Towards a ready-to-use Brain-Computer Interface

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Abstract. In this study, we analyze generalization capabilities to new subjects of a successful classifier based on the Machine Learning technique Support Vector Machines for the P300-Speller Brain-Computer Interface. The goal is to be able to use this Brain-Computer Interface with a pretrained classifier for any new subject. No prior data acquisition from a subject would be necessary. Encouraging mean P300 classification rates of 65.47% were achieved. Furthermore, we discovered that the number of data in the inner crossvalidation set does not affect classification results significantly and can therefore be kept small.

1 Introduction

Brain-Computer Interfaces (BCIs) allow people to steer Computers by thought, which can especially be useful for highly paralysed people. Recently, we showed that the P300-Speller Paradigm can be used to realize a fast interface of more than 80 bits/min transfer rate [1,2]. This was done by exploiting the state-of-the-art Machine Learning technique Support-Vector Machines (SVM), which is based on structural risk minimization and has proven to be successful for many classification problems [3]. Since other approaches focussed on data from one electrode, using this technique we were able to use data from a whole ensemble of electrodes for classification. In the P300-Speller Paradigm, subjects attend to one symbol in a 6x6 matrix. Rows and columns of this matrix are flashing sequentially. When the row/column with the attended symbol gets highlighted, a specific EEG pattern (the so-called P300) results. Reversely, by identifying this component in the EEG, it is possible to infer the symbol in the matrix [4]. Thus, a classifier is needed who should be able to identify this component within a single trial. Since EEG exposes a very low signal-to-noise ratio (SNR), this is an ambitious task for any classifier.

Machine Learning classifiers first need to be trained before being able to perform classification. In the prior studies, the classifier was trained and tested on data from the same subject. Thus, in order to use this interface, a subject would have to first attend in a session for collecting training data. On the other hand, it would be much more desirable for a BCI to use an already trained classifier to avoid these training sessions for the participant and have a ready-to-use BCI.

Therefore, we here investigate the inter-subject generalization properties of a SVM classifier in a BCI, extending previous work focussed primarily on an analysis and optimization of such interfaces for a single subject.

For that purpose, we used data from 5 subjects for classifier training and parameter optimization and applied the classifier on data from a sixth subject. Data from the different subjects were varied within a crossvalidation scheme. We also varied the number of data within the inner crossvalidation scheme and therefore the computational costs, and its impact on classification accuracy.

2 Methods

Experimental setting

Six volunteers participated (age 20-34) in sessions of about 1h each. They were instructed to focus on randomly chosen symbols in a 6x6 stimulus matrix whose rows and columns were flashed with a frequency of 3.3Hz. EEG was derived from 10 electrode positions (Fz,
Cz, C3, C4, Pz, P3, P4, Oz, OL, OR), according to the international 10-20 System. Data was sampled with 200Hz on a Neuroscan Synamps amplifier. Data was analyzed offline.

Figure 1: Example of data set division into the different sets A,B,C and D. The classifier was trained on set A with systematical parameter value variation for the classifier. This was then evaluated on set B. The best parameter values were then used to train set C and evaluate set D. The number of samples for each subject in set A was varied from 25 to 360 samples.

**Data analysis**

Classification performance of an SVM with Gaussian kernel is controlled by the regularization parameter C and the kernel bandwidth \( \sigma \). In order to find optimal values for these parameters, the data set was divided into 6 sets, according to each subject. Data from four subjects was taken to train the classifier (set A), data from another subject (set B) was used as a test set to evaluate the performance for the parameters used in set A. Parameters were then varied systematically. Those parameters resulting in the best performance on set B were then used to train the data from the five subjects (set C) to evaluate data from a sixth person (set D). The sets were permuted within an outer and inner crossvalidation scheme. We also studied the dependence of generalization ability on the number of training samples for set A, since this especially affects the computational demands of the method. In the different conditions, 25, 50, 100, 150, 200, 250, 300, and 360 samples were randomly chosen from each subject for set A.

Figure 2: P300 classification accuracies for the different subjects and (exemplary) three different numbers (25, 150, 360) of samples for set A.
3  Results
The best P300 classification accuracy for single trials was 77.64%, obtained for subject 1 using 100 samples. Worst accuracy was 50.56%, obtained for subject 6 using 250 samples for set A. The mean classification rate was 65.47%. A two-way ANOVA revealed no effect for the factor samples \(\text{F}(7,6) = 0.69, p < 0.68\), but for the factor subject. \(\text{F}(5,8) = 69.6, p < 0.001\).

4  Discussion
A high variance between subjects was observed and the best results are of course below intra-subject P300 classification rates which are often high above 80% [2]. While the classifier reaches good accuracy for some subjects, it reaches almost chance level for others. Happily, for the most subjects in this study, the accuracy was pretty high, and only for one subject very low. Surprisingly, the number of samples in set A does not affect classification performance within the examined range.

5  Conclusion
Although there is a high variance between subjects, encouraging results have been found to make the P300-Speller BCI applicable in a pretrained way to avoid subject training sessions. However, more work is necessary to equalize data between subjects in order to obtain higher classification rates and higher speed. Using more subjects would also be very wishful and maybe subjects like subject 6 should be excluded from classifier training. With the current finding that the size of set A does not affect classification performance very much, computational costs could be kept low in upcoming studies.

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References