Multi-class Classification of Motor Execution Tasks using fNIRS

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Abstract— This paper investigates the problem of classification of multi-class movement execution tasks from signals obtained via functional near infrared spectroscopy (fNIRS). fNIRS data is acquired from five healthy subjects while performing four types of motor execution tasks as well as a non-movement task (five classes in total). Various feature sets are extracted based on the mean of changes in the concentration of oxygenated hemoglobin ([ΔHbO]) signals computed across the $[0-2]$, $[1-3]$, and $[2-4]$ sec intervals. A multi-class support vector machine classifier with a quadratic polynomial kernel (QSVM) is utilized to classify movement and non-movement classes (total of 5 classes) using the data from the three time intervals. Classification results revealed that the average accuracy obtained for data using $[2-4]$ sec interval is higher than the other two (78.55%). In addition, a comparison between the classification results of the data obtained from only the motor cortex vs from multiple regions of the brain is done. Our results demonstrate that by using fNIRS data from different regions of the brain, the classification accuracy is improved by $10-12\%$ as compared to the case when the data is used only from the motor region.

I. Introduction

Functional near infrared spectroscopy (fNIRS) is an emerging non-invasive brain imaging technique which measures changes in the concentration of the cerebral oxygenated hemoglobin ([ΔHbO]) and deoxygenated hemoglobin ([ΔHbR]) [1]. Because of its advantages such as low cost, portability, and relatively high spatial resolution, fNIRS has been considered as a promising non-invasive method for monitoring brain activities in various neuroscience and neuroengineering domains including brain computer interfaces (BCI). The goal of a BCI is to directly convert signals recorded from the brain (e.g. related to user's intention) into commands for controlling external devices to, for example, provide assistance for patients with severe motor disabilities. Hence, accurate classification of signals for discriminating various forms of user's intentions is of a great importance in BCI applications.

fNIRS-based BCIs employ classification to decode the changes in the cerebral concentration of the HbO and HbR related to brain activities. Several research studies have been devoted to using fNIRS in BCI applications. Two main classes of activities used in fNIRS-based BCIs are movement-related activities such as motor execution and imagery [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], and mental activities such as mental arithmetic, object rotation, and mental counting [15], [16], [17], [18], [19], [20], [21], [22], [23], [24]. In [25], [26], [27], both movement-related and mental activities have been considered. In most of these studies, fNIRS signals corresponding to the movement-related and mental activities, have been recorded from the motor and prefrontal cortices, respectively.

An important challenge in the development of the classification algorithms for BCI applications is the number of commands that can be extracted from neural recordings. BCI systems capable of discriminating larger number of tasks are of great interest. Most studies of motor execution/imagery tasks, have only considered binary classification problems [2], [3], [5], [6], [7], [8], [9], [11], [12], [13], [14] . In [4], classification of 2, 3, and 4-class motor execution tasks were investigated, and an average accuracy of 82.5% was reported for the 4-class problem. In [10], 2 and 4-class classification problems were studied for motor imagery tasks where 40.55% average classification accuracy was achieved for the 4-class case.

In this paper, we focus on the classification problem for movement-based tasks as they provide a more natural way for controlling external devices in BCI applications. Four different motor execution tasks and one non-movement task are considered. To the best of our knowledge, this is the first fNIRS study that performs the multi-class classification for 5 motor-related activities. Unlike most existing works, where fNIRS channels are placed in specific regions on the cortex, in our study, fNIRS channels are placed across various regions of the brain including the prefrontal, motor, parietal, and occipital cortices. The mean of [ΔHbO] signals is used to extract features for the classification problem, and a multi-class support vector machine algorithm with a quadratic polynomial kernel (QSVM) is employed as the classifier.

Two major issues exist in extracting a proper set of features from fNIRS recordings: 1) determining the fNIRS time window over which the features are extracted from, and 2) the location of the fNIRS channels where the data is recorded from. In this paper, we investigate these two issues. First, we present the accuracy results for various sets of features obtained from data corresponding to different time intervals of fNIRS recordings. The accuracy results are compared to determine the best time interval that results in the highest accuracy. Second, we evaluate the classification accuracy using the data obtained from several

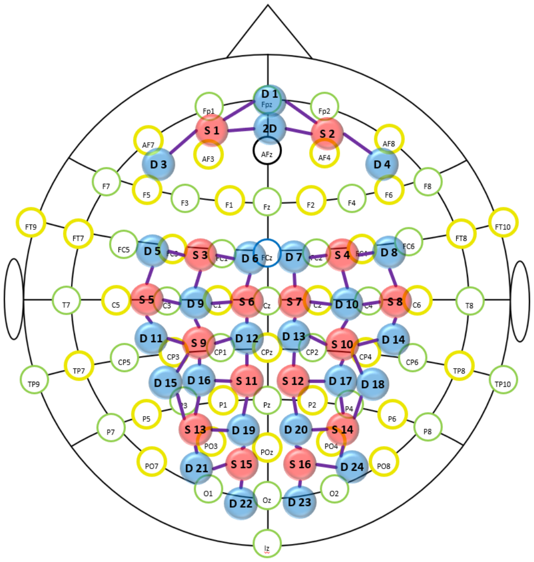

Figure 1. Optodes placement and channel configuration covering pre-frontal, motor, parietal, and occipital cortices following the $10-20$ EEG system (red circles: sources, blue circles: detectors, purple lines: channels).

regions of the brain, and compare the results to the case in which the data is obtained only from the channels located over the motor cortex.

The rest of the paper is organized as follows. The experimental paradigm, and the data collection, pre-processing, and classification procedures are described in Section II. Results and discussions are presented in Section III, and the paper is concluded in Section IV.

II. Methods

A. Experimental Setup

Five healthy subjects aged between $19-35$ 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 7.81 Hz. Sixteen sources and twenty-four detectors were placed over the prefrontal, motor, parietal, and occipital cortices resulting in a total of 54 channels. A source-detector separation of 3 cm was considered. Using this distance ensures that the photons reach the cortex [28], [29]. The map of location of sources (red circles) and detectors (blue circles) and their corresponding channel locations, with respect to the standard $10-20$ electroencephalography (EEG) system, is shown in Figure 1.

The experiment included 3 blocks of dictated motor execution tasks. In each block, subjects were instructed to move a square from the center of the screen towards one of four (up, down, left, and right) directions using a joystick if there was an arrow inside the square pointing to the corresponding direction, or do nothing (center) if there

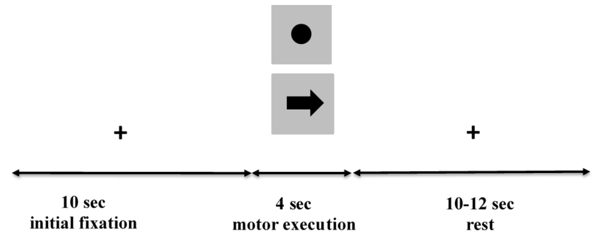

Figure 2. Visual illustration of a single trial.

was a circle inside the square. Each trial consisted of 4 sec post-stimulus motor execution interval followed by a rest interval between 10 and 12 sec (see Figure 2). In each block, 15 trials of each class (directions/center) were performed by each subject (45 trials for each class in total).

B. Pre-processing

fNIRS data from $[-1, 4]$ sec interval, where 0 is the stimulus onset, was selected from each trial, and was pre-processed using nirsLAB [30]. First, data was corrected for drifts and artifacts, then it was filtered using a $[0.01, 0.2]$ Hz band-pass filter to remove the cardiac signal and low-frequency oscillations. Using 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.

C. Feature Extraction and Classification

Features were extracted from intervals of $[0-2]$, $[1-3]$, and $[2-4]$ sec. For each interval, the features were considered as the mean of the [ΔHbO], for all channels. The signal mean was calculated for 1 sec overlapping windows with 50% overlaps (vectors of 54×1 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 then used for the classification. 2-sec length intervals were selected in order to evaluate the classification results using short duration of the recorded data, as compared to other studies that have mostly extracted features from longer intervals (≥ 5 sec) [2], [3], [5], [6], [7], [8], [9], [11], [12], [14].

III. Results and Discussions

Feature extraction and classification presented in Section II were applied to the fNIRS data for the "up", "down", "left", and "right" movements, and the non-movement classes (a total of 5 classes) using features extracted from various intervals. Accuracy results for all subjects are shown in Table I. Moreover, the confusion matrix for the classification using features extracted for the interval of $[2-4]$ sec for an arbitrary subject (Subject 1) is shown in Figure 3.

Comparing the classification accuracy results using features extracted from different intervals, it is observed that for all subjects the accuracy achieved from data obtained over the

Table I
CLASSIFICATION ACCURACY RESULTS FOR MOVEMENT DIRECTIONS OF "UP", "DOWN", "LEFT", "RIGHT", AND NON-MOVEMENT (5 CLASSES) USING FEATURES EXTRACTED FROM DIFFERENT POST-STIMULUS INTERVALS. DATA FROM ALL CHANNELS IS USED.

	$[0-2]$ sec	$[1-3]$ sec	$[2-4]$ sec
Subject 1	72.37 ± 4.51	76.32 ± 2.96	78.73 ± 2.99
Subject 2	74.33 ± 3.38	78.85 ± 3.11	80.75 ± 4.36
Subject 3	69.64 ± 3.61	74.16 ± 4.06	75.83 ± 5.01
Subject 4	74.91 ± 4.58	79.85 ± 3.42	81.27 ± 3.46
Subject 5	69.01 ± 3.21	74.43 ± 3.91	76.19 ± 4.09

Table II
CLASSIFICATION ACCURACY RESULTS FOR MOVEMENT DIRECTIONS OF "UP", "DOWN", "LEFT", "RIGHT", AND NON-MOVEMENT (5 CLASSES) USING FEATURES EXTRACTED FROM DIFFERENT POST-STIMULUS INTERVALS. DATA FROM MOTOR CHANNELS IS USED.

	$[0-2]$ sec	$[1-3]$ sec	$[2-4]$ sec
Subject 1	57.92 ± 3.81	61.14 ± 3.51	65.06 ± 3.48
Subject 2	65.09 ± 3.56	68.91 ± 3.19	68.31 ± 4.68
Subject 3	60.11 ± 4.29	63.06 ± 3.25	62.88 ± 3.77
Subject 4	64.19 ± 3.97	69.01 ± 3.29	70.44 ± 3.62
Subject 5	58.72 ± 4.06	62.08 ± 3.27	64.55 ± 4.05

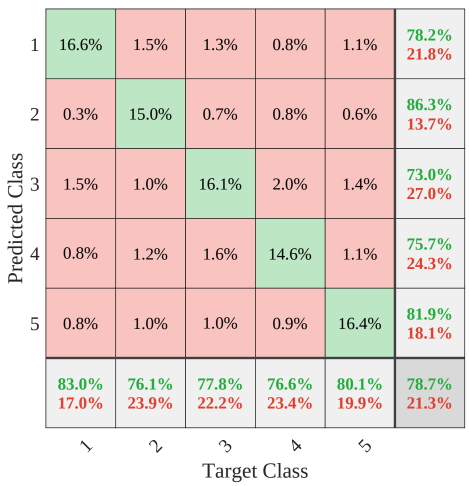

Figure 3. Confusion matrix of classification for an arbitrary subject (Subject 1) using features extracted from $[2-4]$ sec interval. Data from all channels is used.

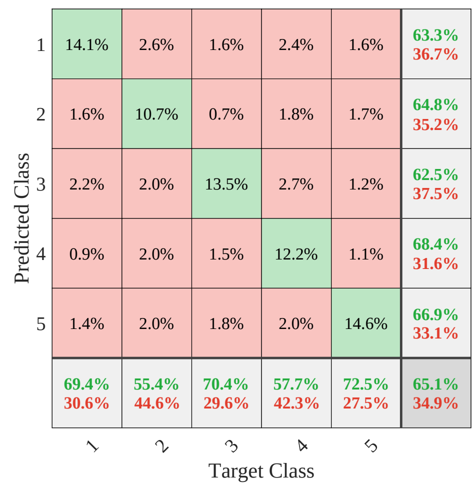

Figure 4. Confusion matrix of classification for an arbitrary subject (Subject 1) using features extracted from $[2-4]$ sec interval. Only data from motor channels is considered.

$[2-4]$ sec interval is higher than the accuracy obtained from data over $[0-2]$ and $[1-3]$ sec intervals.

To investigate the effects of using data from all channels (as opposed to only those placed on the motor cortex) on classification results, classification was also performed considering only the data obtained from the channels placed over the motor cortex. The classification results for all subjects and using the features extracted from various intervals are summarized in Table II. In addition, the confusion matrix of the classification using the features extracted from the $[2-4]$ sec interval for Subject 1 is shown in Figure 4. Similar to the case of using all channels, the highest classification accuracy is achieved for the interval of $[2-4]$.

Table III provides the comparison of the average classification accuracy over all subjects for different intervals, and using two sets of channels (i.e. all channels vs only the motor cortex channels). Using the data from motor channels, the results for average classification accuracy achieved across all subjects were 61.21%, 64.84%, and 66.2% for the $[0-2]$, $[1-3]$, and $[2-4]$ sec intervals, respectively, whereas in the case of using all channels the results for accuracy are increased by $10-12\%$. The data from all channels and $[2-4]$ sec interval give the highest average accuracy of 78.55%.

Table III
AVERAGE CLASSIFICATION ACCURACY RESULTS FOR MOVEMENT DIRECTIONS OF 'UP", "DOWN", "LEFT", "RIGHT", AND NON-MOVEMENT (5 CLASSES) USING FEATURES EXTRACTED FROM DIFFERENT POST-STIMULUS INTERVALS. DATA FROM TWO SETS OF CHANNELS (ALL CHANNELS AND ONLY MOTOR CHANNELS) IS USED.

	$[0-2]$ sec	$[1-3]$ sec	$[2-4]$ sec
All Channels	72.05 ± 3.90	76.72 ± 3.52	78.55 ± 4.04
Motor Channels	61.21 ± 3.95	64.84 ± 3.30	66.25 ± 3.94

To the best of our knowledge, this is the first work on the multi-class classification for 5 activities corresponding to motor execution tasks using fNIRS recordings. Previous fNIRS studies of classification of multi-class movement-related tasks have reported the average accuracy of 82.5% ([4]) and 40.55% ([10]) for 4 classes. In [4], fNIRS data was recorded from 8 channels over the motor cortex, and in [10], 32 channels over the prefrontal cortex were used. In this study, we designed an fNIRS cap with 54 channels over the prefrontal, motor, parietal, and occipital regions to record the fNIRS signals from multiple regions of the brain. Using the data from all channels, an average classification accuracy of 78.55% was achieved across all subjects during the $[2-4]$ post-stimulus interval for 5-class motor execution tasks. This result gives about 12% improvement in accuracy comparing to the case of using channels only from the motor cortex. This finding suggests that the data from brain regions other than the motor cortex contain useful discriminatory information for motor-related tasks, and therefore, should be considered in classification. One possible explanation for this observation is that various brain regions are involved in the planning and performing of motor execution tasks [31], [32]. Moreover, the classification results from three different post-stimulus intervals of $[0-2]$, $[1-3]$, and $[2-4]$ sec, demonstrated that the best accuracy was obtained by using data from the $[2-4]$ sec interval. This might be due to the inherent delays in the hemodynamic response with respect to neural activities, which naturally makes the data from later intervals more informative in terms of differentiation between various brain activities. For instance, in [33], the classification of three mental tasks was performed for the data extracted from two intervals of $[0-2.5]$ and $[2-7]$. The average classification accuracy for $[2-7]$ window was about 10% higher (65.9%) than the $[0-2.5]$ window (57.5%). It is worth mentioning that higher accuracy results can possibly be achieve by using the data from longer intervals. However, as one of the important challenges in improving the practicality of fNIRS-based BCIs has been reducing the computational lag, in this study, we aimed to investigate the classification results using the data from short intervals.

IV. Conclusion and Future Work

In this paper, the classification problem for multi-class motor execution tasks was considered. This study pursued two goals: investigating the effects of using different time intervals of fNIRS data in a trial on the classification accuracy, and examining if using data from different locations of the brain can improve the classification results in contrast to using the data only from the motor cortex (commonly used in the motor-related classification problems). To achieve these goals, we employed a QSVM classifier, with the mean of [ΔHbO] signals as features. Classification accuracy results were computed for different post-stimulus intervals ($[2-4]$ sec intervals of $[0-2]$, $[1-3]$, and $[2-4]$ sec). Results showed that the highest average accuracy was achieved using the $[2-4]$ sec interval (78.55%). To study the effects of using data from different regions of the brain on the classification performance, two sets of the data, one from the prefrontal, motor, parietal, and occipital regions, and another from only the motor region, were considered. The obtained average classification accuracy results improved by $10-12\%$ when using the data from different regions rather than just using data from the motor channels. Future work involves considering other feature extraction and classification algorithms to find the optimal choices for feature sets to achieve better classification performance.

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