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Performance Investigation of Brain-Computer Interfaces that Combine EEG and fNIRS for Motor Imagery Tasks

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Abstract - Brain-Computer Interfaces (BCI) have proved to be a promising tool for neurorehabilitation. However, BCIs based on conventional methods are not highly accurate and reliable, different brain activity patterns are not optimal for all the users of BCIs and has low information transfer rate. Several studies have shown that the combination of different brain signal acquisition methods can lead to higher performance of BCIs. In this paper, we aim to investigate whether the performance of BCI increases if we combine Electroencephalography (EEG) and functional Near Infrared Spectroscopy (fNIRS) simultaneously for classifying Motor Imagery (MI) tasks of right- versus left-hand grasping movement. The results show enhancement in classification accuracy using a multimodal approach of an EEG + fNIRS BCI with an average increase of approximately 8-10% compared to only EEG-based BCI. This indicates that the hybrid approach in Brain-Computer Interface is capable of enhancing the BCI performance.

I. Introduction

Brain-Computer Interface (BCI) is a technology which provides an alternative way of communication with the external world using patterns of brain activity as a replacement of peripheral nerves and muscles [1]. The applications of BCI are not only limited to restoring communication and control in disabled patients due to stroke, autism, or epilepsy, but they have also gained usage by healthy users [2] [3]. Different types of non-invasive brain-activity recording approaches can be used for BCIs, such as the Electroencephalogram (EEG), functional Near Infrared Spectroscopy (fNIRS), the Magnetoencephalogram (MEG), Positron Emission Tomography (PET) and many more [1]. Each modality has its own advantages and disadvantages. However, conventional BCI based on single modalities have shortcomings, such as low to moderate accuracy and reliability, low information-transfer rates, and user acceptance [4]. Different brain activity patterns are not optimal for all users of BCI. Neurophysiological signals can vary significantly from one subject to another which implies that some brain activity patterns can work better for some subjects while they lead to poor performance in others [5]. It has been reported that approximately 20% of users of a motor imagery BCI do not show performance sufficient to control. This is termed 'BCI illiteracy' [6].

EEG is a non-invasive technique which measures changes in voltages associated with neuronal activity using scalp electrodes. It is one of the most commonly used acquisition methods in the field of BCI. It has a high temporal resolution but has low spatial resolution and low signal-to-noise ratio [7].

On the other side, fNIRS measures hemodynamic activity in the form of blood flow, that is the concentration changes of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) resulting from neuronal firing [8]. It applies multiple source/detector pairs of Near Infrared (NI) lights at the wavelength between 650–950 nm. When light enters into the scalp, some of the photons reflect all the way to optodes, which is an optical sensor device, following a trajectory, wherein the HbO and HbR chromophores in the path absorb them with different absorption coefficients [9]. In general, fNIRS is non-invasive, portable and has a relatively low cost. However, it has low temporal resolution due to slow changes in NIRS signals and long delay introduced by the hemodynamic response to reach its maximum [10].

There are several feature extraction and classification methods available for hybrid BCIs [11]. fNIRS-based feature extraction uses the signal mean, the signal slope, signal peak, signal minimum, the skewness and kurtosis, or the number and sum of the peaks. Many of these features can be estimated based on the HbO and HbR activity of the subject's brain. EEG-based feature extraction uses bandpower signals in the μ and β frequency band [12].

Many studies showed the successful implementation of EEG- and fNIRS- based unimodal BCIs [13] [14]. The fusion of these two modalities has also gained interest in research and development of BCI to improve its performance. However,

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research in this field is still in its initial stage and a lot of development is required to use this novel method for clinical purposes. In this paper, we aim to investigate the performance of BCIs by combining EEG and fNIRS modalities to classify motor-imagery tasks.

II. Methods

A. Subjects and Data Acquisition

Nine healthy right-handed subjects aged between 22 and 50 (mean: 31 years), three females and six males, volunteered to participate in the experiments. The experiment (three sessions) lasted around 75 minutes, including the setup time. None of the participants had a history of any neurological, psychiatric or visual disorder and all of them were naive in performing MI tasks. EEG and fNIRS data was recorded using the *g.Nautilus fNIRS* device (g.tec medical engineering GmbH, Schiedlberg, Austria), with eight sources (FCC6h, FCC4h, CCP4h, CCP6h, CCP5h, FCC5h, FCC3h, and CCP3h) of wavelengths between 850 nm and 760 nm and two detectors (C4 and C3) and 15 EEG gel electrodes (Fz, FFC1h, FFC2h, Cz, C1, C5, FC3, CP3, C2, C6, FC4, CP4, CPz, CPP1h, and CPP2h) with ground at AFz. The optodes and electrodes were positioned on the right and left hemisphere of primary motor cortex according to the international 10-5 system. EEG and fNIRS data were recorded with a sampling rate of 250 Hz. Online filtering of EEG data was performed by applying a bandpass filter of 0.5-30 Hz and a notch filter of 48-52 Hz to reduce power line interference which is 50 Hz in Europe. The setup of the hybrid fNIRS-EEG device can be seen in Fig 1.

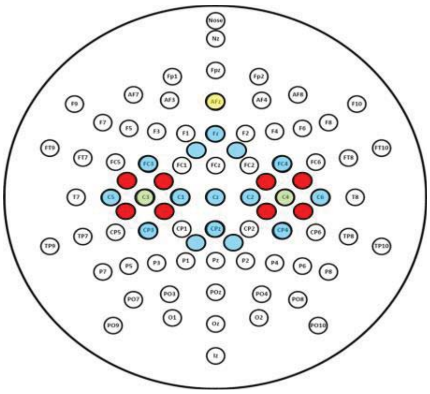

Fig 1. The configuration of EEG electrodes and fNIRS optodes. EEG electrodes (blue filled circles), NIRS detectors (green filled circles) and NIRS sources (red filled circles) were placed following the 10-5 system.

B. Experimental Paradigm

The subjects sat on a comfortable chair at a distance of approximately one meter from a 17 inches widescreen monitor in a dimly lighted room. The subjects were asked to not make any movement and sit a comfortable posture through the experiment. Before the experiment started, the subjects were instructed to blink with the eye, roll their eyeballs and clinch their teeth for quality check of the EEG signal. The experimental paradigm was developed using *MATLAB/Simulink* 2017a (The MathWorks, Inc.) and *g.HiSys* library (g.tec medical engineering GmbH). The screen was divided into two parts: one third of the screen displayed instructions and the other part displayed the avatar. The schematic diagram of the experimental paradigm for a single trial of our study is shown in Fig 2.

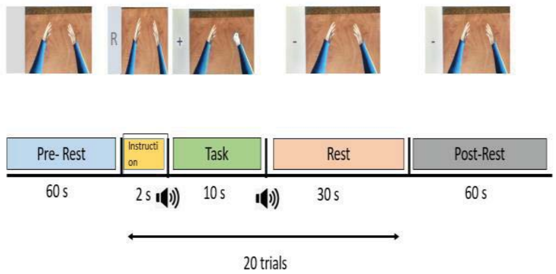

Fig 2. Schematic illustration of the experimental paradigm. Each session consisted of a 60 s pre-rest, 20 trials of 42 s each, and a 60 s post-rest period. A short beep was played at the beginning and at the end of the task period. Every trial started with 2 s of instruction of the task, followed by 10 s of the actual task and a resting period of 30 s.

The experiment consisted of three sessions. Each session consisted of a pre-rest period of 60 s, 20 trials of a motor-imagery task (right- or left-hand grasping; 42 s each) and post-rest period of 60 s. There were 10 right and 10 left hand grasping MI trials in one session. In each trial during the experiment, in initial instruction period lasted for 2 s, followed by 10 s of the task period, which is then followed by 30 s of a rest period. The instruction was visual by displaying "L" or "R" on the screen to indicate left- or right-hand movement imagination during the task period, respectively. The instruction ("L" or "R") of left- or right-hand grasping was randomized to ensure that subjects could not predict the next trial. A short beep was played at the beginning and at the end of the task period. During the task period, the instruction screen displayed "+" and the subjects tried to imagine grasping movement of their left or right hand as instructed in the instruction period. At the same time, they concentrated on the avatar, whose hand performed one movement per second. During the rest period, the instruction screen displayed "-" and the subjects were asked to relax and to avoid thinking and to do any movement. Such a long rest period of 30 s was taken as hemodynamic response takes longer time to settle down to its baseline. All sessions for one subject were performed on the same day with a gap of 5-10 minutes in between.

C. Data Analysis

EEG and fNIRS signal processing was performed offline using *MATLAB* 2017a and *g.BSanalyze* (g.tec medical engineering GmbH). The data (EEG and fNIRS) of three sessions was merged, which lead to 60 trials per subject. The fNIRS raw signals of optical densities were converted into concentration changes of oxy-hemoglobin (HbO) and deoxy-hemoglobin (HbR) by applying Modified Beer-Lambert Law [12] [15]. These signals were then down sampled from 250Hz to 10 Hz and then the data was offset corrected. All fNIRS channels were used for further signal processing. The HbO and HbR signals were then low-pass filtered by applying a 3rd-order recursive Butterworth filter with a cut-off frequency of 0.2 Hz to reduce the physiological noise due to respiration, Mayer waves and heart pulsation. Epochs of 42 s from the data with 12 and 20 s of baseline before and after task were extracted for each trial. After that, baseline correction was performed by subtracting the average from -12 s to -2 s (relative to trial onset), followed by a detrending stage. For classification of right- and left-hand grasping movements, mean and slope of HbO and HbR concentration changes were extracted using a moving time window of 3 s and step size of 1 s. A linear discriminant analysis (LDA) [16] was used as a classifier. Validation was performed by 10 repetitions of 10-fold cross-validation at each time window for both HbO and HbR.

EEG signals were filtered in the μ- and β-band using a 4th-order recursive Butterworth bandpass filter from 8-25 Hz. Epochs were extracted the same way as fNIRS epochs were extracted. The data from -12 s to -2 s (relative to task onset) was subtracted from the EEG signals for baseline correction. To reduce dimensionality and maximize spatial discriminability, the EEG signals were projected onto the four most discriminative Common Spatial Patterns (CSPs) [17], which were computed for each subject individually. After this spatial filter, the feature vector was developed by calculating the variance by using the same moving window and step size as used for the fNIRS features. The extracted EEG features then were normalized and log-transformed. For evaluating the performance, a randomized 10 repetitions of 10-fold cross-validation were applied on all datasets. All processing steps were subject to cross-validation.

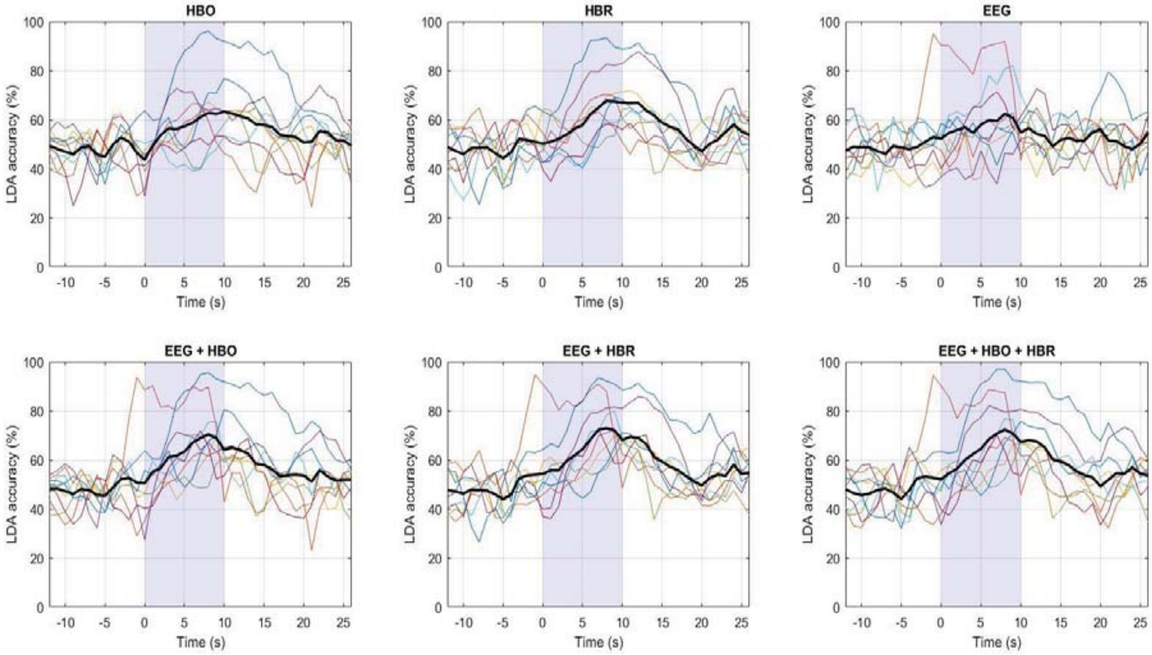

Fig 3. Classification accuracy plots of all subjects. The black line indicates the mean accuracy at different time points for all the subjects. The grey shaded region shows the task time period (0-10 s). The time is given relative to the task onset.

The main challenge in the study was to combine different classifiers. Many studies have shown results by combining feature vectors of different modalities together for example, in [15], LDA was applied as a meta classifier in which weights of the classifier were re-estimated within each cross-validation step, [18] fused all the features of EEG and fNIRS together and applied PCA for dimensionality reduction and [19] used shrinkage LDA as a meta classifier and output of individual classifiers were combined to create feature vectors for meta-classifier. We explored all the possible combinations of EEG and fNIRS i.e. EEG + HbO, EEG + HbR, EEG + HbO + HbR. There are various methods for combining classifier such as majority voting rule, median rule, average rule and many more [20]. In this study, we applied meta classifier based on decision method. The class probability was computed by applying weights in the case of LDA (EEG, HbO and HbR). The class with maximum probability was then selected as the result of the meta classifier. Please note that we gave equal weights to EEG and fNIRS chromophores in meta classification. The cross-validation of the meta-classifier also followed the same approach of cross-validation as for fNIRS and EEG data analysis. The results from the individual classifiers: HbO, HbR, EEG and the combination of these classifiers are summarized in the next section.

III. Results

A. Classification Accuracies

The classification accuracies were calculated for EEG, HbO, HbR, HbO + HbR, HBO + EEG and HbO + HbR + EEG, respectively. The results are summarized in Table 1. Accuracies are given as the percentage of correctly classified trial in the test set. The chance level for this two-class experiment is 50 %.

Subject	HBO [%]	HBR [%]	EEG [%]	HBO + EEG [%]	HBR + EEG [%]	HBO + HBR + EEG [%]
S1	96.7	93.4	79.5	95.5	93.5	97.0
S2	65.0	70.3	62.8	63.3	72.3	79.1
S3	73.7	72.7	57.8	73.2	71.8	71.7
S4	74.2	87.8	53.5	71.8	85.7	86.5
S5	63.0	64.8	60.7	60.8	67.0	67.3
S6	64.7	63.8	83.3	75.7	80.0	81.8
S7	55.8	60.8	73.5	71.8	72.6	70.1
S8	76.8	69.0	64.5	80.5	71.2	75.7
S9	70.7	62.2	95.2	93.7	94.7	94.3
Average	**71.2**	**71.6**	**70.0**	**76.2**	**78.7**	**80.0**

Table 1. Overview of all classification accuracies corresponding to different approaches.

Using only a single biosignal for classification (i.e., HbO, HbR, or EEG individually), the subjects S1, S3, and S8 showed the highest classification accuracy using HbO, the subjects S2, S4, and S5 showed the highest accuracy using HbR, and the subjects S6, S7, and S9 showed the highest classification accuracy using EEG.

By combining HbO and HbR with EEG, three different approaches were taken. The subject S8 scored the highest accuracies by combining HbO + EEG, two subjects S2 and S6 scored the highest accuracies using HbR + EEG and the subject S1 scored the highest accuracies by combining HbO + HbR + EEG. S7 exhibited approximately the same accuracies by implementing HbO + EEG and EEG + HbR, the subjects S4 and S5 showed almost the same maximum classification accuracies using HbR + EEG and HbO + HbR + EEG. In fig. 3, the individual classification accuracy plots of all the subjects are shown with different colors and the average classification accuracy considering all the subjects is shown with a thick black line for different modalities and their combinations. The plots show that combining all three modalities (EEG + HbO + HbR) yields higher amplitudes as compared to their individual classification accuracy plots. The results highlight that the hybrid approach in BCI has ability to enhance the BCI performance.

IV. Discussion

In this study, signal acquisition methods based on fNIRS and EEG were combined to test if a higher classification accuracy can be yielded using the combined modalities. A hybrid BCI which uses features of both biosignals was used to classify the brain activity while participants were performing a motor imagery task for right- and left-hand movement.

In the past, several studies have demonstrated that combining fNIRS and EEG enhances the performance of MI-based BCI systems [15], [16]. Here, we investigated the best combination of features for controlling a hybrid BCI. The results showed that EEG and fNIRS features yield similar results individually (~70%). However, as shown in Table 1, combining the features of both modalities lead to higher accuracies on average compared to using the modalities independently. On average, the accuracy of the hybrid system using HbR, HbO, and EEG was higher than using any subsystem of fNIRS and/or EEG. The relatively weak performance of the EEG classifier may be attributed to the small number of EEG channels. In this setup, 21 EEG electrodes were used, which is fewer than other studies [16].

All subjects except S9 were naïve to the MI attempt. The inexperience could also have an influence on the performance results. Another factor that could have impaired the performance of the EEG classifier is the low number of trials. In particular, this could have negatively influenced CSP, which is an approach deeply affected by overfitting. Being a supervised approach that makes use of labelled data, the limited amount of training data is an important role as only 54 out of 60 trials available for performance evaluation due to the 10-fold cross-validation. The number of 60 trials was chosen due to time management. One session of 20 trials lasted 20 minutes which was long for the concentration of the subjects. We acknowledge that it is a relatively small number compared to other studies [21].

In the results it is shown that S6 and S9 had lower performance when combining modalities than with EEG alone. This small difference could be due to the average calculation of 10 repetitions of 10-fold cross-validation as the two accuracies are nearly identical and only vary in approx. 1-2%.

One of the main disadvantages using this hybrid BCI is the long time it takes to set up both modalities [15]. Dry electrodes may provide an interesting alternative to overcome this issue [22]. Also, the long trial duration of 42s is problematic as it is difficult to maintain the concentration level over such a long period of time. More research is necessary to reduce the recording time.

In Fig. 3, it can be seen that the evolution of the classification accuracy over time depends on the modality. These are important observations for further studies and particularly for implementation of online feedback and classification.

V. Conclusion

In this study, a hybrid BCI using fNIRS and EEG biosignals was investigated. It was found that combining fNIRS and EEG features for classification enhances the performance of the BCI. In future studies, real-time systems using fNIRS-EEG hybrid BCIs will be investigated.

VI. CONFLICT OF INTEREST

AH, PR, CG, JG are employees of g.tec medical engineering GmbH, Austria. The other authors don't declare a conflict of interest.

VII. Acknowledgments

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