On the Effects of Pain on fNIRS Classification

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Abstract: We present the first study of the effects of pain on the classification of fNIRS recordings, and evaluate the performance of a model trained on the pain-free data for classifying the data with the presence of pain.

1. Introduction

Functional near infrared spectroscopy (fNIRS) is a non-invasive neuroimaging technique, which indirectly measures brain activities through monitoring the changes in the concentration of the cerebral oxygenated hemoglobin ([ΔHbO]) and deoxygenated hemoglobin ([ΔHbR]) [1]. Recently, there has been a growing interest in using fNIRS in brain computer interfaces (BCIs). The goal of a BCI is to convert signals recorded from the brain into commands for controlling external devices [2, 3]. Therefore, accurate classification of brain signals is of a great interest in BCI applications. On the other hand, a group of BCI users are patients (e.g. those with motor disabilities) that unfortunately could also suffer from pain due to their injuries. The presence of pain however, is expected to influence brain activities, which could consequently impact the performance of BCIs.

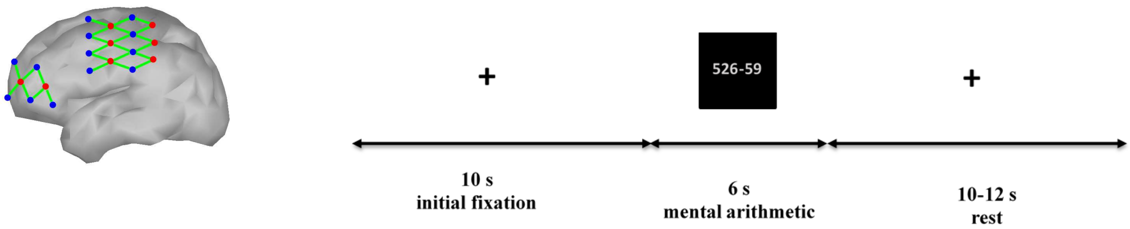
In this study, we investigate how the presence of pain affects the classification accuracy of fNIRS data corresponding to a mental arithmetic task, for the first time. fNIRS data is collected from 2 healthy subjects, and thermal stimulation is used to induce pain. The mean of the [ΔHbR] signal from all channels is used as the feature for classification. A Support Vector Machine classifier with quadratic kernel (QSVM) is employed to classify the data. Our classification results demonstrate that the average classification accuracy for a model that is trained based on pain-free data, is significantly reduced when tested on the data obtained in the presence of pain. These results suggest that a BCI algorithm which is trained and developed using pain-free data, might perform poorly in the presence of pain. Therefore, it is important to consider the pain factor for adapting a BCI algorithm for patients. The rest of the paper is organized as follows: The experimental paradigm and the data collection procedures are described in Section 2. Pre-processing and classification methods are explained in Section 3, and results and discussions are presented in Section 4.

2. Experimental Design

Two healthy right-handed subjects participated in the experiment. Written informed consents approved by the Rutgers' Institutional Review Board (IRB) were obtained prior to the experiments. fNIRS signals were recorded via NIRx System (NIRScout, NIRx Medical Technologies, LLC, wavelengths of 760 nm and 830 nm) at a sampling rate of 10.41 Hz. Sixteen sources and twenty-four detectors were placed over the prefrontal and motor cortices resulting in a total of 50 channels (Fig. 1-a, the same configuration was used on the other hemisphere). Pain was induced through applying heat to the skin (via TSA-II from Medoc). The pain threshold and tolerance in subjects were measured prior to fNIRS recording sessions, and the average of threshold and tolerance temperatures was considered as the pain temperature (average over subjects = $46.4°C$). The fNIRS experiment included 5 pain-free and 5 pain blocks that were implemented in random orders. In each block, subjects were instructed to perform mental arithmetic tasks shown on the screen (mental subtraction of a two-digit number from a three-digit number, or counting backward starting from a two-digit number). During the pain blocks, the subjects were exposed to the thermal pain while they were performing the mental arithmetic tasks. Each trial consisted of 6 sec post-stimulus mental arithmetic interval followed by a rest interval of $10-12$ sec (see Fig. 1-b). In each block, 13 trials of each class (subtraction/backward counting) were performed by each subject (65 trials for each class).

3. Method

fNIRS data from $[-1, 6]$ sec interval, where 0 is the stimulus onset, was selected from each trial and pre-processed using nirsLAB [4]. The data was first corrected for drifts and artifacts and then filtered using a $[0.01, 0.2]$ Hz band-pass filter to remove the cardiac signal and low-frequency oscillations. Using the modified Beer-Lambert law [1], the filtered optical intensity data was converted to the [ΔHbO] and [ΔHbR]. For each trial, the data was then baseline corrected by subtracting the baseline from the original data. The baseline was considered the average of 1 sec of the signal before the onset of the stimulus.



(a) (b)

Fig. 1: (a)- Optodes placement and channel configuration covering prefrontal and motor cortices (red circles: sources, blue circles: detectors,green lines: channels), (b)- visual illustration of a single trial.

For each interval, the features were considered as the mean of the [ΔHbO], for all channels, and was extracted from the interval of $[0-6]$ sec. The signal mean was calculated for 1 sec windows (vectors of 50×1 size). Extracted features from all trials were separated into two randomized groups for training (75%) and testing (25%). A QSVM classifier with 5-fold cross validation was employed for the classification.

4. Results and Discussions

Three classification problems were considered: Case 1- the classifier is trained and tested under the pain-free condition, Case 2- the classifier is trained under the pain-free condition and tested on the pain data, and Case 3- the classifier is trained and tested using pain data. Results for classification accuracy for these three cases are summarized in Table 1.

Table 1: Classification accuracies of mental arithmetic tasks.

	Case 1	Case 2	Case 3
Subject 1	88.15 ± 2.80	50.23 ± 3.54	87.22 ± 2.64
Subject 2	86.73 ± 2.52	47.48 ± 3.87	84.31 ± 2.99
Average	87.44 ± 2.66	48.85 ± 3.71	85.76 ± 2.82

An average classification accuracy of 87.44% is achieved for the normal pain-free condition (Case 1: trained and tested on no pain data). However, when the same classifier model was used to discriminate the pain data (Case 2), the average accuracy is significantly decreased (48.85%). This result suggests that the model that was trained on the pain-free data is not suitable for classification of the pain data. On the other hand, using the classifier that was trained with the pain data leads to the average accuracy of 85.76% when tested on the pain data (Case 3). Therefore, it can be concluded that the added pain results in alteration of brain activities which makes the models that are trained under pain-free conditions, ineffective in classification of neural signals under the pain condition. However, the classification results for Case 3 shows that we can overcome this problem by training the classifier under the pain condition where the changes of the brain activities associated with the pain are taken into account. The results of this study emphasize the significance of considering the pain condition in the development BCI algorithms in order to accommodate the technology for the specific users, and address their special needs. To the best of our knowledge, this is the first work that studies the effects of pain on the classification of fNIRS recordings associated with mental tasks. Our future works involves considering other feature extraction algorithms and find features which are more robust to the pain condition.

Acknowledgement

This work was supported by the NSF (award 1841087).

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