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Differences in Hemodynamic Activations between Motor Imagery and Upper Limb FES with NIRS

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Abstract— **A brain-computer interface (BCI) based on near-infrared spectroscopy (NIRS) could act as a tool for rehabilitation of stroke patients due to the neural activity induced by motor imagery aided by real-time feedback of hemodynamic activation. When combined with functional electrical stimulation (FES) of the affected limb, BCI is expected to have an even greater benefit due to the contingency established between motor imagery and afferent, haptic feedback from stimulation. Yet, few studies have explored such an approach, presumably due to the difficulty in dissociating and thus decoding the hemodynamic response (HDR) between motor imagery and peripheral stimulation. Here, for the first time, we demonstrate that NIRS signals elicited by motor imagery can be reliably discriminated from those due to FES, by first performing a univariate analysis of the NIRS signals, and subsequently by multivariate pattern classification. Our results showing that robust classification of motor imagery from the rest condition is possible support previous findings that imagery could be used to drive a BCI based on NIRS. More importantly, we demonstrate for the first time the successful classification of motor imagery and FES, indicating that it is technically feasible to implement a contingent NIRS-BCI with FES.**

I. INTRODUCTION

Near-infrared spectroscopy (NIRS) has gained traction in recent years as it provides certain advantages.The potentially higher spatial resolution compared to electroencephalography (EEG) and the lower price and portability compared to magnetic resonance imaging (MRI) and magnetoencephalography (MEG) predestine NIRS for certain applications. One desirable application is a brain-computer interface (BCI). For more than a decade EEG-BCIs have been utilized in rehabilitation scenarios [1]. Although the hemodynamic response (HDR) is observed after neural firing with a large time delay of several seconds, it has been shown that regulation of hemodynamics can be achieved with real-time feedback [2]. Although limited to the recording of signals from the outer layers of the cortex, NIRS can nevertheless be useful for detecting oxygenation changes in a number of areas associated with motor tasks. Real-time feedback of activation from these areas could be utilized for applications in motor learning. Activations associated with motor execution and imagery can be reliably classified with machine learning techniques [3]. For a variety of tasks, NIRS signals from different parts of the brain have been shown to be identifiable on the single trial level [4], [5], [6]. First applications of NIRS-BCIs have already been successfully implemented [7]. To make use of a BCI for the rehabilitation stroke patients one major approach is to close the feedback loop by providing haptic feedback. This has been proposed as necessary to facilitate neuronal reorganization [9]. Haptic feedback is expected to evoke hemodynamic activations in areas of the sensorimotor and motor cortex [10] that could be utilized to control the BCI. However, one must ascertain that the BCI can reliably distinguish between activation patterns related to motor imagery and activations due to the afferent haptic feedback, without which the BCI would not be properly operationalized [11]. In addition, self-regulation of brain activation necessarily requires that feedback provided is contingent [12], [13]. To establish contingency in a BCI the classifier needs to be able to distinguish between voluntary activations and stimulus-induced activations. Furthermore a classification accuracy of 70 % is assumed to be the lower bound for a user-friendly BCI application [14]. Functional electrical stimulation (FES) is one established method for providing haptic feedback [11]. In this work we analyze the effect of motor imagery on NIRS signals and the possibility to distinguish the evoked activation from rest. Furthermore we investigate the effect of FES and the feasibility of distinguishing between activations due to motor imagery and FES.

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II. METHODS

A. Experimental design

Eight right handed (81.8±16.4 according to the Edinburgh handedness inventory [15]) healthy volunteers were involved in the study. Their age was 24.8±2.4 years. Six subjects were female.Subjects were seated in a comfortable chair with 2 arm rests on which they placed their forearms, Visual stimuli were presented during the experiment with the software Presentation (Neurobehavioral Systems, Inc., Albany, CA, USA). During the experiment, subjects were asked to perform 2 different tasks: (1) imagine opening and closing their right hand without any actual movement and (2) having their right hand passively moved by FES (2). The block duration of both conditions was 10 s (see Fig. 1). Both conditions were preceded by visual cues of 1 s duration indicating the subjects to prepare for the following task. The stimulation block consisted of 10 subblocks, in which extensor and flexor were alternately stimulated for 1 s at a time. In between the condition blocks a black screen containing the word ”Rest” indicated subjects to relax and rest. The rest times varied pseudorandomly between 10 s and 15 s to avoid anticipation by the subjects. Furthermore varying rest times instead of fixed rest times (and thereby an experimental time constant in the same order of magnitude as the expected effects) avoided synchronisation with physiological effects. Each task

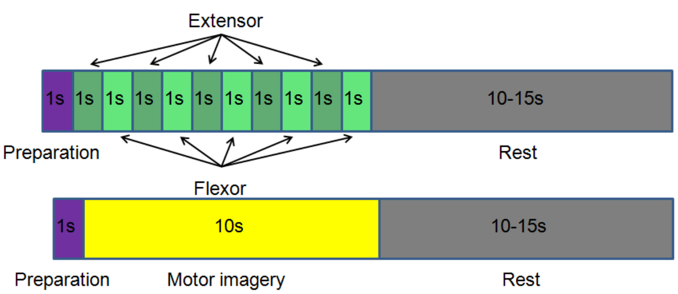

Fig. 1. Time course of a single stimulation block and a single imagery block. Both condition blocks are preceded by a preparation cue of 1 s length. The stimulation block consists of alternating functional electrical stimulation of extensor and flexor. Both condition blocks are succeded by rest condition of pseudorandom length of 10-15 s.

was repeated 30 times in pseudorandom order during the experiment to avoid anticipation effects. The experiment was approved by the ethics commission of the Medical faculty of the Eberhard Karls University, Tübingen.

B. FES

Before the experiment FES parameters were adjusted for each individual. We used the Motionstim 8 stimulator from MEDEL GmbH, Hamburg, Germany. Two unipolar electrodes of oval shape (4x6 cm) were placed on the extensor digitorum communis (EDC) and two electrodes were placed on the flexor digitorum communis (FDC) of the right forearm following physical landmarks. The pulse width was fixed to 300 μs. The stimulation frequency varied between either 20 Hz or 30 Hz. The amplitude was adjusted for each individual to cross the motor threshold of both muscles to produce finger extension and flexion. Average amplitude of stimulation for the EDC was 19.9±3.8 mA and for the FDC was 17.5±3.6 mA. The subjects were instructed neither to move their fingers against or together with the FES driven movements nor to imagine hand movements.

C. Signal Acquisition

To optically image the bilateral motor cortex we used the FOIRE-3000 from Shimadzu Europa GmbH, 47269 Duisburg, Germany operating at 780 nm and 830 nm at a sampling rate of 8 Hz. The optodes were attached to the head with a semi-flexible head mount. Sixteen sources and 16 detectors were arranged in two 4x4 checkerboard topographies centered around C3 and C4 of the international 10-20 system [16], thereby covering most of the primary motor cortex, premotor cortex and somatosensory cortex associated with hand movements, motor imagery and the processing of sensations of the hand [17]. The source-detector distance was about 2.5 cm. The computer on which visual stimuli were shown using Presentation sent trigger signals via a parallel port to the NIRS system, which inserted the corresponding time information into the raw NIRS data. A second computer read out FES triggers from the first computer via TCP-IP protocol. The second computer sent corresponding FES state change commands via an ethernet cable to the FES device. To separate the stimulator for electrical safety reasons from the electronic circuits of the computers a galvanic separation box (MEDEL GmbH, Hamburg, Germany) was used.

D. Signal Processing

Data analysis was performed using NIRS-SPM [18] and SPM 8 [19], both toolboxes for Matlab (The MathWorks, Inc.). Only changes in oxygenated hemoglobin were considered for statistical analysis since those were expected to include the largest concentration changes. The data was detrended (of global trends and of noise components) applying Wavelet-MDL (minimum description length) [20]. To correct for autocorrelations data was smoothed with a filter shaped as a HDR function (precoloring method) [18], [**?**]. The preprocessed data was then statistically analysed based on the general linear model. Interpolated t-statistic maps were computed and thresholded ($p<0.05$) for each contrast. The ratio between the significantly activated area and the total area covered by the probe (4 x 4 optodes, 7.5 cm x 7.5 cm) was computed. The following contrasts were investigated:

- FES vs. Rest
- Motor imagery of hand opening and closing vs. Rest
- FES vs. Motor imagery of hand opening and closing

E. Classification

Data was classified using an offline, linear Support Vector Machine (SVM) based classifier. Raw data was converted using the Beer-Lambert law into concentration changes of oxygenated and deoxygenated hemoglobin [21]. The converted data was lowpass filtered with a zero-phase Chebyshev type II filter. Passband frequency was 0.14 Hz, Stopband frequency 0.141 Hz, Passband ripple 0.5 dB and Stopband attenuation 40 dB. The passband frequency of 0.14 Hz was chosen to remove cardiac, respiratory and Mayer wave frequencies.

To classify FES vs. Rest and motor imagery (MI) vs. Rest both oxygenated and deoxygenated time courses were averaged for each of the 48 channels for 2 non-overlapping time windows of 2.5 s length. For the activation block data the first time window comprised seconds 6-8.5 of the activation block and the second time window comprised seconds 8.5 of the activation block to second 1 of the following rest block. The second time window overlaps the rest block to account for the delay in the HDR. For the rest block data the first time window comprised seconds (-5)-(-2.5) before the onset of preparation of the preceding rest block and the second time window comprised seconds (-2.5)-0. Two time windows contain more temporal information and were as well employed for rest data to allow for simple classification. This method results in 192 (2∗48∗2) features for each of the 30 condition blocks and for each of the 30 preceding rest blocks. The same preprocessing was applied to classify FES vs. MI, while the averaged time windows for both conditions comprised seconds 6-8.5 of the activation block and seconds 8.5 of the activation block to second 1 of the following rest block respectively. To take into account all of the available temporal data a second method of preprocessing was applied before classifying FES vs. MI. In the second method 2 time windows of 5 s of activation were averaged comprising seconds 4-9 of the activation block and second 9 of the activation block to second 4 of the succeeding rest block. This method results in 192 (2∗48∗2) features for each of the 30 condition blocks and for each of the 30 preceding rest blocks. Data was split as a randomly chosen training data

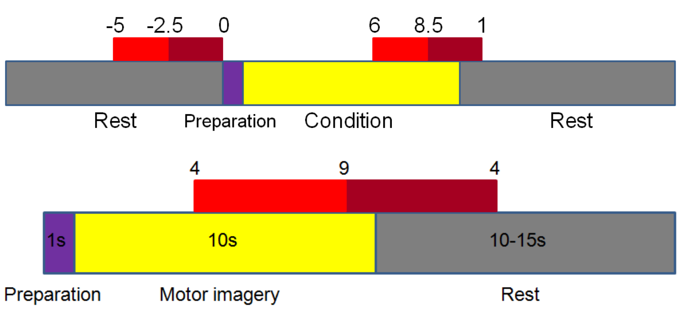

Fig. 2. Time windows used for classification for method 1 and 2 respectively.

set (54 blocks) and a remaining test data set (6 blocks) for each subject. The training data set was normalized (centered around 0 and scaled to [-1,1]) first and the test data set was then normalized based on the parameters of the training data set. Normalization was applied to improve classification results. Then the classifier was trained on the training data set and tested on the test data set. This process was repeated 10 times (10-fold cross-validation).

III. RESULTS

The size of the significantly activated areas as a ratio of the whole monitored cortical surface is reported in table I.

TABLE I

ACTIVATED SURFACE AREA

Subjects	MI vs. Rest	FES vs. Rest	MI vs. FES
1	10.3 %	0.0 %	13.7 %
2	0.3 %	0.0 %	1.4 %
3	1.5 %	1.5 %	2.2 %
4	3.5 %	0.0 %	10.3 %
5	10.2 %	0.0 %	9.0 %
6	14.5 %	9.0 %	3.6 %
7	0.0 %	2.6 %	0.0 %
8	7.3 %	1.4 %	0.1 %
Mean	5.9 %	1.8 %	5.0 %
± Std	5.4 %	3.0 %	5.3 %

For the contrast MI vs. Rest on average 5.9 %±5.4 % of the monitored cortical surface is activated. For the contrast FES vs. Rest on average 1.8 %±3.0 % is activated (including 4 subjects, for whom no area was found to be significantly activated). We expected more cortical areas to be involved in the process of motor imagery, which involves motor planning and movement inhibition, compared to just receiving passive stimulation [17]. On the individual level, too, we found for all subjects but two a larger area activated during motor imagery than during FES. For the contrast MI vs. FES on average 5.0 %±5.3 % is activated. This mean value is slightly smaller than the 5.9 %±5.4 % for the contrast MI vs. Rest, but in the same order of magnitude.

TABLE II

CLASSIFICATION ACCURACIES

Subjects	MI vs. Rest 5 s	FES vs. Rest 5 s	MI vs. FES 5 s	MI vs. FES 10 s
1	66.7	70.0	65.0	70.0
2	65.0	55.0	63.3	75.0
3	71.7	68.3	71.7	73.3
4	81.7	58.3	65.0	76.7
5	61.7	63.3	83.3	80.0
6	66.7	45.0	66.7	76.7
7	65.0	83.3	70.0	70.0
8	73.3	63.3	83.3	91.7
Mean	69.0	63.3	71.0	76.7
± Std	±6.4	±11.3	±8.1	±7.0

The average classfication accuracy for each subject and each method is reported in table II. The chance level for 2-class classification is 50 %. For 60 classified trials the confidence limits of a chance result are [22]:

- 95 % confidence limit: 62.3 %, and
- 99 % confidence limit: 66.1 %.

For the contrast MI vs. Rest data could be classified for all subjects except one within the 95 % confidence limit. Thereby motor imagery can be distinguished from rest. The mean classification accuracy is 69.0 %. Since this is very close to the assumed lower limit of a user-friendly BCI (70 %), we are encouraged by the results to work towards a NIRS-BCI. For the contrast FES vs. Rest data could be classified for all subjects except 3 within the 95 % confidence limit. We could for the first time classify FES induced hemodynamic activations from rest. For both processing methods of the contrast MI vs. FES data could be classified for all subjects within the 95 % confidence limit. For the method that utilized 5 s of activation data could be classified for all except 3 subjects within the 91 % confidence limit. For the method that utilized 10 s of activation data could be classified for all subjects within the 91 % confidence limit. Based on the above results, we conclude that motor imagery can be distinguished from FES in NIRS signals. The longer the included time course, the higher the classification accuracy. The mean classification accuracy for both methods is higher than 70 % (71.0 % and 76.7 % respectively). A NIRS-BCI based on the classifier described above could be activated by motor imagery within nearly user friendly limits ($>$70 %). Once this NIRS-BCI would activate FES feedback, the contigency of feedback could still be ensured within user friendly limits.

IV. CONCLUSIONS

First of all we could verify previous findings about NIRS being able to detect motor imagery. In line with previous work [3] the hemodynamic response evoked by motor imagery can be classified offline above chance level. This finding is important in view of future online applications of motor imagery evoked signals to control an external device. To use such a BCI in rehabilitation applications on patients suffering from motor impairments such as stroke patients, the feedback loop would need to be closed by providing haptic feedback to facilitate neuronal reorganisation [9]. This haptic feedback is expected to evoke hemodynamic activations in parts of the sensorimotor cortex, while at the same time activations of the sensorimotor cortex are utilized to operate the BCI. Therefore we studied the activations evoked by motor imagery and by FES and found that they can be distinguished statistically as well as by an offline classifier. This finding allows for the setup of a haptic NIRS-based BCI, which instead of being driven by activations due to afferent sensations caused by the haptic feedback, would be instead appropiately driven by motor imagery alone. Nevertheless the small activation ratios emphasize the need for a good classifier. Furthermore we verified that activations evoked by FES can be detected with NIRS [10]. In this study we classified FES evoked NIRS signals compared to rest. When comparing hemodynamic activations evoked by motor imagery vs. those evoked by FES, the classification accuracy is higher than 70 %, the assumed lower bound for a feasible BCI application [14]. Our work establishes for the first time that HDR to motor imagery and FES can be reliably distinguished by pattern classification thus paving the way for BCI applications of rehabilitation.

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