TOWARDS UNIFIED ANALYSIS OF EEG AND FMRI
A Comparison of Classifiers for Single-trial Pattern Recognition

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Abstract: Pattern recognition methods, which recently have shown promising potential in the analysis of neurophysiological data, are typically model-free and can thus be applied in the analysis of any type of signal. This study demonstrates the feasibility of, after suitable pre-processing steps, applying identical state-of-the-art pattern recognition method to single-trial classification of brain state data acquired with the fundamentally different techniques EEG and fMRI. We investigated linear and non-linear support vector machines (SVM) and artificial neural networks (ANNs), and it was found that the SVM is highly suitable for the classification of both fMRI and EEG single patterns. However, the non-linear classifiers performed better than the linear ones on the EEG data (linear ANN: 66.2%, SVM: 78.9% vs. non-linear ANN: 71.8%, SVM: 83.2%), whereas the opposite was true for the fMRI dataset (linear ANN: 74.4%, SVM: 77.2% vs. non-linear ANN: 70.5%, SVM: 74.2%). The exciting possibility of concurrent EEG and fMRI registration warrants a need for a unified analysis method for both modalities, and we propose pattern recognition for this purpose. The ability to identify cortical patterns on a single-trial basis allows for brain computer interfaces, lie detection, bio-feedback, the tracking of mental states over time, and in the design of interactive, dynamic fMRI and EEG studies.

1 INTRODUCTION

The utility of pattern recognition in the analysis of neuroscience data has long been understood within the electroencephalography (EEG) community, especially with the advent of brain-computer interfaces demanding online data analysis (Pfurtscheller et al., 1992). More recently, similar approaches have shown great potential in functional magnetic resonance imaging (fMRI) (Norman et al., 2006).

EEG and fMRI signals, although both connected to brain processing, signal different types of activity. The EEG is the electrical signal, measurable at the scalp with electrodes, resulting from the summation over thousands of synchronously activated postsynaptic potentials in the cortex, with time-resolution at the millisecond level but with poor spatial resolution. On the contrary, fMRI is the measure of blood flow changes in the brain (indirectly) related to cortical processing. fMRI suffers from poor temporal resolution, partly due to the inherent hemodynamic response delay, but, on the other hand, provides excellent spatial resolution.

Traditional analysis approaches to EEG and fMRI differ fundamentally. Research EEG is typically treated as time-series, where event-related potentials are formed from averaging over hundreds of events (Fisch, 1999). These are projected onto scalp models, the frequency content is determined, or dipole sources are estimated. Clinically, continuous EEG might be monitored by a highly trained physician. In fMRI, the governing approach is anatomically locating average activity using statistical techniques based on the general linear model and extensive t-testing (Friston et al., 1994). Both fields are thus dominated by the mapping of average, often visual, phenomena in the acquired signal to the experimental condition in question. Moreover, much qualitative interpretation is left to the experimenter or clinician.

High-level pattern recognition, however, does not discriminate between data types. Instead, each instance of the data ('pattern', e.g. an fMRI volume) is treated generically in terms of input features, typically a pre-processed variant of the data variables (e.g. fMRI voxels), with corresponding categories (such as experimental conditions). An algorithm is trained to discriminate between the categories using a designated training dataset where the categories are known.

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The training and classifier function is automatic and follows standardized algorithms: the procedure is entirely data-driven and thus no models are required.

The trained classifier is subsequently applied to new, unseen data to detect and identify patterns which corresponds to the categories. These methods can be used both to localize informative features, for example in fMRI activation detection (Åberg et al., 2008), for visual inspection, but, importantly, they also provide a means to directly map the signal (as measured with EEG or fMRI) to the actual brain state of the subject. That is, a quantitative measure of the brain patterns in question is obtained. The method can be used for lie-detection(Davatzikos et al., 2005), the tracking of subjects mind states over time (Polyn et al., 2005) and more (Norman et al., 2006).

A number of proficient classification algorithms have emerged from the research as the most successful, including support vector machines (SVMs) and artificial neural networks (ANNs). Both exist in implementations capable of discriminating both linear and non-linear data-structures. Typically, linear classifiers perform relatively satisfactorily, especially when time constraints are taken into account (Cox and Savoy, 2003). Non-linear classifiers, however, are in theory superior, especially in combination with a properly pre-processed and selected feature subset (Åberg and Wessberg, 2007).

The increasing interest in combining fMRI and EEG – utilizing the high spatial resolution of the former and the high temporal resolution of the latter – calls for a system which is capable of handling both types of data equally well and conceptually on similar grounds. We therefore present a generic approach to model-free pattern analysis of neuroscientific data. The study aims to evalutate the performance of linear and non-linear state-of-the-art classifiers, namely SVMs and ANNs, on EEG and fMRI data, investigating subject and data differences in parameter and feature selection. This study has in part been previously presented in master's thesis format.

2 METHODS

2.1 EEG Acquisition and Pre-processing

The study was performed in accordance with the Declaration of Helsinki and approved by the University of Gothenburg ethics committee.

Four healthy subjects, three female and one male, one left-handed, participated in the study. The subjects, comfortably seated in a chair, were instructed to move either the left or the right index finger in a brisk, self-paced manner according to cues presented on a screen. The interval between the randomized cues was four seconds, and each cue was presented for three seconds. Between 250-900 movements were registered for each subject. Movements were recorded with accelerometers attached to the fingers (EGAX-5 monoaxial, Entran Inc., Fairfield, NJ, USA). The EEG was acquired at a sampling rate of 256Hz using active electrodes and the Active Two digital EEG amplifier and recording system from Biosemi, Inc. (Amsterdam, The Netherlands), with 32 scalp electrodes positioned according to the extended 10/20 system.

The acquired data was high-pass filtered with cutoff frequency of 1Hz and a reference average of all channels was subtracted. Epochs of -1000 to +500 ms relative to movement were extracted and visually inspected for eye blink artifacts. All data processing was performed with Matlab™ (The Mathworks, Massachusetts, USA) software. For every subject, 400 epochs were randomly selected and divided into training (80%) and validation (20%) data sets containing equal numbers of left and right finger movements.

The wavelet transform, shown to be more effective in single-trial EEG characterization than traditional processing approaches (Trejo and Shensa, 1999), was then used to extract EEG features with the standard Debauchies function (level 3) as mother wavelet. The transform was applied to the data channel by channel for the pseudo-frequencies 1:1:10 Hz, after which the asolute of the obtained 2-dimensional coefficient map was downsampled to 10 by 64 bins. Thus, 640 coefficients were extracted for each of the 32 EEG channels, resulting in a total of 20480 features. The processing was performed using the Matlab wavelet toolbox.

2.2 fMRI Acquisition and Pre-processing

A 1.5 T fMRI scanner (Philips Intera, Eindhoven, Netherlands) with a sense head coil was used to acquire brain scans in five healthy human volunteers, three female and two male. Anatomical scans were collected using a high-resolution T1-weighted anatomical protocol (TR 22ms; TE 10ms; flip angle, 30°; FOV 256mm). Functional scans were collected using a BOLD (blood oxygenation level dependent) protocol with a T2*-weighted gradient echo-planar imaging sequence (TR 3.5s; TE 51ms; flip angle 90°). The scanning planes (6mm thickness, 2.3 x 2.3mm in-plane resolution) were oriented parallel to the line between the anterior and posterior commisure and covered the brain from the top of the cortex to the base of the cerebellum. Each functional scan included 117 volume acquisitions and 25 slices at a spatial resolution of 128 x 128 voxels.

Following a cue from the scanner, an experimenter stroked a seven cm wide soft brush over a 16 cm distance on the right thigh or arm in the distal direction. Each stimulus lasted 3.5 seconds (one single scan volume) and was repeated three times. Arm, thigh and no stimulation of equal duration were performed randomly during the scan.

Data pre-processing was carried out with software developed at the Montreal Neurological Institute. Functional data were motion corrected and lowpass filtered with a 6mm full-width half-maximum Gaussian kernel. The data was shifted by one volume to correct for hemodynamic delay.

Volumes containing thigh stimulation were ignored, resulting in six functional scans including 38 volumes of arm stimulation and 38 volumes of rest. The study was limited to the axial slice most representative of the primary somatosensory cortex, highly involved in the processing of tactile stimuli. For each volume, voxels not containing tissue were discarded and the BOLD-values in the remaining voxels were linearly normalized to the range [0 1]. All volumes were randomized before used in training.

2.3 Feature Ranking

A simple univariate method was implemented for feature ranking and subsequent selection as follows:

$$f_i = \text{abs}(\frac{\mu_0 - \mu_1}{\sigma_0 + \sigma_1}) \quad (1)$$

where μ_0 and μ_1 represent the mean value of feature i over the patterns (volumes and epochs, for fMRI and EEG respectively) belonging to class 0 and 1 respectively, and σ_0 and σ_1 are the standard deviations within each class. The feature ranking value is thus a measure of feature stability, over the patterns, as well as how well it separates the data classes. For subsequent feature selection, the features were thus ranked and a given number was selected accordingly (see the results section).

2.4 Classifiers

Two state-of-the-art classifiers, including support vector machines (SVMs; The Matlab™ toolbox LS-SVMlab; Suykens et al., 2002) and artificial neural networks (ANNs; Matlab™ and the neural network toolbox) were used in this study. For the SVMs, both linear and RBF kernels were evaluated and compared. For the ANNs, fully connected feed forward networks with a backpropagating training algorithm (Levenberg-Marquardt) and the mean square error (MSE) as error function was used. The ANN output was thresholded to yield binary outputs.

Table 1: Resulting classifier parameters for fMRI data.

Method	*Features*	*Parameters*
Linear SVM	550	$\gamma = 2^{-2.5}$
Non-linear SVM	90	$\gamma = 2^7$
Linear ANN	260	$nHidden = 0$
Non-linear ANN	260	$nHidden = 2$

3 RESULTS

All results below refer to the five-fold cross-validation score as averaged over all subjects. There are equal number of categories in each dataset, and the level of chance is thus 50%.

3.1 Number of Features and Classifier Parameters

Table 2: Resulting classifier parameters for EEG data.

Method	*Features*	*Parameters*
Linear SVM	1400	$\gamma = 2^{-2.5}$
Non-linear SVM	500	$\gamma = 2^7, \sigma^2 = 2^9$
Linear ANN	60	$nHidden = 0$
Non-linear ANN	440	$nHidden = 2$

For the SVMs, the number of features to include, the margin γ, and, for the non-linear RBF kernel, the bandwidth parameter, σ^2, require explicit specification. In order to establish a proper parameters a grid search was performed. For each dataset, the specified number of features were selected from the feature ranking list (see equation 1). For the linear SVM, the search was performed with the number of features in the range 10-1000 in combination with $\gamma = 2^{-19} - 2^{21}$. For the non-linear SVM, the feature subset size was varied in the range 10-1000, $\gamma = 2^{-15} - 2^{50}$ and $\sigma^2 = 2^{-5} - 2^{55}$. Smaller steps close to the identified local maxima were investigated. The grid search was repeated for each of the five-fold datasets, and the subsequent parameters were obtained from the maximum average score. Similar results were obtained for the fMRI and EEG data. For the linear SVM, a maxima was obtained at $\gamma = 2^{-2.5}$. For the nonlinear SVM all pairs in a diagonal range

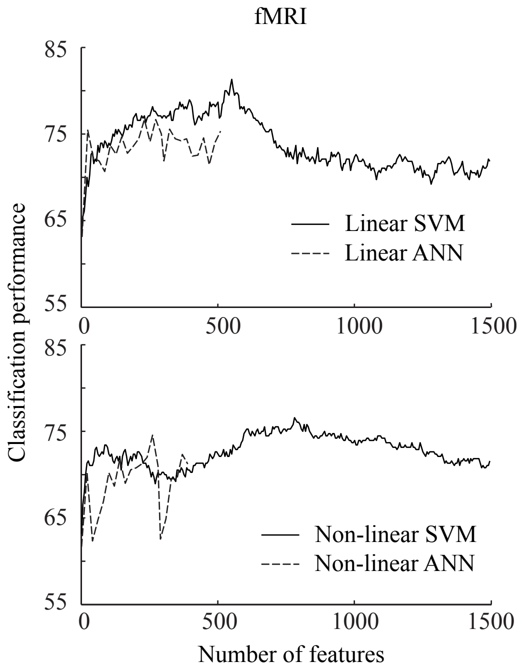

Figure 1: Classification performance as a function of the number of included features for fMRI data.

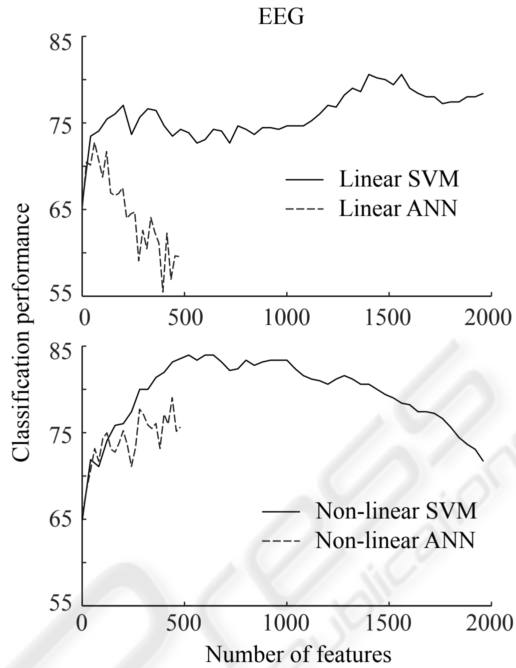

Figure 2: Classification performance as a function of the number of included features for EEG data.

performed well. For reduced complexity and maximal speed of computation, the lowest parameter values were chosen along the high performing diagonal, resulting in $\gamma = 2^7$ and $\sigma^2 = 2^9$.

For the ANN, the number of layers, number of neurons in each layer and type of transfer functions require specification. Due to time constraints, we limited the non-linear, multilayer network to contain only two hidden neurons. We also investigated a (linear) single layer network with only an output neuron. Empirically, the tan-sigmoid function was found suitable for all nodes. The obtained parameters are summarized in tables 1 and 2.

The effect of the number of features included for classification on the performance is presented in figure 1 and 2 for the fMRI and EEG data respectively. Due to excessive time requirements for training of large ANNs, the maximum feature subset sizes were restrained compared to the SVMs.

For the fMRI data, all classifiers show drastic improvement in classification accuracy with the addition of 1 up to 50 voxels (figure 1). Both the linear and non-linear ANNs, however, continue improving slightly and eventually reach a plateau at 100 voxels, without apparent decrease in performance. It is possible that the classification accuracy continues to increase with further addition, but the excessive time requirements renders this unfeasible to investigate. The linear SVM peaks at around 500 voxels, whereas the non-linear SVM continues to increase until 700 voxels. After the peak both classifiers behave similarly, and declines.

On the EEG dataset, the behavior of the classifiers is quite different (figure 2). The linear ANN increases sharply initially, peaks at 50 and 150 features respectively, and then declines in performance rapidly. Where there is a reasonably steep increase until 500 features, and henceforth a sharp decline in performance for the linear SVM fMRI classification, the corresponding EEG data performance sees a steep increase until 250 features and then an alternating performance, that, eventually, beings to increase again. The maximum appears to be reached at 1500 features. The non-linear SVM, on the other hand, peaks at 500 features, after which it declines continuously. Similarly, the non-linear ANN increases continuously, albeit not as sharply as the SVM, until 500 features, after which no further testing was feasible.

3.2 Classification Performance

The algorithms were evaluated using fivefold cross validation and the classifier parameters established above (see tables 1 and 2). In all trials there are equal numbers of patterns from each class so the level of chance is 50%.

As is shown in figure 3, the SVM with a linear kernel and 550 features proved most successful of

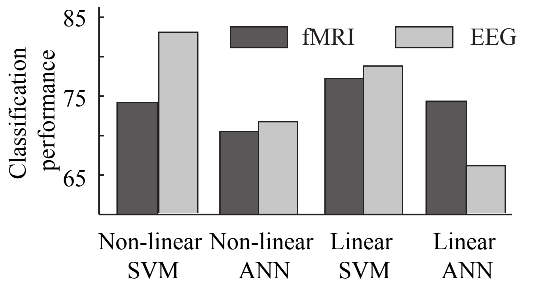

Figure 3: Subject mean classification results on the EEG and fMRI data.

all the methods on the fMRI data with a mean classification rate over all five subjects of 77.2% (range 69.2-83.3%). Second best, the linear ANN with 260 features achieved a mean classification rate of 74.4% (range 65.2-81%). The non-linear classifiers performed worse: the SVM, in combination with 780 features scored 74.2% (range 65.8-81.6%) correct, and the non-linear ANN achieved a subject mean classification rate of 70.5% (range 57.4-78.9%).

For the EEG data, on the other hand, the non-linear classifiers performed better than the linear ones. The SVM, with 500 features, achieved a classification performance of 83.2% (range 71.7-94.7%), whereas the ANN with two hidden neurons and 440 features resulted in a 71.8% (range 66.1-78.7%) correct performance. The linear SVM, in combination with 1400 features, classified 78.9% (range 67.6-91.6%) of the epochs correctly, and the single layer ANN, with 60 features, scored 66.2% (range 62-73.3%).

4 DISCUSSION

In this study we have showed that is is feasible to apply identical pattern recognition algorithms to the analysis of both fMRI and EEG signals. Moreover, we have compared state-of-the-art classifiers, investigated whether non-linear or linear classifiers are suitable for either modality, as well as determined the effect of the number of features on the classification performance on all classifier approaches.

The EEG and fMRI data do, naturally, require different preprocessing methods. Subsequently, however, the proposed analysis method is identical for both modalities and, importantly, the signals are treated in conceptually similar manners. Furthermore, the resulting classifier outputs can be used for instant and direct comparison between the EEG and fMRI signals, which opens up for exciting exploration possibilities. Also, the resulting EEG classifier output can be used as a regressor in various types fMRI analysis, such as standard general linear model activation localization or for pattern recognition purposes.

It was found that, regardless of classifier, the non-linear schemes performed best on fMRI data, while non-linear classifiers achieves higher scores on EEG data. The fact that non-linear classifiers are not superior to linear ones in classifying fMRI data was also observed by Cox and colleges (Cox and Savoy, 2003) using a cubic polynomial SVM. It is likely that the linear separability of the data is a result of the inherent smoothing of the fMRI data, as opposed to the underlying neural signal. The BOLD response is smoothed over some seconds, and the blood flow is increased in a volume with active neurons rather than to single neurons. The EEG features, on the other hand, consist of distinct representations of wavelet scales and points in time, allowing for non-linear relationships to persist.

The superiority of the SVM is expected – although ANNs are represented in fMRI classification literature (Polyn et al., 2005), the SVM has been the successful classifier of choice for a large number of studies made on fMRI-data (Cox and Savoy, 2003; Mitchell et al., 2004; Kamitani and Tong, 2005; Mourão-Miranda et al., 2005; LaConte et al., 2005). Not only does SVM generalize better than the ANN in the present study, but the excessive time requirement for large scale ANN training renders proper evaluation problematic. The ANN classifiers used here, however, verify the suitability of non-linear classifiers for fMRI classification, and vice versa for EEG data. It should also be noted that, within individuals, the fMRI data was randomized and the temporal smoothing over volumes was not taken into account. Thus, the absolute classification numbers achieved on the fMRI data are somewhat exaggerated.

The performance behaved differently as a function of the number of included features, with respect to the linearity of the classifiers and the datasets. Interestingly, for the EEG data, the linear ANN peaked rapidly at a relatively the low number of 50 features and then declined drastically, whereas the same classifier on the fMRI dataset continued to increase in performance until 100 voxels and then leveled out. Moreover, the non-linear SVM behaves very similar on the fMRI data, as does the linear SVM on the EEG data. The detailed mechanisms behind these behaviors require more research, but it is evident that the SVM, both linear and non-linear, on the EEG data as well as the fMRI data, is less sensitive to the data dimensionality than any of the other classifiers.

The feature selection approach, being univariate, is non-optimal for multivariate pattern classification. It has been shown in EEG that with feature selection specifically tailored to a given classifier, the choice of linear or non-linear classifiers become less important (Åberg and Wessberg, 2007). However, stochastic feature selection methods tend to be computationally intensive, and since the univariate feature selection method is substantially faster it can be preferred in time-limited circumstances such as real-time analysis.

This study does not use concurrently registered EEG and fMRI data. In fact, different experimental conditions are used (motor actions versus tactile stimulus), but the underlying problem of single-trial classification and the implications thereof remain. A simultaneous EEG and fMRI registration study is currently in progress, as is further research into the utilization of a unified pattern recognition approach to the analysis of both modalities.

5 CONCLUSIONS

Pattern recognition, where classification models are entirely data-driven, is a suitable approach to a unified, conceptually identical analysis of fMRI and EEG data. Using classifier-based techniques, it is possible to automatically identify and label cortical patterns related to given experimental conditions present in singe-trial data – for signals acquired with EEG as well as with fMRI. Investigating state-of-the-art classifiers, the support vector machine was found to outperform the artificial neural networks, whereas non-linear classifiers performed better than linear such for EEG data and vice versa for fMRI data.

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