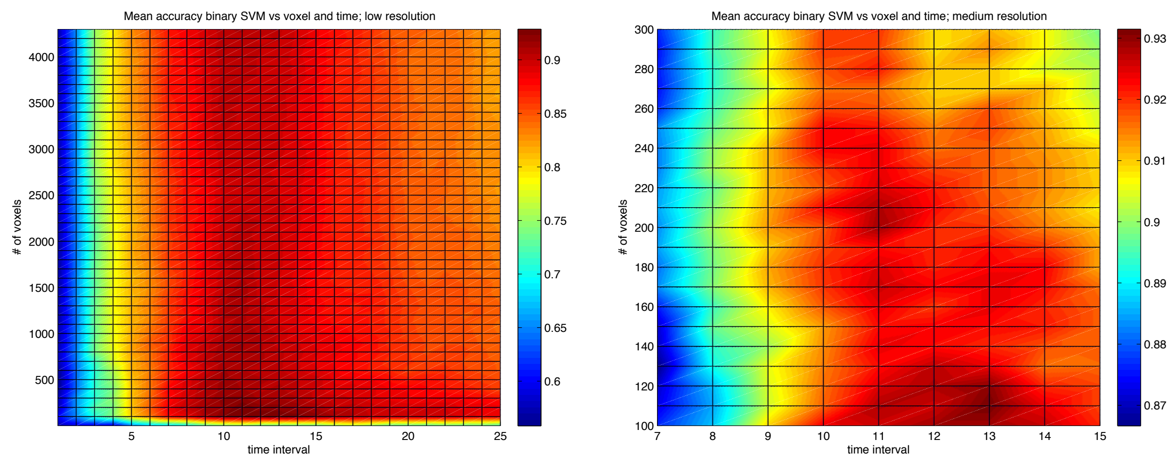

Figure 4 **Grid search for binary svm: mean accuracy vs #voxels and Δt**

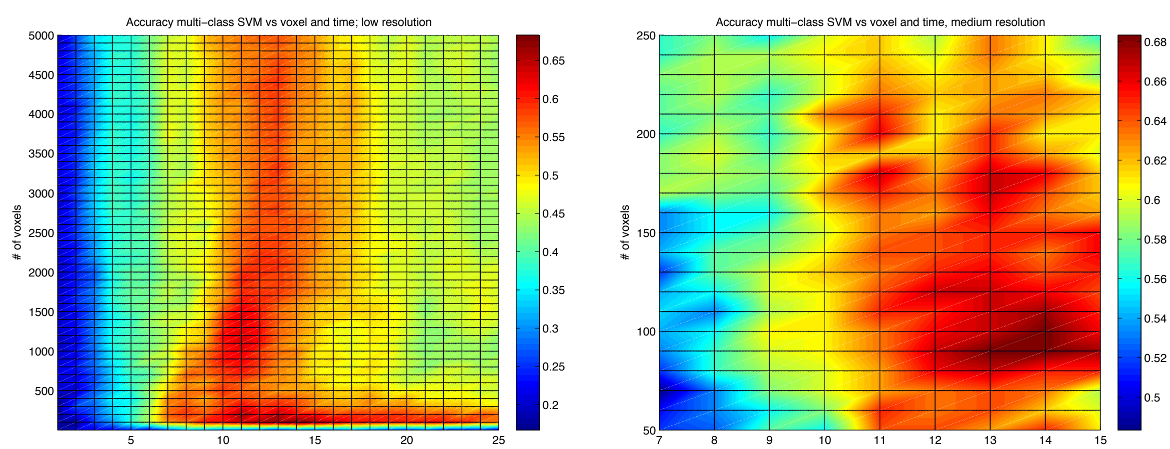

Figure 5 **Grid search for multi-class svm: accuracy vs #voxels and Δt**

4. Comparison to other Approaches

As discussed earlier, binary SVM and one-vs-one multi-class SVM turned out to be the best choice compared to other approaches tested, which we describe in this section.

4.1 Binary Logistic Regression Classifier

We also implemented a binary logistic regression classifier, similar to the method described in Section 3.2 and found it to perform 15% less accurate.

4.2 Multi Class SVM - One vs All

As an alternative to the one-vs-one multi-class classifier (Section 3.3), we tested one-vs-all. One-vs-one achieves an accuracy of up to 68%, whereas one-vs-all only performs slightly better than random classification.

5. Conclusion

In this study we developed binary and multi-class classifiers to label performed motor tasks based on recorded neural activity using fMRI. On average, we achieved 93% accuracy for the binary case and 68% for the multi-class case using optimal parameters. Compared to the other approaches tested, SVM proofed to be the superior method. Based on these results developing a brain-machine interface using fMRI is feasible.

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