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## Using EEG and NIRS for brain–computer interface and cognitive performance measures: a pilot study

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**Abstract:** This study addresses two important problem statements, namely, selection of training datasets for online Brain-Computer Interface (BCI) classifier training and determination of participant concentration levels during an experiment. The work also attempted a pilot study to integrate electroencephalograms (EEGs) and Near Infra Red Spectroscopy (NIRS) for possible applications such as the BCI and for measuring cognitive levels. Two experiments are presented, the first being a mathematical task interleaved with rest states using NIRS only. In the next, integration of the EEG-NIRS with reference to P300-based BCI systems as well as the experimental conditions designed to elicit the concentration levels (denoted as ON and OFF states here) during the paradigm, are presented. The first experiment indicates that NIRS can be used to differentiate a concentrated (i.e., mental activity) level from the rest. However, the second experiment reveals statistically significant results using the EEG only. We present details about the equipment used, the participants as well as the signal processing and machine learning techniques implemented to analyse the EEG and NIRS data. After discussing the results, we conclude by describing the research scope as well as the possible pitfalls in this work from a NIRS viewpoint, which presents an opportunity for future research exploration for BCI and cognitive performance measures.

**Keywords:** BCI; brain-computer interface; cognitive performance; EEG; electroencephalogram; NIRS; near infra red spectroscopy; P300.

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## 1 Introduction

Among the numerous possible modalities for measuring brain activity in Brain–Computer Interface (BCI) systems, the scalp electroencephalogram (EEG) (Hoffmann et al., 2007; Palaniappan, 2008) and optical Near Infra Red Spectroscopy (NIRS) (Sitaram et al., 2007; Nagaoka et al., 2010; Coyle et al., 2006) have been popular, since they are non-invasive, simple and comparatively user friendly. Recently, BCI systems are being explored for novel applications like computer cursor control (Wilson and Palaniappan, 2011), authentication (Gupta et al., 2008) and gaming (Lalor et al., 2005) and therefore, gauging participant concentration or motivational levels during the experimental sessions is of great interest. In spite of the rich complementary information provided by concurrent EEG and NIRS recordings, very few research groups have worked on that perspective. So far, studies (Kennan et al., 2002; Hirshfield et al., 2009; Salvatori et al., 2006) have focussed on simultaneous EEG–NIRS recordings in the occipital cortex or around the midline lobes, showing synchronisation of neural and hemodynamic activities during tasks. In Kennan et al. (2002), the authors showed that regions of peak hemodynamic activity are in closest proximity to the areas of peak electrical activity during an auditory oddball paradigm. In Hirshfield et al. (2009), an increase in HbO and a decrease in Hb were reported for oddball stimuli during auditory paradigms, using optodes placed on either side of the midline lobe. The work presented in Salvatori et al. (2006) on concomitant recording of EEG–NIRS highlights that concentration variations directly reflect the increase in blood oxygenation required to support neural activity during a visual stimulus paradigm. In these studies, the EEG electrodes and the NIRS optodes were primarily placed around the visual cortex area

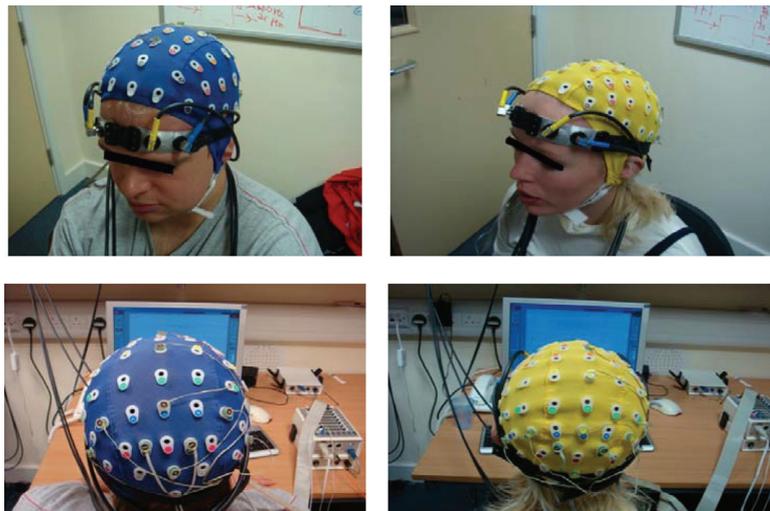
of the brain. Although early attempts to integrate the EEG and NIRS for monitoring brain functions have been made, there is definitely a lot of scope for research in this direction for BCI and cognitive applications.

EEG–NIRS integration could be used to address two applications, namely, selection of training datasets for online BCI classifiers and participant concentration monitoring during an experiment. Selection of training datasets to train a classifier is often a precursor for all online BCI experiments. The performance of an online classification depends entirely on the training dataset used to train the classifier. Factors like level of concentration, fatigue and workload cannot be gauged from EEG data (in standard BCI paradigms) to select the training dataset or monitor participant performance. With this scenario in mind, we embarked on a pilot study to integrate EEG and NIRS to help gauge the participants' levels of concentration while they perform the experiment. NIRS optodes were placed in the frontal cortex (i.e., Brodmann area 10), responsible for memory and executive function, while EEG electrodes responsible for electrical activity during visual paradigms were chosen, as in Hoffmann et al. (2007), around the midline parietal region. To the best of the authors' knowledge, this is a novel approach where concomitant EEG–NIRS recording is used for challenging BCI problems. This integration could be performed for any BCI-based paradigm (such as Donchin's P300, motor imagery, slow cortical potentials, etc.).

## 2 Methodology – signal acquisition, design and participant setup

The design, setup and positioning of EEG electrodes and NIRS optodes are shown in Figure 1. The participants were seated in a chair facing a computer monitor at distance of 70 cm. Automated synchronised recording of multi-modal signals are commonly used, but difficulties in setting a common trigger for the EEG and NIRS devices prompted us to manually employ two BCI researchers to perform the synchronised recording sessions to obtain concurrent EEG–NIRS recordings while the participants were performing the experiment.

**Figure 1** Design, setup and positioning of NIRS optodes (upper half) and EEG electrodes (lower half) (see online version for colours)



### 2.1 EEG data collection

The EEG data were collected with a Biosemi Active Two system using a sampling rate of 256 Hz. Since the purpose of this study was to investigate the integration of EEG with NIRS, the eight optimum channels for BCI reported in Hoffmann et al. (2007) as configuration-II for able-bodied participants were used. Two recorded mastoid channels were used as reference channels, bringing the total number of EEG channels to 10. A Graphical User Interface (GUI) was developed using Visual Basic software and integrated into the Biosemi data logging software. The participants were asked to refrain from blinking during the experiment, which was performed in a room shielded from electromagnetic interference. A short break was given after every session.

### 2.2 NIRS data collection

A multichannel CW-NIRS Instrument from Artinis Medical Systems (Oxymon Mk III) was used for data acquisition. Two sources and two detectors were mounted on a custom designed headgear, made to hold the optodes on the participant's forehead. Each source emits two wavelengths at 764 and 859 nm and the data was recorded at a sampling rate of 10 Hz. The headgear was made of linoleum and holes were punched to hold the optodes 3 cm apart. The distance of 3 cm was selected due to the depth of tissue that NIRS can interrogate, which is dependent on the distance between the source and the detector. A greater separation in size between the source and the detector would result in a greater imaging depth. However, if the separation is greater than 5 cm, the optical signal would weaken and might become unusable (McCormick et al., 1992; Zhang et al., 2007; Gratton et al., 2006). The optodes were carefully set-up, so that they would not affect the EEG electrodes. Since they were placed on the forehead, care was also taken that artifacts due to hair were not introduced. The Oxysoft software, provided by Artinis Medical Systems, was used to record both the channels (T1 and T2) at a sampling frequency of 10 Hz; the samples were then analysed in MATLAB.

### 2.3 Signal processing for EEG and NIRS

The EEG and NIRS data collected were analysed separately and the signal processing techniques are detailed below.

#### 2.3.1 Signal processing for EEG

The data were referenced to the average of the mastoids channels and a forward-reverse Butterworth band-pass filter with cut off frequencies (1 Hz and 12 Hz) was used to filter the data, to obtain the signals in the P300 spectral range. Filters with forward and reverse filtering to avoid phase distortion were used. Each trial was 256 samples in length and phase-locked to stimulus occurrence. To remove eye blinks and artifact activity, windsorising, as described in Hoffmann et al. (2007), was implemented, due to its simplicity and effectiveness. The data was normalised and the recorded eight channels were used for classification.

#### 2.3.2 Signal processing for NIRS

The optical data was filtered to remove motion artifacts and systematic physiological activities such as breathing and heartbeat by using an elliptical band-pass filter with 0.01 Hz

and 0.8 Hz as cut-off frequencies. These values are similar to those in other studies (Zhang et al., 2007; Gratton et al., 2006; Naito et al., 2007). These filter parameters also removed the baseline drift, as shown by the authors in Plichta et al. (2006) and Schroeter et al. (2004).

#### 2.4 Experimental study

Two experimental studies were performed during this research work. In the first study, we accessed the performance of NIRS during mathematical and relaxing states. In the second study, we embarked on EEG-NIRS integration, addressing two applications, namely, selection of the training dataset for the online BCI classifier and participant concentration monitoring during an experiment. During both studies, participants were seated in a chair facing a computer monitor at a distance of 70 cm and the purpose of the experiments was explained for motivated involvement. The participants voluntarily signed a written consent form and the experiments were approved for ethics.

##### 2.4.1 Mathematical and relaxation tasks using NIRS

During this study, three participants were asked to perform ten mathematical tasks (as presented in Table 1), which involved a combination of high level subtraction and addition, following the BODMAS rule (Brackets of Division Multiplication Addition and Subtraction) order of operations. The mathematical tasks were interleaved, with periods of relaxation (around 60 seconds), during which the participant relaxed/gazed at a white screen. Baseline recordings were also recorded at the beginning and the end of the experiment.

**Table 1** Examples of mathematical tasks for NIRS study

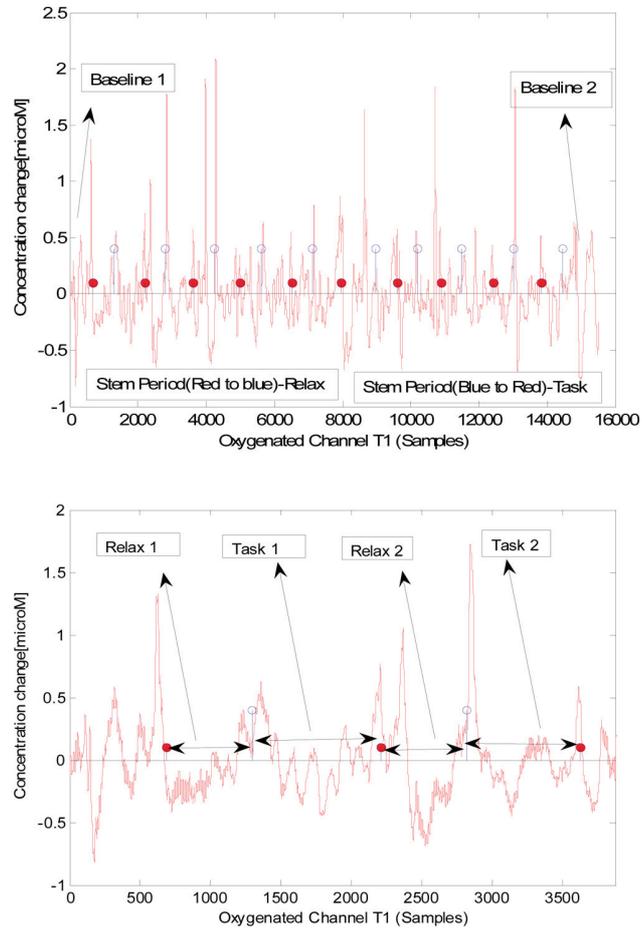
Task 1	$(107 + 235) - (78 - (-12)) + 49 = ?$
Task 2	$(155 - 65) - (-18 - (-24)) + 79 = ?$
Task 3	$(138 - (-27)) - (121 + 42) + 21 = ?$

### 3 Analysis, results and discussion of first experiment

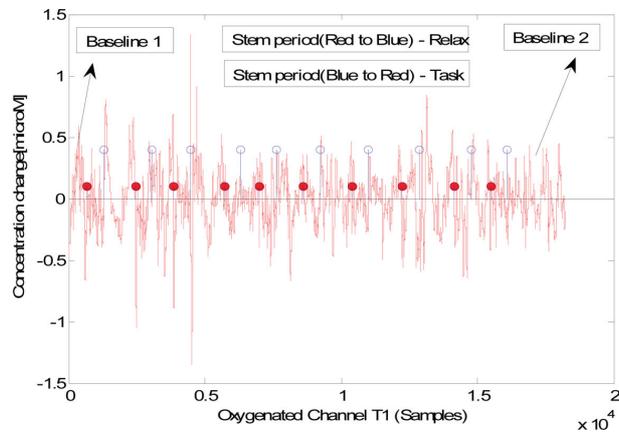
Signal processing was performed, as discussed in the earlier section. The first 15 seconds during the task and relaxation phases were considered, because it was reported to be the duration of rapid change in NIRS oxygenation levels in recent studies (Salvatori et al., 2006; Ayaz et al., 2006). For the accumulated task and relaxation trials, ensemble averages were calculated. The results for the three participants are depicted in Figures 2–4. Ten interleaved periods of task and relaxation are depicted in Figures 2–4 using coloured stem lines. The periods between red and blue stems indicate rest, while the periods between blue and red stems indicate task states. The recorded baselines are also illustrated in the figures. To give a clearer picture, two instances of task and relaxation phases are expanded and shown in Figure 2. As anticipated, we noticed a higher oxygenation mean value from the ensemble trials during the math task than the relaxation phase for all participants. This is presented in Table 2.

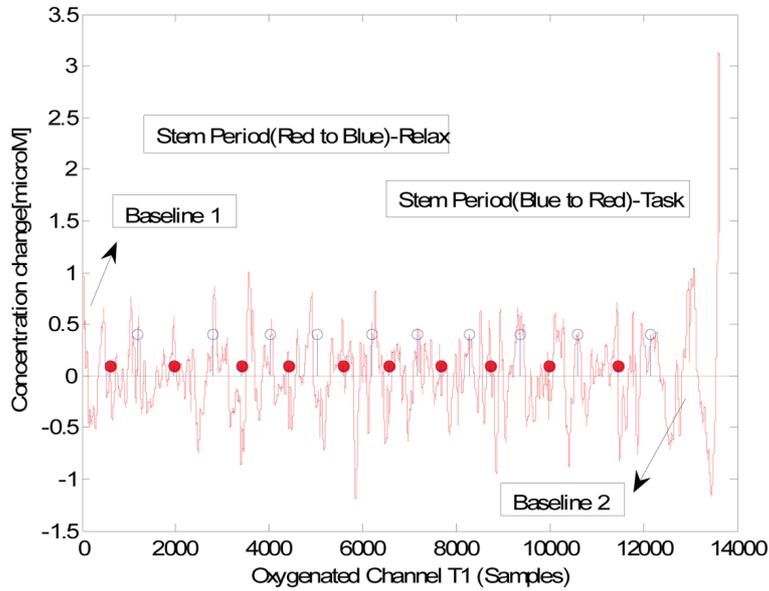
Table 3 tabulates the means of every interleaved, task and relaxation phase. A t-test was performed using the t-test2 MATLAB command and statistically significant differences were observed at the 5% significance level for participants one and two only, which is tabulated in Table 3.

**Figure 2** NIRS signals during ten interleaved task and relaxation phases for participant 1 with two instances expanded for easier understanding (see online version for colours)



**Figure 3** NIRS signals during ten interleaved task and relaxation phases for participant 2 (see online version for colours)



**Figure 4** NIRS signals during ten interleaved task and relaxation phases for participant 3 (see online version for colours)**Table 2** Mean and standard deviations of the ten mathematical tasks and relaxation phases

<i>Participant</i>	<i>Mean and std of task trials (Channel 1, HbO)</i>	<i>Mean and std of rest trials (Channel 1, HbO)</i>
1	0.1741 ± 0.1973	-0.039 ± 0.1498
2	0.0863 ± 0.1932	-0.0887 ± 0.1280
3	0.151 ± 0.234	-0.0195 ± 0.324

**Table 3** Statistical analysis for mathematical tasks and relaxation phases (first 15 seconds)

<i>Participant 1 (Channel 1, HbO)</i>		<i>Participant 2 (Channel 1, HbO)</i>		<i>Participant 3 (Channel 1, HbO)</i>	
<i>Mean of each task phase</i>	<i>Mean of each rest phase</i>	<i>Mean of each task phase</i>	<i>Mean of each rest phase</i>	<i>Mean of each task phase</i>	<i>Mean of each rest phase</i>
0.3159	0.2478	0.4678	-0.2544	0.0260	0.0705
0.5057	-0.1712	0.1806	-0.2064	0.4162	-0.2083
0.3538	-0.0534	-0.2222	0.0192	0.0632	-0.2702
0.2492	-0.1043	0.0248	0.1164	-0.3758	0.1361
0.0724	-0.0456	0.0831	0.0043	0.4252	0.0408
-0.1266	-0.2180	0.1130	-0.0654	0.1549	-0.0038
-0.0757	-0.0747	0.0687	-0.2864	0.0977	-0.3413
0.1938	0.0299	-0.1199	-0.1026	0.2722	0.0882
0.2106	0.1645	0.2650	-0.0254	0.1139	-0.4214
0.0423	-0.1741	0.0017	-0.0863	0.3209	0.7139
t-test p = 0.0137		t-test p = 0.0282		t-test p = 0.1937	

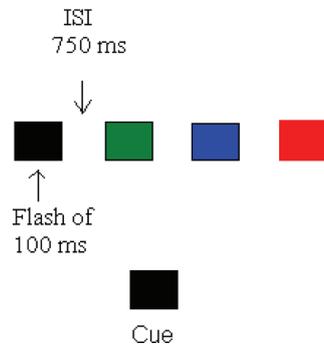
#### 4 Experimental design of EEG–NIRS integration for P300 BCIs

Integration of the EEG and NIRS for BCI application was studied with reference to the P300 oddball paradigm. A 4-class BCI oddball paradigm was used for this EEG–NIRS integration study. The EEG and NIRS data were recorded concurrently from four participants, when the participants perceived different colour flashes on a white background within a single square block, as shown in Figure 5. Two level tasks were used wherein stimuli with black and red colours were used as target cues, while the colours green and blue flashed more frequently and were denoted as non-targets. The participants were instructed to focus and keep a count of the cue (target) colour during the first two sessions (S1 and S2), referred to as Task or ON state, while they gaze/relax (rest or OFF state) during the third session (S3). The participants in this case effectively concentrate on the target colour and the counting of the number of target blocks requires concentration. The experiment and protocols developed in this study have been designed to gain more insight about the workload experienced by a participant during the task ('ON' state) and the rest ('OFF' state). To prevent habituation, the number of recorded blocks during each session was varied. The recorded sessions were as follows:

- session S1 – 36 blocks to train the classifier, wherein the participant counts cue flashes mentally (ON state)
- session S2 – 40 blocks for each cue, wherein the participant counts the cue flashes mentally (ON state)
- session S3 – 40 blocks for each cue, wherein the participant gazes at the flashes (OFF state).

The experimental time during session S1 was 4.08 minutes, while S2 and S3 sessions were 4.53 minutes in duration. A baseline recording of 60 seconds was made before each session. The impedance levels of the EEG electrodes and the positioning of the NIRS optodes were also checked after each session, during the break. The experiments were designed to infer the effect of training classifiers with data, wherein the participant concentrates on the experiments (ON state) and during instances when he/she does not concentrate on the experiment (i.e., gets onto the OFF state). A concurrent recording of EEG–NIRS provides complementary hemodynamic information from NIRS parameters.

**Figure 5** One colour block illustrating a sequence of flashes (total number blocks in each session was either 36 or 40). Note that only one block flashed on the screen at a time. The cue was the target colour (either black or red) (see online version for colours)



## 5 Analysis and results of the second experiment

The signal processing techniques for the EEG and NIRS data were implemented as discussed in an earlier section. The concurrently recorded EEG and NIRS sessions were analysed in two different ways to study the utility of simultaneous recordings for BCI applications.

### 5.1 Training dataset selection

Two Bayes linear discriminant analysis (LDA) classifiers with the same parameters were trained using S1 session (participant concentrates) and S3 session (participant does not concentrate) datasets. The block by block classification accuracy for each colour cue, black and red, over time using session S2 data, for classifiers trained on S1 session (participant concentrates) and S3 session (participant does not concentrate) datasets are shown diagrammatically in Figure 6(a) for one participant. Similar results were obtained for the other participants. The single trial classification accuracies achieved for both the discussed cases are depicted in the first and second columns of Table 4 for the four participants. Each session (S2 and S3) had 40 blocks, with each having four colours. Each colour was flashed for 100 ms with an ISI<sup>1</sup> of 750 ms.

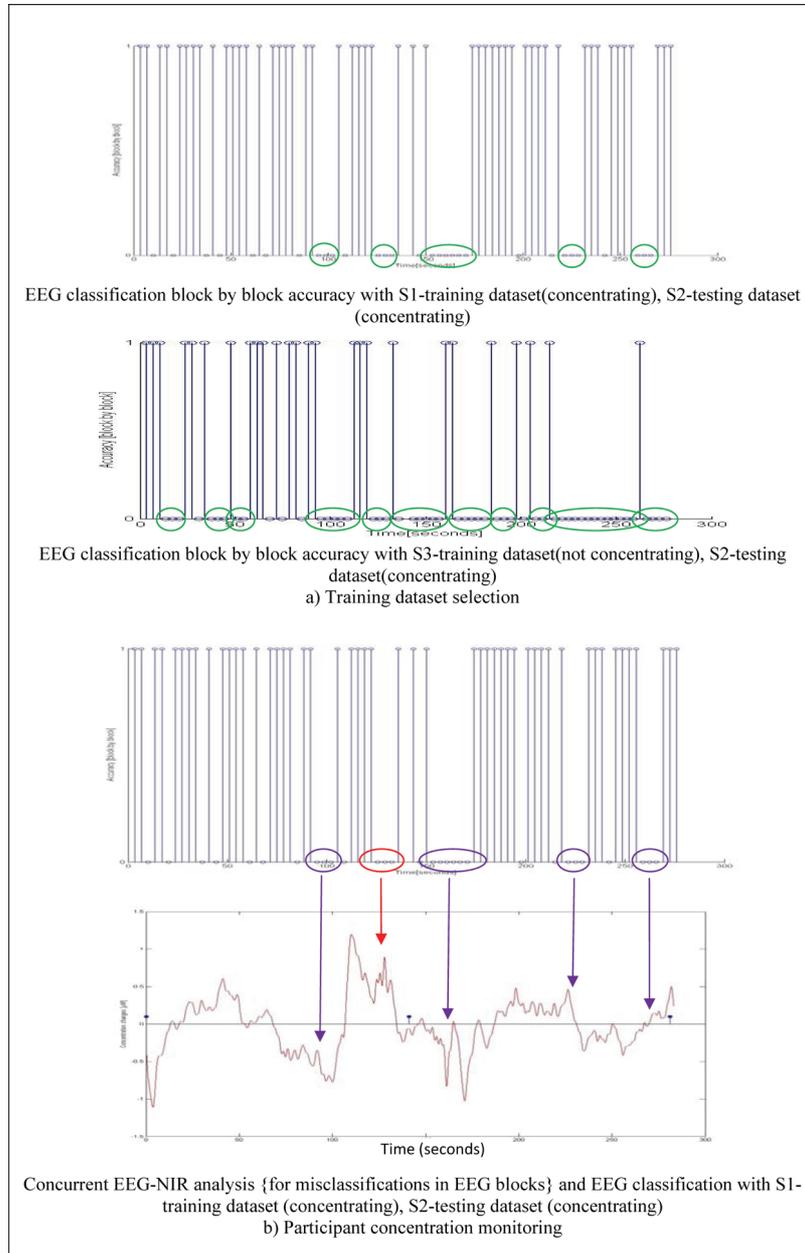
The x-axis in Figure 6(a) represents time, highlighting block by block EEG classification accuracy, as shown by the y-axis. The time is calculated as 40 blocks  $\times$  4 colours  $\times$  850 ms/1000 ms = 136 seconds. The stem plot in the figures highlights the classification over time. A value of 1 on the y axis indicates correct detection and a 0 indicates incorrect detection for each block (four colour flashes). Green ovals represent EEG block misclassifications above two in sequence.

In another analysis, the Bayes LDA classifier was trained using the S1 dataset (concentrating) and the S3 dataset (not concentrating) was used as testing data. Poor EEG classification was achieved and is depicted in the final column of Table 4. The mean and standard deviations for sessions S2 (concentrating) and S3 (no concentration) were calculated for the NIRS data so as to gauge the possibility of selecting an effective training dataset from the NIRS parameters. However, the results obtained had no statistically significant difference between the two sessions (S2 and S3) in the recorded NIRS data. Nevertheless, the results from the EEG indicate the importance of selecting training data where the participant concentrates, as shown by the higher number of green ovals – 11 ovals as compared to 5 ovals.

**Table 4** EEG classification accuracies (%) for various combinations of training and testing datasets

Parti- cipant	S1-Training Dataset (Concen- trating), S2-Testing Dataset (Concentrating)	S3-Training Dataset, (No Concentration), S2-Test- ing Data (Concentrating)	S1-Training Dataset, (Concen- trating), S3-Testing Data (No Concentration)
1	73.75 %	27.50%	23.75%
2	48.75%	25.00%	16.25%
3	62.50%	32.50%	22.5%
4	56.25%	30.00%	23.75%

**Figure 6** Simultaneous EEG-NIR recording for one participant (see online version for colours)



## 5.2 Participant concentration monitoring

The use of concomitant EEG–NIRS in monitoring real-time participant concentration levels was also explored, as depicted in Figure 6(b). Due to space constraints, only the concomitant EEG–NIRS from one participant is shown here. EEG block misclassifications above two in

sequence were considered and the corresponding NIRS levels were analysed as illustrated in Figures 6(b). During most instances where poor classification accuracy for EEG was obtained (as shown by the ovals), a corresponding low/minimum in the oxygenated blood of the NIRS was noticed, as shown by the red and purple arrows (purple arrows show the correct dip in NIRS close to the poor classification accuracy, while red arrows do not indicate a dip). However, consistent results were not observed for all the poor classification instances, as can be seen from Figure 6(b). Nevertheless, as this is only a pilot study, the results obtained are reported here.

## 6 Discussion

The use of EEG–NIRS integration in selecting training datasets as well as real-time monitoring of participant concentration was attempted. However, results due to the integration were not statistically significant from an NIRS viewpoint. The possible pitfalls/speculations in this study could be the absence of trigger information and synchronisation of EEG and NIRS recordings, which would have helped in doing an accurate averaging analysis of NIRS data. Further, as the EEG has a higher frequency signal than NIRS, the concurrent real-time analysis might not have given effective results. NIRS was recorded from the forehead, while EEG was recorded in the midline parietal region, wherein this temporal difference and thus, differences due to the placements of the EEG electrodes and the NIRS optodes might have caused the poor results. Further, the NIRS speed of operation is limited by the nature of metabolic response as well as inherent delays, thereby making real-time concurrent analysis a difficult task. It is also to be noted that the P300 is a relatively fast-paced paradigm and so direct correlation was perhaps not possible to achieve. All said and done, one important motivation observed in this pilot study was the positive results obtained from an EEG viewpoint, highlighting the importance of selecting the correct training dataset to achieve good online classification. However, it is hoped that this work will motivate further research on these lines.

**Table 5** Mean and standard deviation of NIRS data for sessions S2 (concentrating) and S3 (no concentration)

Participant	S2: Mean and std, HbO ( $\mu\text{m}$ )			S3: Mean and std, HbO ( $\mu\text{m}$ )		
	Colour 1	Colour 2	Total	Colour 1	Colour 2	Total
1	0.0185 $\pm$ 0.33	-0.0055 $\pm$ 0.23	0.0068 $\pm$ 0.29	0.0212 $\pm$ 0.38	-0.0113 $\pm$ 0.31	0.0052 $\pm$ 0.35
2	0.0644 $\pm$ 0.03	-0.0141 $\pm$ 0.38	0.0248 $\pm$ 0.36	-0.0232 $\pm$ 0.39	0.0246 $\pm$ 0.39	-0.0007 $\pm$ 0.40
3	0.0016 $\pm$ 0.19	0.0021 $\pm$ 0.18	0.0018 $\pm$ 0.18	-0.0241 $\pm$ 0.23	0.0021 $\pm$ 0.21	-0.0111 $\pm$ 0.22
4	0.0231 $\pm$ 0.45	-0.0457 $\pm$ 0.26	-0.0111 $\pm$ 0.37	-0.0079 $\pm$ 0.28	0.0095 $\pm$ 0.39	0.0007 $\pm$ 0.34

## 7 Conclusion

EEG has been popular as a modality for applications such as BCI and measuring cognitive levels. In recent times, research groups have started exploring the use of NIRS to obtain the control commands for BCI-based applications. Taking this idea forward, an attempt

to integrate the EEG and NIRS to solve challenging BCI issues, namely training dataset selection and participant concentration monitoring, was made. This study presented a recording setup using EEG electrodes and NIRS optodes, signal processing techniques and experiments performed. The study, involving mathematical tasks and relaxation states, provided motivating results conforming to those in the literature, where oxygenation mean values from the ensemble trials during math tasks were higher than during relaxation phases for all participants. It was envisaged that the complementary information provided by NIRS could be effectively used to select training datasets and monitor participant concentration using EEG–NIRS integration. Motivating results were obtained using EEG datasets only, as illustrated in Tables 4–5. Possibly, having a synchronised system with triggers for the EEG as well as NIRS and making an attempt on a slower-paced paradigm like motor imagery could probably have given better success. Though EEG–NIRS integration studies are still in their infancy, this work is hopefully a motivation for further exploration on that front for the BCI research community and for cognitive performance measures.

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## Note

Inter–stimulus interval (ISI), which is the time between two flashes.