Combined EEG-fNIRS Decoding of Motor Attempt and Imagery for Brain Switch Control: An Offline Study in Patients With Tetraplegia

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***Abstract*—Combining electrophysiological and hemodynamic features is a novel approach for improving current performance of brain switches based on sensorimotor rhythms (SMR). This study was conducted with a dual purpose: to test the feasibility of using a combined electroencephalogram/functional near-infrared spectroscopy (EEG-fNIRS) SMR-based brain switch in patients with tetraplegia, and to examine the performance difference between motor imagery and motor attempt for this user group. A general improvement was found when using both EEG and fNIRS features for classification as compared to using the single-modality EEG classifier, with average classification rates of 79% for attempted movement and 70% for imagined movement. For the control group, rates of 87% and 79% were obtained, respectively, where the "attempted movement" condition was replaced with "actual movement." A combined EEG-fNIRS system might be especially beneficial for users who lack sufficient control of current EEG-based brain switches. The average classification performance in the patient group for attempted movement was significantly higher than for imagined movement using the EEG-only as well as the combined classifier, arguing for the case of a paradigm shift in current brain switch research.**

***Index Terms*—Brain switch, electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), tetraplegia.**

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I. Introduction

MOTOR-IMPAIRED individuals, such as tetraplegia patients, could potentially benefit from the use of a brain–computer interface (BCI). Such a system would enable them to control e.g., a wheelchair or orthosis, driven partially or completely by mental actions [1], [2]. Many BCIs are based on changes in sensorimotor rhythms: event-related desynchronization (ERD) and-synchronization (ERS) [3], which can be detected in the electroencephalogram (EEG) of an individual who is intending, imagining or executing movement.

"Brain switch"-type BCIs detect one specific mental state from ongoing brain activity, i.e., the default or "rest" state. Therefore, their output is limited to a binary decision: either keeping the system in its current state or switching it to the second state. However, this drawback comes with the benefit of a low level of complexity on the part of both the system and the user. The user is only required to perform a certain task when there is an intention for communication or system change. In the remaining time the user can relax or focus on a different task. As for the detection performance, the distinction between one motor task and a baseline state may be more robust than the distinction between two different types of motor task, thus limiting the number of errors [4]. A brain switch could also function as the "on/off button" of a regular BCI, which in turn may have a more complex set of tasks or instructions and therefore a larger range of outputs [5].

Although brain switch systems driven by motor tasks are typically based on electrophysiological signals, some studies have shown the feasibility of using functional near-infrared spectroscopy (fNIRS) instead [6], [7]. Optical BCIs make use of concentration changes in the cerebral blood flow during increased neural activity, for instance motor tasks during which an increase of oxygenated hemoglobin (oxy-Hb) along with a decrease in deoxygenated hemoglobin (deoxy-Hb) occurs [8]. Recently a few studies have looked into the possibility of combining these hemodynamic responses with their electrophysiological counterparts, in a multimodal or "hybrid" BCI [9]. Fazli *et al.* showed promising classification performance in healthy participants when combining features from both modalities [10]. In the current study, we examined whether this principle works in patients with tetraplegia, an important target user group of brain switch technology.

Secondly, we tested the difference in performance between attempted and imagined movement. In most BCI studies,

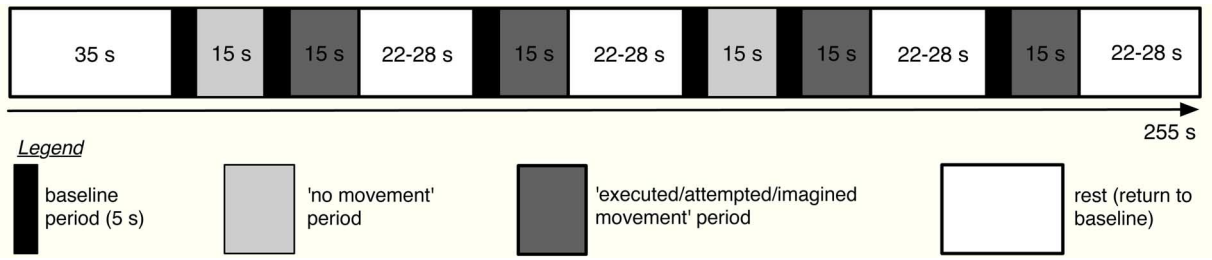

Fig. 1. Visualization of experimental sequences. Sequences consisted of two trials of each condition: "executed/attempted movement," "imagined movement," and "no movement." The 5 s before each movement period were used as a baseline for computing grand average plots of the brain responses.

healthy subjects as well as patients are instructed to perform motor imagery only, regardless of their motor abilities. However, motor imagery requires active inhibition of motor neural activation. Apart from the fact that brain patterns during motor imagery are less distinguishable from rest than motor execution patterns [4], the task may also feel less natural, and therefore more difficult, to perform. Therefore, letting a motor-impaired individual attempt rather than imagine a certain movement may result in higher performance rates. Here, using EEG and fNIRS separately as well as in combination, we test the feasibility of using motor attempt instead of motor imagery as a task for brain switch control.

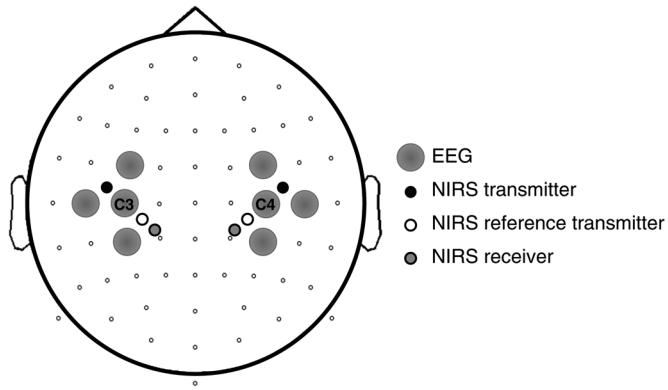

Fig. 2. EEG and fNIRS channel configuration.

II. Methods

A. Participants

Ten male patients with tetraplegia (mean age 48.9 years) and 12 male controls (mean age 45.9 years) participated in the study. Nine patients had a complete lesion at C5-C6, one patient had a complete lesion at level C4-C5. Impairments had all been caused by traumatic spinal cord injury (SCI). The time since the injury varied between 11 and 40 years (mean 25.2 years). The protocol was approved by the institutional review board and all participants gave informed consent. After data collection, data from three patients and four controls were excluded from further analysis due to insufficient signal quality and excessive artifacts in one or both modalities.

B. Materials and Procedures

Subjects were presented with six sequences of movement tasks with visual instructions, each sequence consisting of six task trials (Fig. 1). Each trial lasted 15 s. The three types of task participants were asked to perform were "rest" (do nothing), "movement" (tap your fingers and thumb continuously), and "imagined movement" (imagine tapping your fingers and thumb continuously). When patients received the instruction of "movement" they were asked to attempt performing the actual movement even though the movement could not truly be executed. Each type of movement was performed 12 times with the trials equally divided over all sequences. Instructions were presented randomly, with the restriction that the first sequence trial was always "rest." Intervals between trials lasted between 27 and 33 s to ensure sufficient recovery time (i.e., return to baseline levels) for the hemodynamic responses. After "no movement" trials however, the return to baseline period lasted only 5 s as no significant deviation from baseline should have occurred. Total recording time per participant, including short breaks, was approximately 30 min.

EEG was recorded with an 8-channel passive Porti system (TMSi, Enschede, the Netherlands), the electrodes placed on positions C3, FC3, C5, CP3, C4, FC4, C6, and CP4 according to the international 10/20 system. Data was sampled at 2048 Hz and acquired with the Fieldtrip toolbox in MATLAB [11].

Two fNIRS channels were recorded with a continuous-wave system (Oxymon MK III, Artinis, Zetten, The Netherlands). Six optical fibers with straight ends were used: two transmitters (wavelengths 764 and 858 nm) and one receiver per channel. For each channel, an inter-optode distance between the target transmitter and the receiver of 35 mm was chosen, whereas the reference transmitter was placed at 10 mm from the receiver in order to correct for hemodynamic noise from e.g., the scalp and skull [12]. The channels were positioned around C3 and C4. Data was sampled at 250 Hz and acquired with Oxysoft version 3.0.43.

EEG electrodes and fNIRS optodes were mounted side-by-side on a specially constructed cap. Fig. 2 shows the full configuration.

All patient recordings and two control recordings took place at the participants' homes, the remaining control experiments were conducted at the institutional lab.

C. Analyses

1) EEG: After downsampling the EEG data to 256 Hz and removing the DC offset, linear detrending was performed to remove slow drifts. Visual inspection of the data revealed class-specific data contamination in a very low number of trials and channels, which were therefore excluded from further analysis.

Spectral features were averaged over all subjects in order to compute a grand average time-frequency plot visualizing the power decrease (ERD) during the movement tasks.

2) fNIRS: The optical signals from the fNIRS acquisition device were converted to hemoglobin changes using the modified Beer Lambert law [13]. This converts the optical density changes to oxygenated (O_2Hb) and deoxygenated (HHb) concentration changes (in the literature, O_2Hb and HHb are sometimes referred to as HbO and HbR, respectively). The differential pathlength factor (DPF) was selected individually for each subject according to their age [14]. Slow drifts were removed with a 0.01 Hz high pass filter. In order to enhance the signal to noise ratio, the concentration changes for the reference transmitter were scaled to fit the obtained concentration changes from the target transmitter with a least squares approach [15]. Subsequently, the scaled concentration changes of the reference transmitter were subtracted from the far transmitter. This was done to correct for systemic noise, including hemodynamic changes from scalp and skull, and was performed for O_2Hb and HHb and both channels. Since activities faster than 0.2 Hz were not expected the concentration changes were further low pass filtered to 0.2 Hz and were baselined for each trial and channel to the period from -5 to 0 s before task onset. The filtered O_2Hb and HHb changes were used as the features for classification.

Computation of the grand average plots included two further preprocessing steps. First, because of the large individual variations in O_2Hb and HHb, the concentration changes were normalized so that the actual/attempted movement condition had unit power. Subsequently, the imagined movement condition was normalized for each subject with the same scaling factor as for the actual/attempted movement condition.

3) Classification: For both modalities, trials were split into 3-s segments. This increases the number of training examples to 60 per movement condition and allows for estimation of the classifier performance for a specific segment and hence time period. For EEG classification power spectral features between 8 and 24 Hz (5 frequency bins $\times$ 8 channels) were used, which were computed using Welch's method with a 4 Hz frequency resolution [16]. For fNIRS, three separate classifiers were trained: an O_2Hb classifier using the average O_2Hb concentration change for both channels (1 average $\times$ 2 channels), an HHb classifier using the respective HHb concentration changes and an $(O_2 + H)Hb$ classifier using both the O_2Hb and HHb average concentration changes for both channels (2 averages $\times$ 2 channels). The EEG classifier was evaluated on the time period of 0–15 s while the fNIRS classifiers were evaluated on the time period of 3–18 s, since a slower response was expected for the latter.

Performance of an L_2-regularized linear logistic regression classifier [17] was computed for both EEG and fNIRS for three binary problems to distinguish each individual movement condition from the "rest" condition: 1) "executed movement" versus "rest" (controls only), 2) "attempted movement" versus "rest'" (patients only), and 3) "imagined movement" versus "rest" (both groups). Classification performance was evaluated with a chronological (block-wise) 12-fold cross-validation where a block corresponded to one 15-s trial, i.e., five consecutive 3-s segments. For each fold two blocks (one per condition) were removed from the training set to make the test examples.

In order to facilitate a probabilistic combination of the EEG and each of the three fNIRS classifiers, the obtained linear predictions were calibrated separately for each classifier. The calibration was performed by fitting the classifiers' linear predictions to the logistic function so each classifier returns valid probabilities [18]. For any set of single predictions [here, we consider the prediction of the EEG classifier and the prediction of the fNIRS classifier(s)] the class membership decision of the segment was based on simple addition of each classifier's linear predictions. This corresponds to a naive Bayesian combination of the predictions, irrespective of the modality (see the Appendix).

The binomial confidence with the Agresti–Coull correction [19] was used to test for performance significantly higher than chance. The statistical significance between the obtained classification rates of different classifiers and task conditions was evaluated using a one-tailed dependent samples t-test. Statistical significance between the control group and the patient group was determined by means of a two-tailed independent samples t-test.

III. Results

Group average responses for all movement conditions show expected patterns in both measuring modalities. Time-frequency plots visualizing spectral features from the EEG during and after the movement tasks (Fig. 3) show a clear ERD/ERS pattern in the control group for actual movement and a relatively similar though weaker pattern for imagined movement, whereas for the patient group only ERD is clearly visible in either condition. In Fig. 4, normalized fNIRS group averages for O_2Hb and HHb are shown, with the two fNIRS channels averaged. A typical increase in O_2Hb can be observed for both groups and movement types. The expected decrease in HHb is observed in all conditions except for attempted movement in the patient group.

The individual classification results for each movement type and measuring modality are shown in Table I (control group) and Table II (patient group). The EEG single-segment classification rates for the healthy subjects are on average 84% and 77% for actual and imagined movement, respectively. For the patient group the average rates are significantly lower ($p < 0.05$) at 73% and 63% for the two movement types. The fNIRS single-segment classification rates for the healthy subjects are 77% for actual and 59% for imagined movement, whereas for the patients the rates are 70% and 65% for attempted and imagined movement, respectively. Contrary to EEG-classification, the performance of the fNIRS classifiers is not significantly different between the control group and the patient group. For EEG, the difference in classification rates between actual/attempted and imagined movement is significant ($p < 0.05$) while for fNIRS in the control group actual movement rates are significantly higher than imagined movement rates ($p < 0.01$), but in the patient group the difference between attempted and imagined movement does not reach significance ($p = 0.19$).

When the EEG classifier is combined with the fNIRS classifier, a significant increase as compared to EEG classification

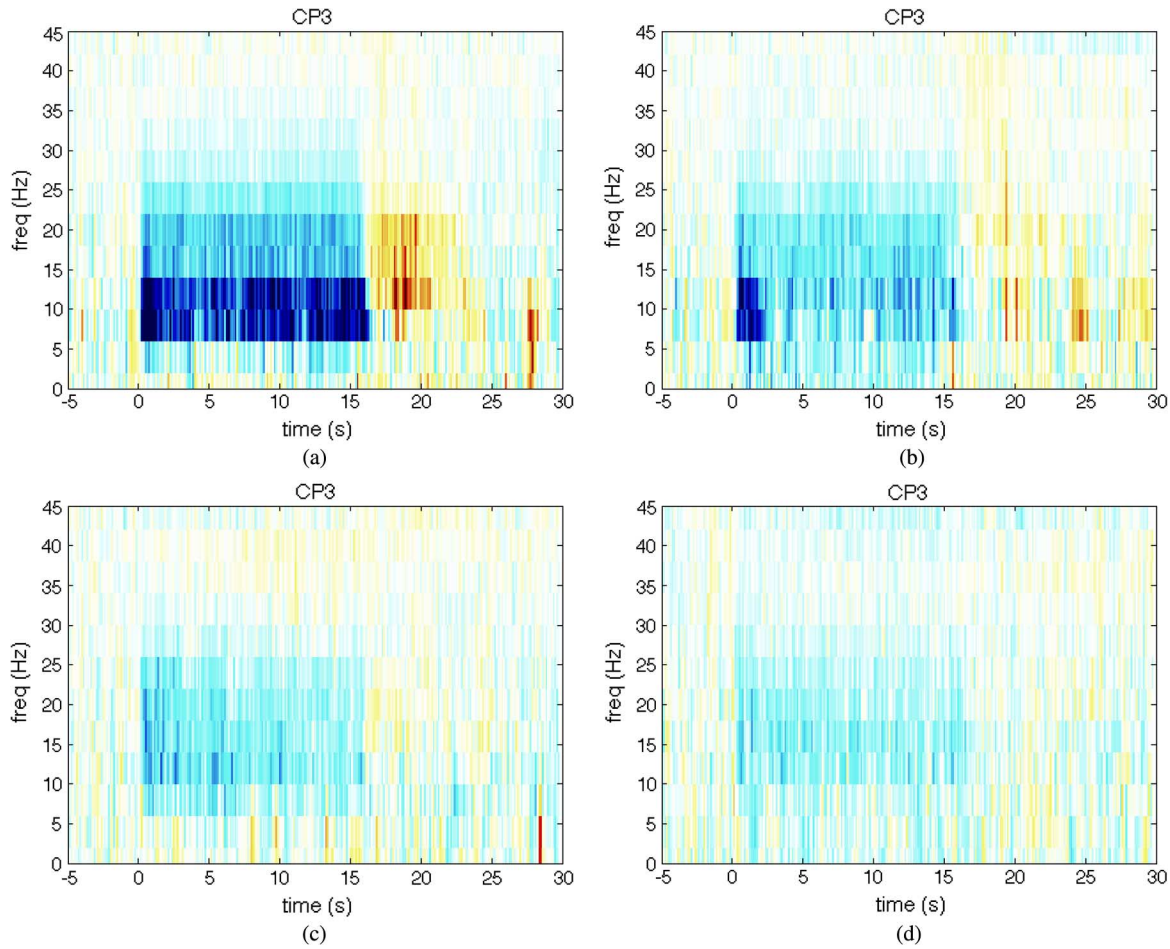

Fig. 3. Average time-frequency plots from the EEG, channel CP3. Blue represents a power decrease, red a power increase. "AM" is the attempted or actual movement condition, "IM" is the imagined movement condition. (a) Controls AM. (b) Controls IM. (c) Patients AM. (d) Patients IM.

only is observed in the classification performance for each condition ($\mathrm{p} < 0.05$), except for motor imagery in the control group ($\mathrm{p} = 0.12$). Utilizing both modalities the classification rates for the control subjects rise to 87% (actual) and 79% (imagined). For the patients the combined rates are 79% (attempted) and 70% (imagined). Also for the combined classifier the performance is significantly higher in the actual and attempted movement condition than in the imagined movement condition ($\mathrm{p} < 0.05$).

IV. Discussion

Adding hemodynamic information to the more commonly used electrophysiological features may improve brain switch performance. Here, for an important target user group of such systems, namely patients with tetraplegia, it was shown that a combination of both modalities indeed improves classification performance as compared to an EEG-only BCI. Secondly, for both EEG alone and the combined EEG-fNIRS classifier it was shown that classification performance is higher when patients are asked to attempt their movement rather than perform motor imagery.

For every condition except the motor imagery condition in the control group, the combined classifier yielded a significantly better performance. Interestingly, Fazli *et al.* [10] found significant improvement for motor imagery but not motor execution. However, that study differs in two major respects as compared to the study presented here. Firstly, classification was based on a traditional left-versus right hand paradigm, rather than the brain-switch approach we adopted here, i.e., movement versus no movement. Secondly the number of channels used was much higher in that study: 24 fNIRS channels and 37 EEG channels, as compared to two fNIRS channels and eight EEG channels in our study.

The fact that performance improves by adding an additional modality, indicates that the decisions made by the individual classifiers are at least to some degree uncorrelated, even though they are derived from the same underlying neurological processes. Indeed, the mean correlation of the decision values between EEG and fNIRS over all groups and conditions turns out to be as low as 0.07. The gain of the combined classifier is apparent for most users whose classification performance based on only EEG is relatively low. This could mean that several users who have been considered to be "BCI illiterate" [20] until now based on low EEG-BCI performance, may in fact turn out to be able to control a BCI relatively well, using the same task, but by expanding the hardware with (or replacing it by) fNIRS channels.

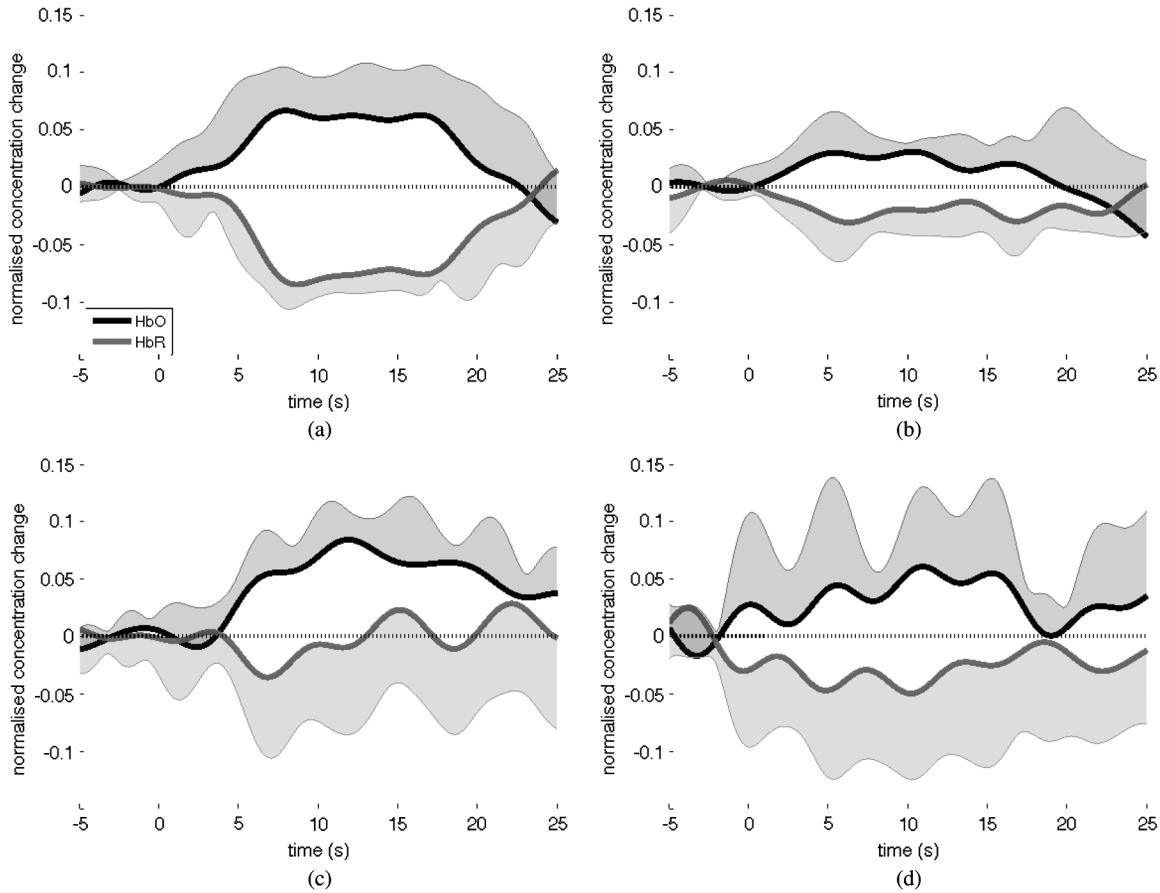

Fig. 4. Grand average normalized concentration changes for both fNIRS channels. O_2Hb (black) and HHb (gray) are shown, along with the variance over subjects (shaded area, one standard deviation from the mean). (a) Controls AM. (b) Controls IM. (c) Patients AM. (d) Patients IM.

We obtained the classification performance reported here with a relatively low number of channels, which has important implications for practical usability as it allows for a very quick setup. Further research might provide insight into whether a simple montage consisting of any low number (4–10) of combined EEG and fNIRS channels means an improvement over using the same number of channels from a single modality. If that proves to be the case, simply replacing certain EEG channels with fNIRS rather than adding extra channels would mean performance increase of the brain switch without compromising too much on setup time.

The current performance might be improved by using more advanced methods of combining the EEG and fNIRS features as well as by optimizing the experimental paradigm. In this offline study, trials were split into 3-s segments. Additional analysis of the full 15-s trials of the current data set showed a large performance increase when delaying the time until a decision is made. When the combined EEG-fNIRS classifier decides after the full 15 s, accuracy for the patient group is 90% for attempted movement and 82% for imagined movement. To fully determine the possible speed/accuracy tradeoff of brain switch control with the paradigm presented here, an online study using the full trials is required. Furthermore, a limitation of the current study is the relatively low number of trials per participant. Therefore, a more extensive study with larger amounts of data per participant would be an important step towards validation of the setup proposed here. However, a longer experimental duration would be needed, making participation more strenuous for the patients.

As a result of the inherent slowness of the BOLD response [21] detection of O_2Hb and HHb concentration changes is slightly delayed as compared to detection of ERD. For the same reason, it is also sustained until after movement has stopped. ERD on the other hand disappears almost instantly after movement has stopped and is replaced by ERS. Until a few seconds after movement offset, fNIRS features could continue to be classified in a similar fashion as during the movement, while the post-movement ERS could be incorporated as an extra EEG feature. With a more efficient use of data like this, the movement period could possibly be shortened to e.g., 5 or 10 s without performance loss. Although in the time-frequency plots of the current data set ERS is not clearly visible for the patient group, more extensive analysis would need to be performed to quantify the actual benefit of a combined ERD/ERS classifier for this group.

An issue that has not been addressed in the current study is intersession variability. Ideally, a brain switch such as the one proposed here would not require recalibration prior to every single use. As hemodynamic responses especially suffer from variations over time, sophisticated methods for reducing or even eliminating recalibration time are of great importance [22].

Although traditionally SMR-based BCIs exploit signals induced by motor imagery, a few studies have adopted motor

TABLE I

INDIVIDUAL AND MEAN CLASSIFICATION RATES BASED ON SINGLE 3-S SEGMENTS FOR THE CONTROL GROUP. EACH SUBCOLUMN OF THE FNIRS COLUMN REPRESENTS THE SINGLE-SEGMENT CLASSIFICATION RATES FOR ONLY OXY FEATURES (O_2Hb), ONLY DEOXY FEATURES (HHB) AND WHEN BOTH CHROMOPHORES ARE USED FOR CLASSIFICATION ($(O_2 + H)Hb$). EEG+ SUBCOLUMNS REPRESENT THE COMBINATION OF THE CLASSIFIER OUTPUTS OF THE EEG CLASSIFIER WHEN COMBINED WITH EITHER THE O_2Hb, HHB OR THE $[(O_2 + H)Hb]$ CLASSIFIERS. FOR EEG CLASSIFICATION THE SEGMENTS BETWEEN 0 AND 15 S AFTER TASK ONSET WERE USED, FOR FNIRS THE SEGMENTS BETWEEN 3 AND 18 S AFTER TASK ONSET. COMBINATION WAS PERFORMED BY ADDING THE PREDICTIONS OF THE EEG CLASSIFIER FOR THE WHOLE TIME RANGE (0–15 S) AND THE NIRS CLASSIFIER FOR A REDUCED TIME RANGE (3–15 S). CLASSIFICATION RATES ABOVE 62% ARE SIGNIFICANTLY HIGHER THAN CHANCE ($p = 0.05$)

	Actual movement							Imagined movement						
	fNIRS			EEG	EEG+			fNIRS			EEG	EEG+		
	O_2Hb	HHb	$(O_2+H)Hb$		O_2Hb	HHb	$(O_2+H)Hb$	O_2Hb	HHb	$(O_2+H)Hb$		O_2Hb	HHb	$(O_2+H)Hb$
Subject														
C1	0.68	0.83	0.82	0.83	0.83	0.87	0.86	0.56	0.76	0.71	0.78	0.78	0.80	0.78
C2	0.57	0.96	0.97	0.91	0.93	0.97	0.97	0.55	0.80	0.75	0.90	0.89	0.93	0.92
C3	0.53	0.72	0.76	0.78	0.78	0.80	0.83	0.41	0.55	0.58	0.71	0.71	0.71	0.71
C4	0.64	0.83	0.84	0.88	0.86	0.91	0.91	0.37	0.64	0.60	0.66	0.64	0.70	0.68
C5	0.62	0.69	0.63	0.67	0.67	0.70	0.68	0.30	0.22	0.23	0.64	0.64	0.64	0.64
C6	0.43	0.51	0.47	0.84	0.84	0.84	0.84	0.44	0.38	0.38	0.88	0.88	0.88	0.88
C7	0.80	0.73	0.82	0.91	0.91	0.92	0.93	0.68	0.53	0.72	0.79	0.79	0.79	0.78
C8	0.88	0.80	0.88	0.88	0.95	0.91	0.93	0.79	0.74	0.81	0.78	0.88	0.88	0.88
mean	0.64	0.76	0.77	0.84	0.85	0.86	0.87	0.51	0.58	0.59	0.77	0.78	0.79	0.79

TABLE II

INDIVIDUAL AND MEAN CLASSIFICATION RATES BASED ON SINGLE 3-S SEGMENTS FOR THE PATIENT GROUP. SEE TABLE I FOR FURTHER DETAILS. * FOR P2, EEG CHANNELS FC3 AND CP3 WERE REMOVED. THEREFORE, EEG CLASSIFICATION RATES FOR THIS SUBJECT ARE BASED ON SIX CHANNELS ONLY

	Attempted movement							Imagined movement						
	fNIRS			EEG	EEG+			fNIRS			EEG	EEG+		
	O_2Hb	HHb	$(O_2+H)Hb$		O_2Hb	HHb	$(O_2+H)Hb$	O_2Hb	HHb	$(O_2+H)Hb$		O_2Hb	HHb	$(O_2+H)Hb$
Subject														
P1	0.52	0.56	0.46	0.80	0.80	0.80	0.80	0.27	0.62	0.56	0.76	0.76	0.75	0.76
P2*	0.75	0.53	0.73	0.63	0.74	0.61	0.75	0.70	0.38	0.71	0.52	0.68	0.50	0.69
P3	0.59	0.57	0.57	0.58	0.61	0.58	0.63	0.68	0.59	0.69	0.63	0.71	0.59	0.73
P4	0.66	0.51	0.63	0.64	0.68	0.65	0.66	0.56	0.59	0.61	0.53	0.50	0.51	0.57
P5	0.77	0.33	0.78	0.79	0.83	0.79	0.86	0.61	0.61	0.68	0.77	0.77	0.77	0.80
P6	0.85	0.70	0.89	0.78	0.89	0.83	0.90	0.65	0.52	0.66	0.52	0.68	0.56	0.68
P7	0.84	0.54	0.84	0.88	0.91	0.88	0.92	0.63	0.68	0.65	0.68	0.68	0.73	0.68
mean	0.71	0.53	0.70	0.73	0.78	0.74	0.79	0.58	0.57	0.65	0.63	0.68	0.63	0.70

attempt instead [23], [24]. BCI paradigms are commonly tested with healthy users, whose actual movements might induce confounding factors as compared to patients in whom no true muscle activation may be present. Motor imagery is considered a relatively representative task of eventual application use: if a patient cannot use actual movement to control the BCI, neither should a healthy user when testing the feasibility of the BCI. However, why the complex task of motor imagery is often retained when moving from healthy subjects to potential users remains unclear. In the current study we compared BCI performance for both types of movement within the same subjects. Here we have shown that for both the individual EEG classifier and the combined classifier attempted movement yields a significantly higher average classification rate than imagined movement. This may partly be explained by the fact that all patients had retained at least some form of movement in their upper extremities, mostly their wrists. Even though the fingertapping movement could not be executed, the attempt may have triggered slight activation of other arm muscles. In the future, a systematic comparison between patients with different levels of impairment may provide insight into the influence of residual activity in certain muscles on signal strength and therefore chance of detection during attempted movement.

A second explanation could be that motor imagery and attempt are intrinsically different tasks in one very important respect: whereas during attempted movement the *intention* of moving is in fact present, imagery requires suppression of true movement (intention). Mentally, motor attempt is the exact same task as motor execution, except for the lack of sensory and visual feedback. Imagery on the other hand, although requiring many of the same processes as execution, is driven by a different intention.

Regardless of which of these or other factors mostly contribute to stronger signals during attempted movement, this advantage could and should be exploited, as the gain in performance is apparent. Without trying to generalize over *every* BCI paradigm and user group, we conclude that at least for the particular application of a brain switch for patients with acquired (rather than congenital) impairments, the actual source of the signals is irrelevant as long as the user retains control. For patients with congenital impairments however, who were not included in this study, somatosensory representations of limbs may be different than for SCI patients.

In addition, EMG signals could be incorporated in the system, thus introducing another component to the hybrid BCI. Instead of using the residual movement and the brain signals for different control outputs, their signals could be merged in order to increase brain switch performance [25]. Moreover, in an fMRI study cortical activation patterns of attempted movement in patients with tetraplegia were shown to correspond well to those

of executed movement in healthy controls [26], whereas another study showed similar results in patients with paraplegia [27]. This might be an indication that if motor attempt will be used by patients for BCI control, it is favorable to test the paradigm with healthy users performing actual instead of imagined movement.

On average, the patients in this study became paralyzed 25 years ago. Nevertheless, movement-related signatures could be detected in every patient in at least one modality and most often in both EEG and fNIRS. In the literature, both invasive and noninvasive recording methods have been demonstrated to be feasible for neuroprosthesis control in patients with tetraplegia [1], [28]. The current evidence adds to the impression that noninvasive methods, in this case a combined EEG-fNIRS system, could provide adequate brain switch control for motor-impaired individuals. Although noninvasive systems may not (yet) be as robust as invasive alternatives, the advantage of avoiding surgery makes it worthwhile exploring this area further.

Summarizing, we have shown that for an important target group of brain switch technology, namely patients with tetraplegia, a combined EEG-fNIRS classifier yields promising performance rates, especially when the users are instructed to attempt their movements rather than imagine them. Further research is needed to shed light on the feasibility of this paradigm in an online setting.

APPENDIX

For the EEG-fNIRS combined classifier, as well as for obtaining the predicted labels of the full 15-s trials (see discussion), individual classifier predictions were summed. Here, we show that this is equivalent to a naive Bayesian combination of the single example (from now on: "trial") probabilities.

The logistic regression classifier gives the posterior probability $p(c = y|x_i)$ which is the probability that the true class of trial i is y given the trial data x_i. When considering multiple predictions we get

$$p(c = y|x_1, \ldots, x_k) \equiv p\left(c = y| \bigcap_{i=1}^{k} x_i\right). \tag{1}$$

Using Bayes theorem and the conditional independence of x_i given the class we get

$$p\left(c = y| \bigcap_{i=1}^{k} x_i\right) = \frac{p\left(\bigcap_{i=1}^{k} x_i|c = y\right) p(c = y)}{p\left(\bigcap_{i=1}^{k} x_i\right)} = \frac{\prod_{i=1}^{k} p(x_i|c = y)p(c = y)}{p\left(\bigcap_{i=1}^{k} x_i\right)} \tag{2}$$

assuming $p(c = y) = p(c = -y)$, using Bayes theorem on $p(x_i|c = y)$ and given that $p(\bigcap_{i=1}^{k} x_i) = \prod_{i=1}^{k} p(x_i|c = y)p(c = y) + \prod_{i=1}^{k} p(x_i|c = -y)p(c = -y)$ gives

$$p\left(c = y| \bigcap_{i=1}^{k} x_i\right) = \frac{\prod_{i=1}^{k} p(c = y|x_i)}{\prod_{i=1}^{k} p(c = y|x_i) + \prod_{i=1}^{k} p(c = -y|x_i)}. \tag{3}$$

For logistic regression the mapping of linear predictions is done through the logistic function

$$p(c = y|x_i) = \frac{1}{1 + e^{-yf_i}} \tag{4}$$

where f_i are the linear predictions based on data x_i. Using the fact that

$$\prod_{i=1}^{k} p(c = -y|x_i) = \prod_{i=1}^{k} \frac{1}{1 + e^{yf_i}} = e^{-y\sum_i^k f_i} \prod_{i=1}^{k} \frac{1}{1 + e^{-yf_i}} = e^{-y\sum_i^k f_i} \prod_{i=1}^{k} p(c = y|x_i). \tag{5}$$

Combining (3) and (5) we obtain

$$p\left(c = y| \bigcap_{i=1}^{k} x_i\right) = \frac{1}{1 + e^{-y\sum_i^k f_i}} \tag{6}$$

showing that the naive Bayesian combination of single trial probabilities is equal to the logistic transformation of the summed linear classifier predictions.

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