Single-trial classification of NIRS data from prefrontal cortex during working memory tasks

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***Abstract*—This study presents single-trial classification performance on high density Near Infrared Spectroscopy (NIRS) data collected from the prefrontal cortex of 11 healthy subjects while performing working memory tasks and idle condition. The NIRS data collected comprised a total of 40 trials of n-back tasks for 2 difficulty levels: n=1 for easy and n=3 for hard. The single-trial classification was performed on features extracted using common average reference spatial filtering and single-trial baseline reference. The single-trial classification was performed using 5×5-fold cross-validations on the NIRS data collected by using mutual information-based feature selection and the support vector machine classifier. The results yielded average accuracies of 72.7%, 68.0% and 84.0% in classifying hard versus easy tasks, easy versus idle tasks and hard versus idle tasks respectively. Hence the results demonstrated a potential feasibility of using high density NIRS-based BCI for assessing working memory load.**

I. INTRODUCTION

Working memory refers to the limited capacity system that is temporarily maintained in our brain to store information in order to support our thought processes by providing an interface between perception, long-term memory and action [1]. Working memory is vital in a wide range of cognitive functions, and its impairment is observed in a wide range of psychiatric or neurological disorders, making it clinically important [2]. There were evidences in humans and mice that working memory training improves general cognitive ability [3]. There were also evidence that training working memory impacted the structural connectivity of the brain, thus underlaid improvement of working memory capacity, cognitive functions, and altered functional activity following working memory training [4].

In studies of Near Infrared Spectroscopy (NIRS)-based Brain-Computer Interface (BCI), the detection of left and right motor imagery from hemodynamic responses was first demonstrated in [5], and later in [6], [7]. Besides the use of NIRS-based BCI for motor imagery, studies have also shown that other cognitive tasks, such as performing mental arithmetic, generally resulted in an increase of oxyhemoglobin associated with a decrease of deoxyhemoglobin in the prefrontal cortex [8]. The feasibility of using a low density 16 channels NIRS-based BCI for assessing level of numerical cognition was demonstrated in [9], [10]. Recently, a multi-modal NIRS and fMRI study had shown that NIRS can be used to measure hemodynamic signal from prefrontal cortex activation during working memory task [11].

Single-trial analysis of NIRS data for mental arithmetic tasks were presented in [12], [13], and single-trial NIRS data for working memory was recently presented in [14]. This study presents a single-trial analysis on the classification performance of high density NIRS data collected from the prefrontal cortex of 11 healthy subjects in order to further investigate the feasibility of using NIRS-based BCI for assessing working memory load.

II. METHOD

This section describes the experiment that collected high density NIRS data during working memory tasks, the computation of the hemodynamic responses from the NIRS data collected, and the feature extraction and selection method used in the study.

A. NIRS data collection

The data was collected from 11 healthy subjects recruited from staffs and students of the Brain-Computer Interface laboratory in the Institute for Infocomm Research, A*STAR. Ethics approval and informed consent were obtained.

The NIRS data was collected using the DYnamic Near-Infrared Optical Tomography (DYNOT) Imaging System (NIRx Medizintechnik GmbH, Berlin, Germany) with wavelengths 760 and 830 nm, sampling rate 1.81 Hz, using 32 co-located optodes that served as source and also detector on the prefrontal cortex of the subject's head as shown in Figure 1(a). The optodes were fixed on the prefrontal cortex using an open scaffolding structure with individually spring-loaded fibers to ensure stable optical contact. The setup measured 32 channels from 32 detectors for each source for each wavelength, and this dense fiber grid setup yielded a total of 1024 channels for each wavelength. However, only 372 channels for each wavelength with source and detector distances between 1.5 to 3.5 cm measured using the Xensor digitizer for each wavelength were used in this study.

During the NIRS data collection, the subjects were seated in a comfortable chair in a room with normal lighting. They were instructed to relax, minimize movement, and to respond as quickly and as correctly as possible by pressing a key on the keyboard.

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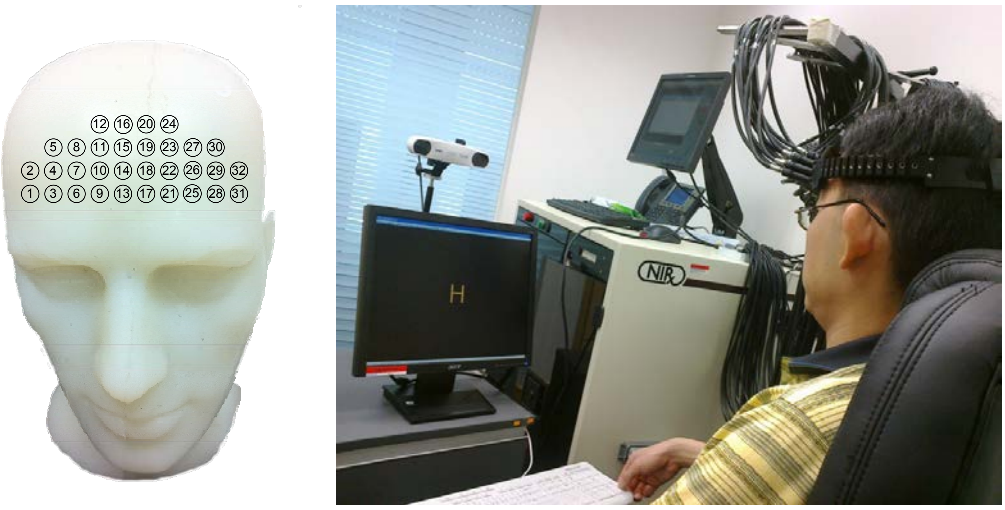

(a) (b)

Figure 1. (a) NIRS data are collected using 32 co-located source and detectors over the prefrontal cortex. (b) NIRS data collection setup whereby the n-back working memory training task is presented to the subject on the screen and the answer is captured using a keyboard.

The subjects underwent a total of 40 trials of *n*-back working memory training tasks that were evenly distributed into 2 difficulty levels of easy and hard. The subject was instructed to monitor a series of stimuli and to respond whenever a stimulus was the same as the n^{th} previously presented stimuli, where n was set to 1 for the easy task and 3 for the hard task. This *n*-back working memory task requires on-line monitoring, updating, and manipulation of remembered information and is therefore assumed to place great demands on a number of key processes within working memory [15].

At the start of each trial, the subject was instructed on the screen to respond to 1 or 3-back task for 5 s. For each trial, a stimuli list of a total of 20 stimuli was constructed from 21 consonant uppercase alphabets. Each trial comprised of 4 situations whereby the current stimuli corresponded to the previous or 3rd previous stimulus for the 1-back or 3-back task respectively. Each stimulus in the stimuli list was presented for 2 s, and each trial lasted 5 + 20×2 = 45 s. A period of 20 s rest condition was given between each trial. The response from the subject was evaluated during each trial, and correct or wrong responses were tracked and displayed on the screen. The 40 trials of data from each subject were collected in two separate recordings that comprised 20 trials each, and each run lasted approximately 22 minutes with an inter-run break of 5 minutes.*NIRS data processing*

Let the optical density for wavelength λ from a channel c be OD_c^{λ}. The normalized change in optical density $\Delta\overline{\mathrm{OD}}_c^{\lambda}$ was computed by dividing each time sample with the mean of the optical signal acquired for the entire session. Next, $\Delta\overline{\mathrm{OD}}_c^{\lambda}$ was low-pass filtered using Chebychev type II filter with a cut-off frequency of 0.14 Hz and pass-band attenuation of 0.02 dB. The low cut-off frequency was chosen relative to the low sampling rate. Linear-detrending was then performed to remove the drift (low frequency bias) in the NIRS data due to subject movement, blood pressure variation, or instrumental instability [16]. After filtering and detrending, unity was added to bring the mean of the optical density to unity instead of zero. The optical density changes were represented as $\Delta\mathrm{OD}_c^{\lambda}$ after these preprocessing steps.

C. Computing hemodynamic responses

The optical density changes of the two wavelength ($\Delta\mathrm{OD}_c^{\lambda_1}$, $\Delta\mathrm{OD}_c^{\lambda_2}$) were converted to changes in HbO_2 ($\Delta[HbO_2]_c$) and HB ($\Delta[Hb]_c$) by solving [6]

$$\begin{bmatrix} \Delta[\mathrm{HbO}_2]_c \\ \Delta[\mathrm{Hb}]_c \end{bmatrix} = \left(\mathbf{E}^T\mathbf{E}\right)^{-1}\mathbf{E}^T \begin{bmatrix} \Delta\mathrm{OD}_c^{\lambda_1} / L^{\lambda_1}\mathrm{DPF}^{\lambda_1} \\ \Delta\mathrm{OD}_c^{\lambda_2} / L^{\lambda_2}\mathrm{DPF}^{\lambda_2} \end{bmatrix}, \quad (1)$$

where

$$\mathbf{E} = \begin{bmatrix} \varepsilon_{HbO_2}^{\lambda_1} & \varepsilon_{Hb}^{\lambda_1} \\ \varepsilon_{HbO_2}^{\lambda_2} & \varepsilon_{Hb}^{\lambda_2} \end{bmatrix}, \quad (2)$$

ε^{λ} is the wavelength-dependent extinction coefficient, L^{λ} is the path length from source to detector, and DPF^{λ} is the differential path-length. In this study, the values of ε^{λ} were obtained from [17], and DPF^{λ} = 6.3 and 6.0 were used for λ = 760 and 830 nm respectively.

D. Feature extraction method

NIRS signals are often dominated by noise and artifacts of both physical and physiological origin, such as subject's movement, heartbeat, respiration effects and other trends [18]. Therefore, the Common Average Reference (CAR) Spatial Filtering [19] was performed on $\Delta[HBO_2]_c$ to further reduce the noise and artifacts that were common in all the

TABLE I EXPERIMENTAL RESULTS ON THE 5×5-FOLD CROSS-VALIDATIONS ACCURACIES IN CLASSIFYING THE SINGLE-TRIAL HIGH DENSITY NIRS DATA ON EASY VERSUS HARD (EVH), EASY VERSUS IDLE (EVI), AND HARD VERSUS IDLE (HVI) TASKS USING THE MIBIF TO SELECT 8, 10, AND 12 OUT OF 686 EXTRACTED FEATURES AND USING THE SUPPORT VECTOR MACHINE (SVM) CLASSIFIER.

	Correct Responses		Overall	8 Features			10 Features			12 Features		
Subjects	1-back	3-back	Responses	EvH	EvI	HvI	EvH	EvI	HvI	EvH	EvI	HvI
CC	77	60	85.6	67.5	59.0	86.0	72.0	61.5	88.5	70.5	64.5	87.5
J	77	70	91.9	70.0	86.5	92.5	73.0	88.5	94.0	67.5	89.0	93.5
KK	78	58	85.0	72.5	88.0	90.0	73.5	89.0	90.0	71.5	90.0	91.5
DL	75	77	95.0	84.0	72.0	82.5	81.5	71.5	82.5	84.0	71.5	81.5
HD	76	60	85.0	78.5	64.0	88.0	76.0	61.5	89.0	73.0	63.5	90.5
A	78	65	89.4	80.5	78.0	87.0	79.5	79.0	86.5	80.0	77.5	87.5
BJ	80	79	99.4	71.5	55.0	87.0	69.0	54.0	86.0	69.5	54.0	87.0
JH	74	68	88.8	58.0	46.0	64.5	57.5	44.5	67.0	56.0	50.5	69.0
DO	80	79	99.4	66.5	56.0	81.5	67.5	51.0	81.5	70.0	48.0	81.5
DK	78	66	90.0	71.5	61.0	77.5	69.5	62.5	79.5	73.5	64.0	78.5
RK	80	71	94.4	79.5	83.0	90.0	82.5	83.0	88.5	80.5	81.5	90.0
Average	77.5	68.5	91.25	72.7	68.0	84.2	72.9	67.8	84.8	72.4	68.5	85.3

channels using

$$\Delta\overline{[\mathrm{HbO_2}]}_c(t) = \Delta[\mathrm{HbO_2}]_c(t) - \frac{1}{n_c}\sum_{j=1}^{n_c}\Delta[\mathrm{HbO_2}]_c(t), \quad (3)$$

and CAR was similarly performed on $\Delta[\mathrm{HB}]_c$.

Subsequently, Single-trial Baseline Reference (SBR) [19] was performed on $\Delta[\mathrm{HBO_2}]_c$ to reduce noise and artifacts in each specific channel using

$$\Delta[\mathrm{HbO_2}]_c = \frac{2}{T}\left(\int_{T/2}^{T}\Delta\overline{[\mathrm{HbO_2}]}_c(t) - \int_{0}^{T/2}\Delta\overline{[\mathrm{HbO_2}]}_c(t)\right), \quad (4)$$

and SBR on $\Delta[\mathrm{HB}]_c$ was similarly performed.

The SBR method first computes the baseline reference for a single trial NIRS data from the average of the first half of the time segment *T*, then subtracts this baseline reference from the next half of the time segment for $\Delta[\mathrm{HBO_2}]_c$ and $\Delta[\mathrm{HB}]_c$ respectively. The extracted feature vector for the i^{th} trial is then formed whereby $\Delta[\mathrm{HBO_2}]_c$ and $\Delta[\mathrm{HB}]_c$ are computed from equation (4).

E. Feature selection and classification

Feature selection was performed to select discriminative features using the Mutual Information-based Best Individual Feature (MIBIF) algorithm [20] on the training data. The MIBIF algorithm required the specification of *k*, the number of features to select. In this study, the MIBIF algorithm was used to select a range of *k*=8, 10, and 12 features, and the Support Vector Machine (SVM) was used to classify the selected features. This values of *k* were chosen to investigate if the number of features has an effect on the classification accuracies.

III. EXPERIMENTAL RESULTS

The performance of single-trial classification on the NIRS data collected from the 11 subjects was evaluated by performing 5×5-fold cross-validations on the easy versus hard (EvH) tasks, easy versus idle (EvI) tasks, and hard versus idle (HvI) tasks. The fixed time segment *T* in equation (4) for classifying the EvH tasks was set to 38 s and for the EvI and HvI was set to 18 s due to the 20 s of rest given between each trial. Table I shows the number of correct subject responses from each subject for the easy 1-back and hard 3-back tasks, the overall accuracies from each subject responses, and the classification accuracies obtained on the features extracted using the method described in section II.D and the MIBIF algorithm to select 8, 10, and 12 features of the EvH, EvI, and HvI tasks.

The total number of subject responses for the 1-back and 3-back tasks were 80 each, since 20 trials were collected for each tasks, and each trial comprised of 4 responses. The overall accuracies from each subject responses were computed based on these correct responses over the total number of responses. The results in Table I showed that the average number of correct responses across subjects was higher for the 1-back task compared to the 3-back task. This showed that the 3-back task is in general more difficult and thus more demanding compared to the 1-back task.

The results in Table I showed that averaged classification accuracies of selecting 8 features for the EvH, EvI and HvI tasks yielded an accuracy of 72.8%, 68.0% and 84.2% respectively across the 11 subjects. The results from selecting 8 features showed a larger variation in the classification accuracies across the subjects for the EvI tasks (±14.2) compared to the EvH (±7.5) and HvI tasks (±7.8). Given that the 95% confidence estimate of the classification accuracy for 40 trials at chance level is in the range of 27.5% to 68.0% using the inverse of binomial cumulative distribution, the single-trial NIRS classification results showed that the 7 out of 11 subjects performed at chance level for the EvI tasks, but only 3 and 1 subjects performed at chance level for the EvH and HvI tasks respectively

Most subjects with good working memory are able handle the 1-back task with ease. The 3-back task by nature demands a higher working memory load since the subjects have to continually adjust the information in their working memory to incorporate the most recent stimulus while simultaneously rejecting or ignoring more temporally distant stimuli [12]. As such, it is postulated that the higher variation in the EvI tasks may be due to less discriminable single-trial NIRS data, which resulted in a larger number of subjects that yielded single-trial classification performance at chance level. In contrast, the results on a lower number of correct responses for the 3-back task showed that more subjects found the task more demanding. The results also showed that there was a lower variation in the classification accuracies across the subjects for the HvI tasks compared to the EvI tasks. As such, it is postulated that the lower variation in the HvI tasks may be due to a more discriminable single-trial NIRS data compared to the EvI tasks, which resulted in a smaller number of subjects that yielded single-trial classification performance at chance level for the HvI tasks.

The results in Table I also showed the averaged classification accuracy across the EvH, EvI and HvI tasks for selecting 8, 10, 12 features were 75.0, 75.2 and 75.4 respectively. Hence the results showed that increasing the number of features selected slightly improved upon the overall classification accuracies, by the improvements are not statistically significant (p=0.645 and 0.414 from paired student's t-test respectively).

IV. Conclusion

This study investigated single-trial classification performance of high density NIRS data collected from the prefrontal cortex of 11 healthy subjects while performing 1-back, 3-back tasks and the idle condition. The classification performance was evaluated using 5×5-fold cross-validations on the easy versus hard (EvH) tasks, easy versus idle (EvI) tasks, and hard versus idle (HvI) tasks. Since different time segments were chosen for the EvH compared to the EvI and HvI tasks, the performance of multi-class classification was not performed.

The results showed higher classification accuracy for HvI compared to EvI tasks, postulated to a more discriminable NIRS signal as a result of increased working memory load in performing the harder 3-back task. In addition, the results showed that the average accuracy across the 11 subjects in classifying the EvH tasks on features extracted using the Common Average Reference (CAR) Spatial Filtering and Single-trial Baseline Reference (SBR) method [19] was around 72%. The result yielded accuracy similar to single-trial classification of NIRS data for numerical cognition [19], albeit slightly lower compared to the results of 78% on single-trial classification of NIRS data for 3 levels of mental workload from 10 subjects in [14]. Hence the results further demonstrated the feasibility of using NIRS-based BCI for assessing working memory load.

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