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Improved Classification of Auditory Evoked Event-Related Potentials

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Abstract

In this study we report on the improvement of classification accuracy in an auditory P300 paradigm, by using stepwise linear discriminant analysis (SWLDA) with an increased number of channels and analytic shrinkage-regularized LDA (sLDA) as classifier. The investigations were evaluated on recordings of 10 healthy subjects and 12 patients in a minimally conscious state. The results for healthy subjects were promising, significant improvements could be found by increasing the number of channels using SWLDA, as well as, for using sLDA instead of SWLDA. Single trial classification accuracies up to 85.1% could be achieved for healthy subjects. For the patients the results were less promising. However, for one patient improvement reaching up to an accuracy of 71.3% could be achieved.

1 Introduction

A promising approach, when considering the application of Brain-Computer Interface (BCI) systems to patients diagnosed with minimally conscious state (MCS), is the use of single-switch BCIs (ssBCIs) [6]. Such an ssBCI can be based, for example, on motor imagery or on responses to visual, tactile or auditory stimulation. However, while the visual ability might be considerably impaired in such class of patients, the auditory pathway is usually preserved. Therefore, the auditory system might be one of the last remaining channels usable for BCI-based communication [3]. Recently we proposed the concept of a novel auditory single-switch BCI and investigated the transition of a paradigm from healthy subjects (HS) to patients (PA) in MCS [4]. The paradigm was evaluated in 10 HS and applied to 12 PA. In 8 of the 10 HS significant single-trial classification accuracies up to 77.2 % could be reached using stepwise linear discriminant analysis (SWLDA). However, for MCS patients only a small number of classification results were above chance level and none of the results were sufficient for communication purposes. We speculated that the inclusion of all recorded channels instead of only three pre-selected channels might yield better classification results.

In the present work, we investigated this issue by using all recorded channels for SWLDA classification in HS and PA. However, due to the low number of trials available from patient measurements, there is a risk of overfitting the data when using all channels for classification. Therefore, we also used analytic shrinkage-regularized LDA (sLDA) which clearly outperforms SWLDA at low trial to feature ratios [1].

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2 Methods

Subjects, Experimental Paradigm and Data Recording: We used the data of the 10 HS (mean age 27.6 ± 3.0 SD years) and 12 PA (45.8 ± 18.2 years) in MCS, recorded in our previous study, using an auditory based P300 BCI [4]. Briefly summarized, two tone streams (low, LTS, at 396 Hz, and high, HTS, at 1900 Hz) with infrequently appearing deviant tones (297 Hz for the LTS and 2640 Hz for the HTS) at random positions were presented. The tones of both streams were intermixed (LHL_LHL_, L..low tone, H..high tone, _..silent gap; for details and a schematic illustration see [4]). As in this way the LTS was twice as fast as the HTS, the percentage of deviant tones was different (20% for HTS and 10% for LTS) to generate the same absolute number of deviants in both streams. For the experiment, subjects were instructed visually, for HS, or auditory, for PA, to focus attention on one of the streams during one run. For the HS 80 runs (40 runs for each stream; with 4000/400 (standard/deviant) tones in the LTS and 1800/400 in the HTS) were recorded. Taking into account the reduced attention span of the patients, one to two sessions, each with 20 runs (10 for each stream), were recorded. In HS the EEG was recorded at 15 positions with a sampling rate of 512 Hz (filter setup: 0.5–100 Hz) using active electrodes. For PA recording a reduced channel set (9 positions) was used to facilitate measurements in a clinical environment. For the electrode setup see [4].

Data Analysis and Classification: Data recorded from HS and PA were analyzed in the same way. Raw signals were filtered with a 3^{rd} order Butterworth low-pass filter (cut-off frequency at 10 Hz) and down-sampled to 64 Hz. In our previous work three EEG channels (Fz, Cz, Pz) were used for classification (SWLDA, with 10x10 cross-validation; for details see [4]). Only time points between 200 and 800 ms after tone onset were used as features.

In the present work, we performed two classification approaches: Firstly we used the data of all recorded channels for SWLDA classification. Secondly we investigated also the performance of sLDA instead of the SWLDA. In general, the classification performance of an LDA crucially depends on accurate estimates of the class means and the common covariance matrix. If enough data are available, an accurate estimate is unproblematic. However, in cases where insufficient data are available or the data are contaminated by outlier (e.g. during PA recordings), conventional estimation of the covariance matrix fails. In those cases, the covariance matrix is ill conditioned. One can improve the conditioning of the covariance matrix by regularization. An efficient regularization method is analytic shrinkage. This so-called analytic-shrinkage-regularized LDA (sLDA) is computationally very efficient and outperforms other methods at low trial to feature ratios [1]. For both approaches the classification was carried out as follows: 1) To detect the P300 the deviant tones were classified against the standard tones for each target stream separately, and 2) to investigate the attentional modulation of the P300, the target deviant tones were classified against the non-target deviant tones for each stream separately. By performing the second investigation, it should be possible to infer which stream was attended. For the first investigation random subsampling with 100 iterations was applied to account for the very different numbers of deviant and standard segments. Classification results were compared with the real level of chance [2] to identify random results.

3 Results

Results are shown for P300 and attentional modulation detection. Figure 1 depicts the averaged (mean ± SD) classification accuracies for P300 and attentional modulation detection, using either SWLDA with 3 channels (SWLDA_3), all channels (SWLDA_{all}), or sLDA classifier with

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all channels (sLDA$_{all}$) for both groups (HS,PA). The results are shown for LTS and HTS. Table 1 summarizes the subject specific SWLDA and sLDA classification results of all 10 HS. The values in the table represent the mean accuracies over all cross-validation folds.

	P300						Attention					
Subj.	SWLDA $_3$		SWLDA $_{all}$		sLDA $_{all}$		SWLDA $_3$		SWLDA $_{all}$		sLDA $_{all}$	
	LTS	HTS	LTS	HTS	LTS	HTS	LTS	HTS	LTS	HTS	LTS	HTS
HS01	*57.3*	*61.2*	*58.0*	*62.5*	***64.0***	***68.2***	55.2	*57.8*	55.8	56.0	***58.6***	***59.3***
HS02	*70.7*	*61.8*	*73.5*	*63.6*	***76.7***	***65.2***	*62.6*	*62.8*	*61.9*	*62.9*	***65.3***	***69.4***
HS03	*77.2*	*72.0*	*78.2*	*73.3*	***85.1***	***77.7***	*69.5*	*70.4*	*70.9*	*69.2*	***75.9***	***74.8***
HS04	*62.2*	*57.2*	*64.3*	*57.9*	***67.2***	***61.4***	*56.9*	53.5	*59.4*	*57.4*	***61.1***	***61.2***
HS05	*63.9*	*60.7*	*65.2*	*61.5*	***69.2***	***65.8***	*63.5*	*61.0*	*65.4*	*65.5*	***67.2***	***71.2***
HS06	*71.5*	*64.4*	*78.7*	*75.0*	***81.3***	***79.7***	*65.5*	*65.5*	*71.6*	*76.7*	***76.5***	***78.8***
HS07	*61.9*	54.4	*62.9*	55.6	***67.2***	***59.8***	53.3	55.6	54.1	54.6	***56.7***	***58.1***
HS08	*67.2*	*59.7*	*74.0*	*65.1*	***80.7***	***72.1***	*58.9*	*60.2*	*61.0*	*62.2*	***65.9***	***69.3***
HS09	*56.8*	55.4	*59.6*	*57.6*	***62.6***	***58.6***	52.8	52.1	53.4	53.0	**54.7**	**55.9**
HS10	56.0	52.6	*60.9*	53.6	***64.4***	***56.7***	51.4	50.6	51.4	53.4	***57.0***	***60.3***
Mean	64.5	59.9	67.5	62.6	71.8	66.5	59.0	59.0	60.8	61.1	63.9	65.8
SD	7.1	5.6	7.8	7.1	8.3	7.9	6.1	6.3	6.7	7.7	7.7	7.9

Table 1: SWLA and sLDA classification accuracies (in %) for the HS for P300 and attentional modulation detection using either 3 or all channels. All results significantly better than random [2] ($\alpha = 1\%$) are indicated in *italic*. Highest subject specific accuracies are indicated in **bold**.

In healthy subjects the P300 condition revealed a statistically significant difference in accuracy depending on which classification method was used, $\chi^2{}_{(5)} = 39.94, p < 0.001$. Post hoc analysis with Wilcoxon signed-rank tests was conducted with a Bonferroni correction applied, resulting in a significance level set at $p \leq 0.012$. There were significant differences between the SWLDA$_3$ and sLDA$_{all}$ (LTS: $Z = -2.805, p = 0.005$; HTS: $Z = -2.803, p = 0.005$) and SWLDA$_{all}$ and sLDA$_{all}$ (LTS: $Z = -2.803, p = 0.005$; HTS: $Z = -2.803, p = 0.005$). The attentional modulation condition showed also a significant difference in classification accuracies depending on the method used, ($\chi^2{}_{(5)} = 38.11, p < 0.001$) and the follow up Wilcoxon signed-rank test showed significant differences between SWLDA$_{all}$ and sLDA$_{all}$ (LTS: $Z = -2.805, p = 0.005$; HTS: $Z = -2.803, p = 0.005$) and between SWLDA$_3$ and SWLDA$_{all}$ (LTS: $Z = -2.49, p = 0.012$).

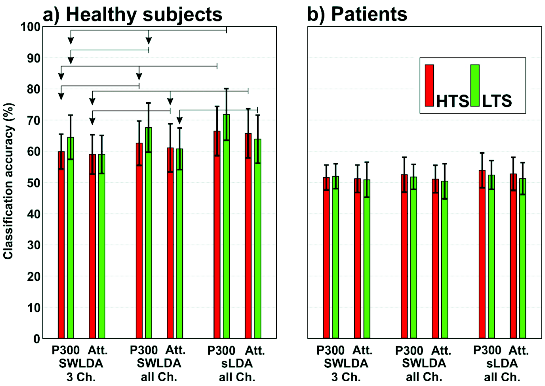

Figure 1: Mean ($\pm$ SD) classification accuracies (in %) for a) healthy subj. and b) patients (for P300 and attentional modulation detection; separated for LTS and HTS) using SWLDA and sLDA classifier. Significant differences are indicated.

	P300					
	SWLDA $_3$		SWLDA $_{all}$		sLDA $_{all}$	
	LTS	HTS	LTS	HTS	LTS	HTS
Mean	51.9	51.5	51.7	52.4	52.3	53.8
SD	4.0	3.9	4.1	4.2	4.6	5.6
	Attention					
	SWLDA $_3$		SWLDA $_{all}$		sLDA $_{all}$	
	LTS	HTS	LTS	HTS	LTS	HTS
Mean	50.8	51.1	50.3	51.0	51.2	52.7
SD	5.6	4.4	5.6	4.4	5.1	5.3

Table 2: Mean ($\pm$ SD) SWLDA and sLDA classification accuracies (in %) for the patient group for P300 and attentional modulation detection using either 3 or all channels.

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For the patients (see Table 2 for mean ± SD accuracies) the Friedman test reported significant differences between the classification methods only for the P300 condition, $\chi^2_{(5)} = 13.28, p = 0.021$. The follow up Wilcoxon signed-rank test revealed no significant results. Nevertheless, in one of the patients (PA09; CRS-r score: 18; Cause: Hemorrhagic stroke) a P300 could be classified above chance level. In more detail, by using sLDA, the accuracy for the HTS was improved up to 71.3% ($SWLDA_3$: 63.0%; $SWLDA_{all}$: 65.3%), which is significantly better than random [2] ($\alpha = 1\%$). However, for the LTS all classification accuracies ($SWLDA_3$: 64.8%; $SWLDA_{all}$: 65.0%; $sLDA_{all}$: 65.2%) remained below chance level.

4 Discussion and Conclusion

For the HS group the classification accuracies could be significantly improved by using sLDA and the inclusion of all recorded channels. However, unlike healthy subjects, for the patient group the results were less encouraging. Although in some PA the single-trial classification accuracies could be improved, they remained mainly below chance level. However, an accuracy significantly better than chance level [2] could be reached in one subject (71.3%).

Concluding, as stated by Blankertz et al. [1], *"the use of a higher number of channels is potentially advantageous for ERP classification"* and improves the classification accuracy in HS using either SWLDA or sLDA. For the PA recordings further studies should aim on investigating the use of additional electrode positions (especially frontal/fronto-lateral [5]). Furthermore, as concluded in [4], improvements on the used paradigm (e.g. include spatial information [5] if possible) are still required to take into account the specific needs and capabilities of the patients.

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