Using NIRS as a predictor for EEG-based BCI performance.

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***Abstract*— Multimodal recordings of EEG and NIRS of 14 subjects are analyzed in the context of sensory-motor based Brain Computer Interface (BCI). Our findings indicate that performance fluctuations of EEG-based BCI control can be predicted by preceding Near-Infrared Spectroscopy (NIRS) activity. These NIRS-based predictions are then employed to generate new, more robust EEG-based BCI classifiers, which enhance classification significantly, while at the same time minimize performance fluctuations and thus increase the general stability of BCI performance.**

I. Introduction

A whole range of non-invasive neuroimaging methods have been employed for the use of BCI in humans, but to date, EEG is the most widely used technology in this context. Some of the main reasons are relatively low costs, fast setup times, partly attributable to the advent of dry electrode technology [1], [2] and subject-independent classifiers [3] that have recently become available, but also the high temporal resolution that EEG offers.

However, EEG sensory motor rhythm (SMR)-based BCI still suffers from a number of problems. Unfortunately, not all subjects are able to alter this rhythm and thus SMR-based BCIs do not work for all subjects. Recently simultaneous recordings of NIRS and EEG have not only been shown to increase BCI performance, but also enabled some subjects to operate a BCI, who previously were not able to do so [4].

While EEG has the highest temporal resolution of all neuroimaging methods, NIRS on the other hand is dependent on changes of blood flow, as it measures oxygenated and deoxygenated hemoglobins ([HbO] and [HbR]) in the superficial layers of the human cortex. The temporal resolution of NIRS is therefore orders of magnitudes lower, lowering the upper bound of Information Transfer Rates for NIRS-based BCIs substantially.

Some subjects, who are able to operate SMR-based BCIs, experience a high level of non-stationarities in their BCI performance, as can be seen in Figure 1. While other possible solutions have been proposed, such as adaptive models [5], [6] or stationary subspace analysis [7], here we present the first multi-modal approach to this problem. We find NIRS features that predict future EEG-based BCI performance and employ this prediction to estimate novel classifiers, that reduce the performance fluctuations.

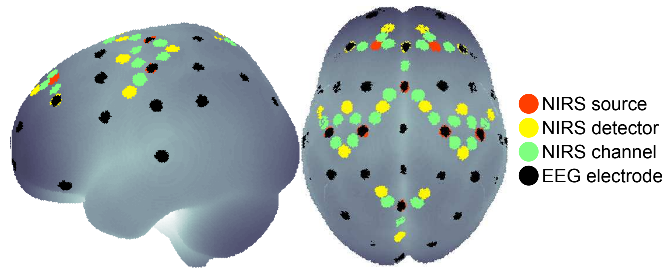

Fig. 2. Locations of EEG electrodes; sources, detectors and actual measurement channels of NIRS. Note that electrodes and optodes might share a location. Figure is adopted from [4].

II. Methods

A. Experimental Setup

Simultaneous measurements of EEG and NIRS were performed. The NIRS-System (NIRScout 8-16, NIRx Medizintechnik GmbH, Germany) was equipped with 24 optical fibers (8 sources with wavelengths of 850 nm and 760 nm, 16 detectors convolving to 24 measurement channels). Frontal, motor and parietal areas of the head were covered as shown in Figure 2, adopted from [4]. The sampling frequency was $f_{\mathrm{NIRS}} = 6.25$ Hz. Attenuation changes at 760 and 850 nm are converted into changes of oxygenated and deoxygenated hemoglobin, based on a modified Beer-Lambert law [8]. NIRS data was low-pass filtered at 0.2 Hz using a one-directional filter method, namely a 3^{rd} order Butterworth-filter.

EEG, electrooculogram (EOG) and electromyogram (EMG) were recorded with a multichannel EEG amplifier (BrainAmp by Brain Products, Munich, Germany) using 37 Ag/AgCl electrodes, 2 bipolar EMG, 2 bipolar EOG (vertical as well as horizontal EOG), sampled at $f_{\mathrm{EEG}} = 1$ kHz and downsampled to 100 Hz by means of a Chebyshev digital filter. NIRS probes and EEG electrodes were integrated in a standard EEG cap (extended 10-20 system with a possibility of 256 electrodes) with inter-optode distances between 2 and 3 cm. The optical probes are constructed, such that they fit into the ring of standard electrodes. This enables us to situate the NIRS channel positions according to the standard 10-20 system, as can be seen in Figure 2.

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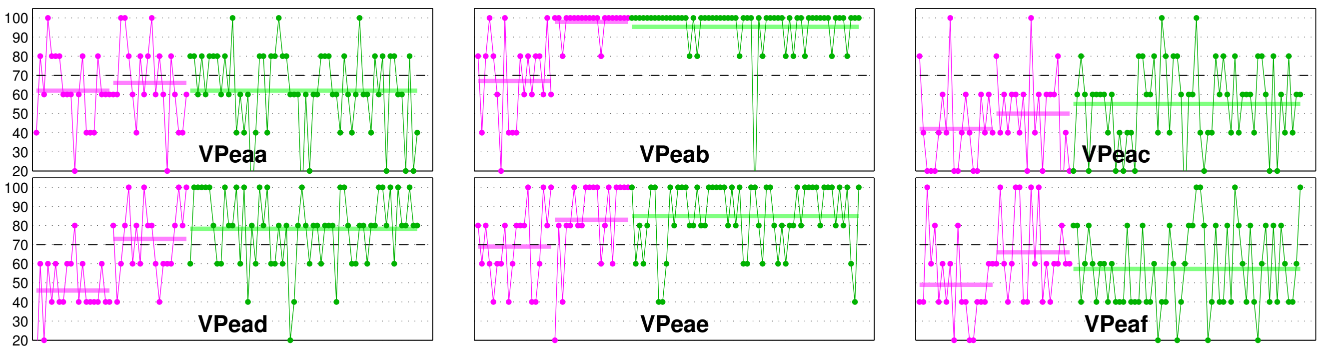

Fig. 1. The EEG classification rate is generally non-stationary in time. Here we show the fluctuations in performance for the first 6 subjects. Each dot represents the classification performance of 5 trials. On the y-axis the classification accuracy is depicted in percent, the x-axis represents time-course of the experiment. The magenta color shows early stages of the experiment, where the classifier is not yet considered to be stable, green color indicates a later state of the experiment, where the classifier is kept constant. Horizontal lines show average classification performance.

B. Paradigm and Data Analysis

Fourteen healthy, right-handed volunteers (aged 20 to 30) participated in the study, which lasted approximately four hours. Subjects were seated in a comfortable chair with armrests and instructed to relax their arms during recordings. The participants were instructed to perform left hand and right hand motor imagery, according to the paradigm.

a) EEG Classifier estimation: 2 blocks of real-time EEG-based, visual feedback controlled motor imagery (50 trials per block per condition) were recorded for the estimation of the EEG classifier. The first 2 s of each trial began with a black fixation cross, that appeared at the center of the screen. Then, as a visual cue an arrow appeared pointing to the left or right and the fixation cross started moving for 4 s, according to the classifier output. After 4 s the cross disappeared and the screen remained blank for 10.5 ± 1.5 s. The online processing was based on the concept of *coadaptive calibration* [6].

The user was given instantaneous EEG-based BCI feedback for the two blocks of motor imagery. During the first block of 100 trials a subject-independent classifier, depending on band power estimates of laplacian filtered, motor-related EEG channels, was used. For the second block subject-dependent spatial and temporal filters were estimated from the data of the first block and combined with some subject-independent features to form the classifier for the second block. During the online feedback features were calculated every 40 ms with a sliding window of 750 ms. For further details on *coadaptive calibration* we would like to refer the reader to [6].

b) Fast Feedback: Once the EEG classifier is estimated a feedback block with 300 trials and a relatively short interstimulus interval of 7 s is recorded, lasting a total of 35 minutes. As before the first 2 s of each trial began with a black fixation cross, that appeared at the center of the screen. Then a visual cue in form of an arrow appeared to indicate the required class and the fixation cross started moving for 4 s, according to the classifier output. After the 4 seconds, the cross disappeared and the screen remained blank for short time interval of 1 ± 0.5 s before the next trial began.

c) Offline Data Analysis: The long intertrial intervals in the first two blocks were chosen to evaluate the NIRS signals with respect to motor imagery. The results have been reported in [4]. Here, we only investigate the 300 trials of the fast feedback dataset. These trials are split into chronological blocks of 5 trials each, resulting in 60 blocks and the EEG-BCI performance of these smaller blocks are computed. For each block the EEG-based classifier output *out* is multiplied by its true label $\tilde{y}$ and summed over the 5 trials within the block, resulting in the performance y of the given block:

$$y_k = \sum_{i=1}^{5} \tilde{y}_i \cdot \mathrm{out}_i \quad , \tag{1}$$

where i is the trial within block k. By calculating the performance this way, one obtains a continuous performance measure, which in our case is preferable to a mere 0-1 loss, since it is more accurate and also more suitable for the purpose of regressing NIRS features onto this measure, as will be explained in the following paragraphs. The overall performance is subtracted from each block-performance, such that a 'time course' of above and below average EEG-BCI performance is obtained.

The NIRS signal is cut into multiple epochs, each with a width of 2 s, preceding each 5 trial block by 2, 4, 6, 8 and 10 seconds. Noisy channels are discarded and the signal is transferred into the spectral domain. An ℓ_1-regularized regression optimization problem [9] is formulated (and implemented with CVX [10]) to identify spectral NIRS features predicting the EEG performance of the following 5 trials:

$$\underset{\beta}{\mathrm{argmin}} \quad ||y - \beta X||_2 + \lambda ||\beta||_1 \tag{2}$$

where X are the preceding NIRS features, β the regressor and λ the regularization variable. Please refer to Figure 3 for a graphical explanation. The thin black boxes on the upper part represent trials, where left and right hand motor imagery are cued. The optimization problem is repeated 60 times and each time a different block is left out, resulting in a performance prediction for each block. Using the predictions

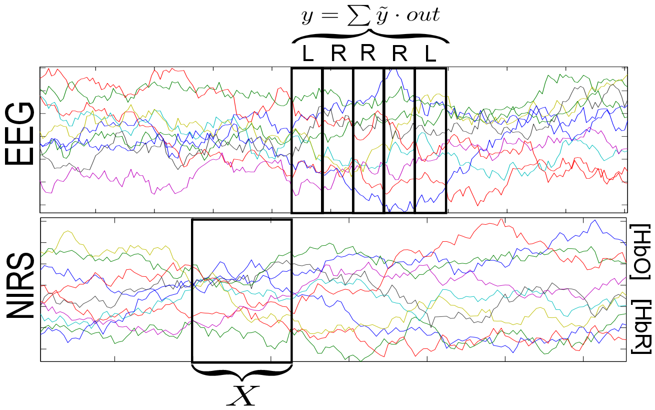

Fig. 3. Top: The continuous EEG during the fast feedback phase. Bottom: The simultaneously recorded continuous [HbO] and [HbR] NIRS chormophores. Note that random data is shown here for visualization purposes.

as well as the actual performances the correlation coefficient and it's p-value are calculated. The corresponding p-values test the hypothesis of zero correlation. Since the method is repeated a number of times for various intervals, the p-values are Bonferroni corrected.

Depending on the prediction of the NIRS, the EEG data is grouped into three categories: blocks with good performance, medium performance and bad performance. All three groups have even number of trials (100 trials per group). A validation scheme is setup, where one block (consisting of 5 trials) is left out as a test-set. Using the training set we calculate four EEG classifiers: one for each group, defined by the performance prediction, and a fourth, comprised of all training data. The individual classifiers consist of a fixed broadband temporal filter (5^{th} order Butterworth digital filter with $[5-30]$ Hz), a spatial filter (CSP, see [11] for further details) and a linear classifier (LDA). In a second step we train a meta-classifier, combining all four individual classifiers, based on the training set. The outputs of this meta-classifier are then compared to the true labels of the left-out trials and its 0-1 loss is computed. This procedure repeated for all blocks. As a baseline we use the EEG classifier that was trained on all training data.

III. Results

In Table I the results of the optimization problem, defined by Equation 2, are shown. For 9 out of 14 subjects the p-values of the correlation coefficients, which were calculated between predicted and actual EEG performances are significant.

Table II shows the classification results of all subjects as well as their means. A paired t-test between the standard procedure of treating all training trials the same, as compared to a meta-classifier that combines four classifiers, based on the performance of blocks, results in a value of $p = 0.013$ (this is indicated by a '$*$' in Table II).

subject	all	meta	good	medium	bad
ae	18.7	20.3	25.0	19.3	24.3
aj	10.7	8.7	14.3	14.7	22.7
ah	4.3	4.0	5.0	15.3	6.0
an	3.7	3.3	2.7	3.0	3.7
ai	21.0	11.7	20.0	12.0	25.0
al	12.3	14.7	20.3	16.0	27.0
af	48.0	44.3	49.7	48.0	44.0
aa	42.7	41.0	41.7	45.0	45.7
ag	29.3	21.7	24.0	35.7	35.7
ad	24.0	20.3	21.3	21.7	31.0
ak	14.7	11.0	33.0	15.7	16.0
am	46.0	38.0	41.7	41.7	41.0
ac	35.7	33.7	38.0	37.3	41.0
ab	13.0	13.0	14.0	12.7	14.0
mean	23.1	**20.4***	25.0	24.1	26.9

TABLE II

PERCENTAGE CLASSIFICATION LOSS OF ALL INDIVIDUAL SUBJECTS AS WELL AS THEIR MEANS. *all* STANDS FOR THE STANDARD PROCEDURE, WHERE ALL TRAINING TRIALS ARE CONSIDERED THE SAME, *good* USES ONLY TRAINING TRIALS FROM BLOCKS WITH GOOD PERFORMANCE, *medium* USES TRIALS WITH AVERAGE PERFORMANCE, *bad* TRIALS WITH LOW PERFORMANCE AND *meta* STANDS FOR A META-CLASSIFIER, WHICH COMBINES CLASSIFIERS OF *all*, *good*, *medium* AND *bad*.

To evaluate whether our method reduces the performance variability during the feedback session, we calculate the standard deviation over all 60 blocks for the standard method, where all trials are treated the same, as well as for the meta classifier. Figure 4 shows the results in form of a scatter-plot. As can be seen, our proposed method reduces the variability of performance in 11 out of 14 subject, in one subject the variability is the same and for two subjects the standard procedure has lower performance fluctuations. A paired t-test reveals a significant relationship with $p < 0.05$.

IV. Discussion and Conclusions

While in this paper we show results of an offline study, there is per se no reason, why the presented method could not be applied in an online setting. In fact preparations have begun for a real-time feedback study that will enable us to evaluate the results presented here.

In its present form our novel method is validated with a fixed broadband temporal filter. However, this approach is not ideal in the sense that subject-specific physiology, which shows a high degree of subject-to-subject variability, is not taken account of. However, the presented method could easily be extended, such that subject-dependent temporal filters would be included. A whole range of methods have previously been shown to accomplish that task successfully. Filter-banks have been proven useful for SMR-based BCIs [12], [13] in this sense, but also heuristics [11] are able to model this variability appropriately, among others.

Concluding, we may state that our novel approach of combining NIRS and EEG is a viable technique, suitable for SMR-based BCI, since it preserves the responsiveness

subject	an	ab	ae	aj	af	ah	am	ai	ad	ag	aa	ak	al	ac
cc	0.66	0.56	0.54	0.49	0.48	0.48	0.44	0.43	0.41	0.37	0.36	0.35	0.32	0.18
p	5.3e-07	1.5e-04	3.0e-04	0.003	0.004	0.004	0.016	0.020	0.040	0.135	0.162	0.235	0.550	6.523

TABLE I

CORRELATION COEFFICIENTS (CC) AND P-VALUES (P) OF PREDICTED VS. ACTUAL EEG PERFORMANCES.

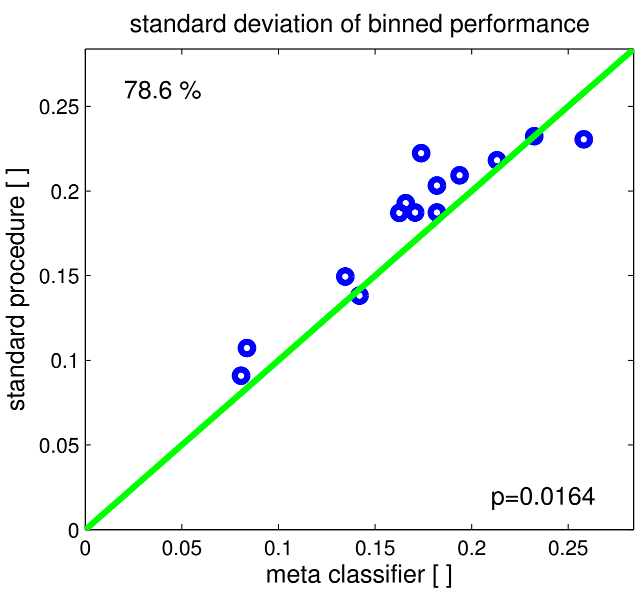

Fig. 4. Scatter-plot of the standard deviation of performance over all blocks. Each dot represents a single subject. The percentage on the top left indicates for how many subjects the meta classifier has lower standard deviation. p indicated the significance of a paired t-test.

of the EEG, while at the same time significantly enhancing classification rates, as well as minimizing performance fluctuations.

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