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 Electroencephalogram (EEG) and Near Infra Red Spectroscopy (NIRS) for possible applications such as BCI and measuring cognitive levels. Two experiments are presented, the first being a mathematical task interleaved with rest states using NIRS only. Next integration of 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 rest. However, the second experiment reveals statistically significant results using EEG only. We present details about equipment used, participants as well as 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.

1. Introduction

Among the numerous possible modalities for measuring brain activity in Brain-computer Interface (BCI) systems, scalp EEG [1, 2] and optical NIRS [3-5] 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 [6], authentication [7] and gaming [8], 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 in that perspective. So far, studies [9-11] have focussed on simultaneous EEG-NIRS recordings in occipital cortex or around midline lobes, showing synchronisation of neural and hemodynamic activity during task. Authors in [9] showed that regions of peak hemodynamic activity are in closest proximity to areas of peak electrical activity during an auditory oddball paradigm. In [10], an increase in HbO and a decrease in Hb were reported for oddball stimuli during auditory paradigms, using optodes placed on either side of midline lobe. The work presented in [11] on concomitant recording of EEG-NIRS highlight that concentration variations directly reflect the increase in blood oxygenations required to support the neural activity during a visual stimulus paradigm. In these studies, the EEG electrodes and NIRS optodes were primarily placed around the visual cortex area of the brain. Although early attempts to integrate EEG and NIRS for monitoring brain function 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 dataset for online BCI classifier 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 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 participant levels of concentration while the person performs 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 paradigm were chosen as in [1], around the midline parietal region. To the best of the author's 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 is 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 due to 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 the concurrent EEG-NIRS recordings while the participant was performing the experiment.

2.1 EEG data collection

The electroencephalogram (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, eight optimum channels for BCI reported in [1] 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. The 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 detector. A greater separation in size between source and 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 be unusable [12-14]. The optodes were carefully set-up, so as to not affect the EEG electrodes. Since it was placed on the

forehead, care was also taken that artifacts due to hair are not introduced. Oxysoft software provided by Artinis Medical systems was used to record both the channels (T1 and T2) at a sampling frequency of 10Hz, which were then analyzed in Matlab.

{Insert Figure 1 around here}

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 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 the stimulus occurrence. To remove eye-blinks and artifact activity, windsorising as described in [1] 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 with other studies [13-15]. These filter parameters also removed the baseline drift as shown by the authors in [16, 17].

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 the EEG-NIRS integration addressing two applications namely, selection of training dataset for online BCI

classifier and participant concentration monitoring during an experiment. During both studies, participants were seated in a chair facing a computer monitor at distance of 70 cm and the purpose of 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, which involved a combination of high level subtraction and addition, following 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 end of the experiment.

{Insert Table 1 around here}

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 as the durations of rapid change in NIRS oxygenation levels in recent studies [11, 18]. For the accumulated task and relaxation trials, ensemble averages were calculated. The results for three participants are depicted in Figures 2-4. Ten interleaved periods of task and relaxation are depicted in the Figures 2-4 using coloured stem lines. The period between stems red and blue indicate rest, while the period between stems blue to red indicates task state. 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 values from the ensembled trials during math task than the relaxation phase for all participants. This is presented in Table 2.

Table 3 tabulates means of every interleaved, task and relaxation phases. A t-test was performed using ttest2 MATLAB command and statistically significant differences were observed at 5 % significance level for participants one and two only which is tabulated in Table 3.

{Insert Figures 2-4 around here}

{Insert Table 2-3 around here}

4. Experimental Design of EEG-NIRS Integration for P300 BCIs

Integration of EEG-NIRS for BCI application was studied with reference to 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 participant perceived different colour flashes on white background within a single square block as shown in Figure 5. Two level tasks were used wherein stimulus with black and red colours were used as target cues while colours green and blue flashed more frequently and were denoted as non-targets. The participant was 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 he/she gazes/relaxes (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 task ('ON' state) and 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 EEG electrodes and positioning of NIRS optodes was 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.

{Insert Figure 5 around here}

5. Analysis and Results of the Second Experiment

The signal processing techniques for EEG and NIRS data were implemented as discussed in earlier section. The concurrently recorded sessions of EEG and NIRS were analyzed 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 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[1] of 750 ms.

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

In another analysis, Bayes LDA classifier was trained using S1 dataset (concentrating) and 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 deviation for the 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 NIRS parameters. However the results obtained were not statistically significant different between the two sessions (S2 and S3) in the recorded NIRS data. Nevertheless, the results from EEG indicate the importance of selecting training data where the participant concentrates as shown by the higher number green ovals – 11 ovals as compared to 5 ovals.

{Insert Table 4-5 around here}

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 contraints, only the concomitant EEG-NIRS from one participant is shown here. EEG block mis-classifications 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

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

the oxygenated blood of the NIRS was noticed as shown by the red and purple arrows (purple arrow shows the correct dip in NIRS close to the poor classification accuracy while red arrow does 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.

{Insert Figure 6 around 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 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. Also EEG being a higher frequency signal than NIRS which is a lower frequency signal, 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 (i.e. differences due to placement of EEG electrodes and NIRS optodes) might have caused the poor results. Also NIRS speed of operation is limited by the nature of metabolic response as well as the inherent delay, thereby making real-time concurrent analysis a difficult task. Also P300 being a relatively fast paced paradigm, direct correlation was perhaps not possible to achieve. All said 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.

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 EEG-NIR to solve challenging BCI issues, namely training dataset selection and participant concentration monitoring was made. This

study presented the 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 those in the literature where oxygenation mean values from the ensembled trials during math task were higher than the relaxation phase 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 EEG as well as NIRS and making an attempt on a lesser fast paced paradigm like motor imagery could probably give better success. Though EEG-NIRS integration studies are still in infancy, this work is hopefully a motivation for further exploration on that front for the BCI research community and cognitive performance measures.

References

[1]   U. Hoffmann, J. M. Vesin, T. Ebrahimi and K. Diserens, "An efficient P300-based brain-computer interface for disabled subjects", Journal of Neuroscience Methods, vol. 167, no. 1, pp. 115-125, 2007.

[2]   R. Palaniappan, "Two-stage biometric authentication method using thought activity brain waves," International Journal of Neural Systems, vol. 18, issue 1, pp.59-66, 2008.

[3]   R. Sitaram, H. Zhang, C. Guan, M. Thulasidas, Y. Hoshi, A. Ishikawa, K. Shimizu and N. Birbaumer, "Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain-computer interface," Neuroimage, vol.34, no.4, pp.1416-1427, 2007.

[4]   T. Nagaoka, K. Sakatani, T. Awano, N. Yokose, T. Hoshino, Y. Murata, Y. Katayama, A. Ishikawa and H. Eda, "Development of a new rehabilitation system based on a brain-computer interface using near-infrared spectroscopy," Advances in Experimental Medicine and Biology, vol.662, pp.497-503, 2010.

[5]   S. Coyle, T. Ward and C. Markham, "Brain-computer interface using a simplified functional near-infrared spectroscopy system," Journal of Neural Engineering, vol.4, pp. 219–226, 2006.

[6] J. Wilson and R. Palaniappan, "Analogue mouse pointer control via an online steady state visual evoked potential (SSVEP) brain-computer interface," Journal of Neural Engineering, vol. 8, no.2, 2011, doi: 10.1088/1741-2560/8/2/025026.

[7] C.N. Gupta, R. Palaniappan, and S. Swaminathan, "Novel analysis techniques for a brain biometric system," International Journal of Medical Engineering and Informatics, vol. 1, issue 2, pp. 266 – 273, 2008.

[8] E. Lalor, S. P. Kelly, C. Finucane, R. Burke, R. Smith, R. Reilly and G. Mc-Darby, "Steady-state VEP-based brain-computer interface control in an immersive 3-D gaming environment," EURASIP Journal on Applied Signal Processing, vol. 19, pp. 3156-3164, 2005.

[9] R. P. Kennan, S.G. Horovitz, A. Maki, Y. Yamashita, H. Koizumi and J.C. Gore, "Simultaneous recording of event-related auditory oddball response using transcranial near infrared optical topography and surface EEG," Neuroimage, vol. 16, pp.587-592, 2002.

[10] L. M. Hirshfield, K. Chauncey, R. Gulotta, A. Girouard, E. T. Solovey, R. J.K. Jacob, A. Sassaroli and S. Fantini, "Combining electroencephalograph and functional near infrared spectroscopy to explore users' mental workload," Lecture Notes in Computer Science, vol.5638/2009, pp. 239-247, 2009.

[11] G.Salvatori, L.Bulf, S.Fonda and L.Rovati, "Combining near infrared spectroscopy and electroencephalography to monitor brain function," Proceedings of the IEEE Instrumentation and Measurement Technology Conference, pp. 32-36, 2006.

[12] P.W.McCormick, M. Stewart, G. Lewis, M. Dujovny and J.I.Ausman, "Intracerebral penetration of infrared light," Journal of Neurosurgery, vol. 76, pp. 315-318, 1992.

[13] Q. Zhang, E.N. Brown and G.E. Strangman, "Adaptive filtering to reduce global interference in evoked brain activity detection: a human participant case study," Journal of Biomedical Optics, vol.12, no.6, 2007.

[14] G. Gratton, C.R. Brumback, B.A. Gordon, M.A. Person, K.A.Low and M. Fabiani, "Effects of measurement method, wavelength, and source-detector distance on the fast optical signal," NeuroImage, vol.32, no.4, pp.1576-1590, 2006.

[15] M. Naito, Y. Michioka, K. Ozawa, Y. Ito, M. Kiguchi and T. Kanazawa, "A communication

means for totally locked-in ALS patients based on changes in cerebral blood volume measured with near-infrared light," IEICE Transactions on Information Systems, vol. 90, no.7, pp.1028-1037, 2007.

[16] M.M. Plichta, M.J. Herrmann, C.G. Baehne, A.C. Ehlis, M.M. Richtera, P. Paulic and A.J. Fallgatter, "Event-related functional near-infrared spectroscopy (fNIRS): Are the measurements reliable?" NeuroImage, vol.31, pp.116-124, 2006.

[17] M. L. Schroeter, S. Zysset and D. Yves von Cramon, "Shortening intertrial intervals in event-related cognitive studies with near-infrared spectroscopy," NeuroImage, vol.22, 341-346, 2004.

[18] H. Ayaz, T. H. Patterson, M. SchuHheis, M. Izretoglu and B.Onaral, "Brain computer interface based on fNIR; A tool for individuals suffering from amyotrophic lateral sclerosis (ALS) or various types of paralysis," School of Biomedical Engineering, Science and Health Systems Biomedical Technology Showcase, 2006. Available at Drexel E-Repository and Archive iDEA, http://idea.library.drexel.edu/
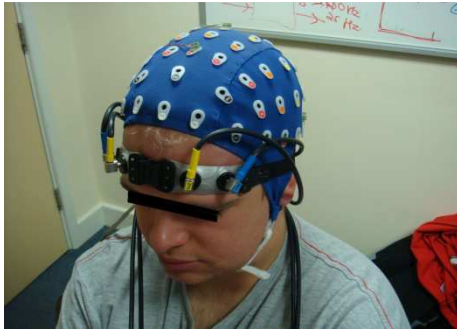
Figure 1: Design, setup and positioning of NIRS optodes (upper half) and EEG electrodes (lower half).
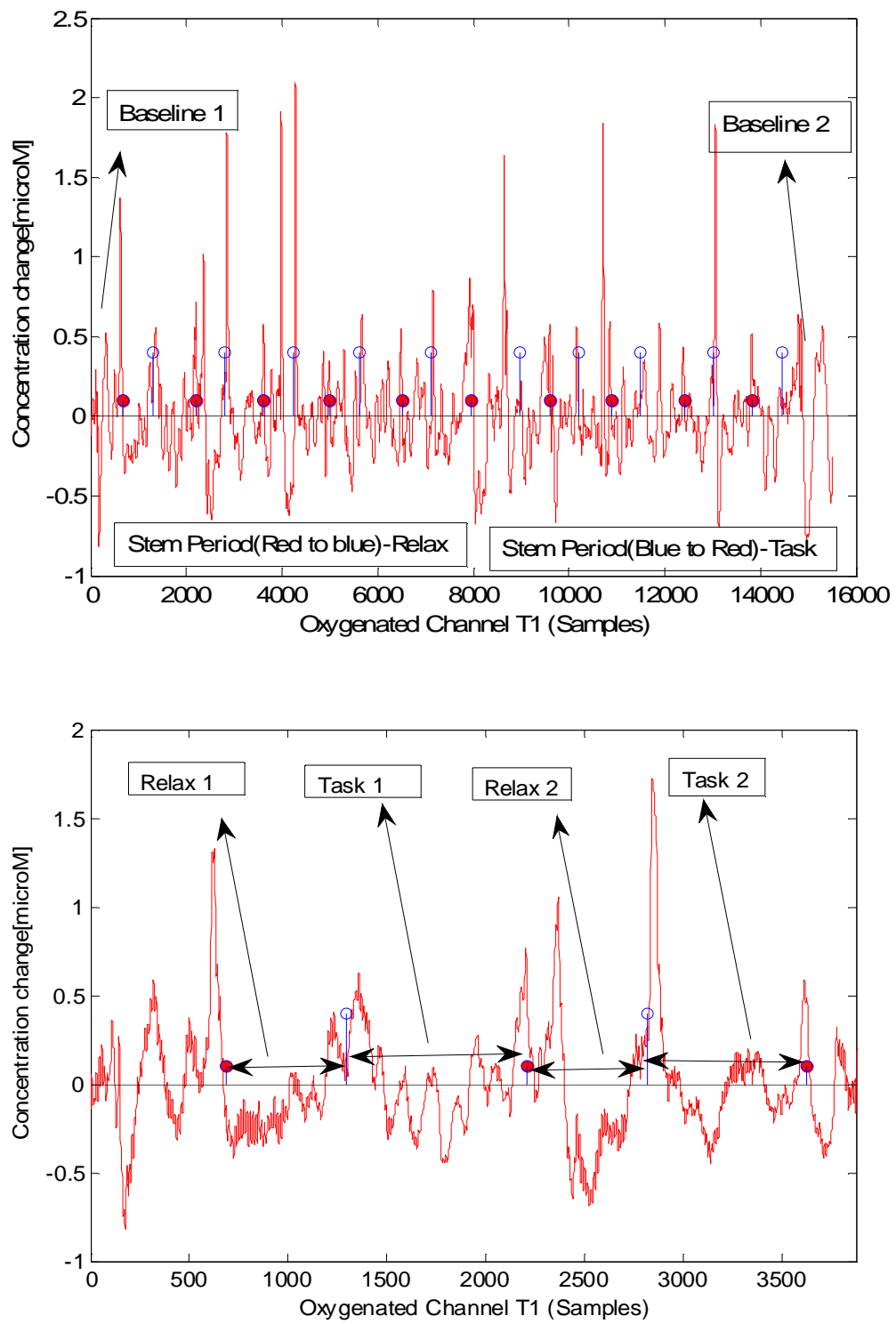
Figure 2: NIRS signal during ten interleaved task and relaxation phases for participant 1 with two instances expanded for easier understanding.
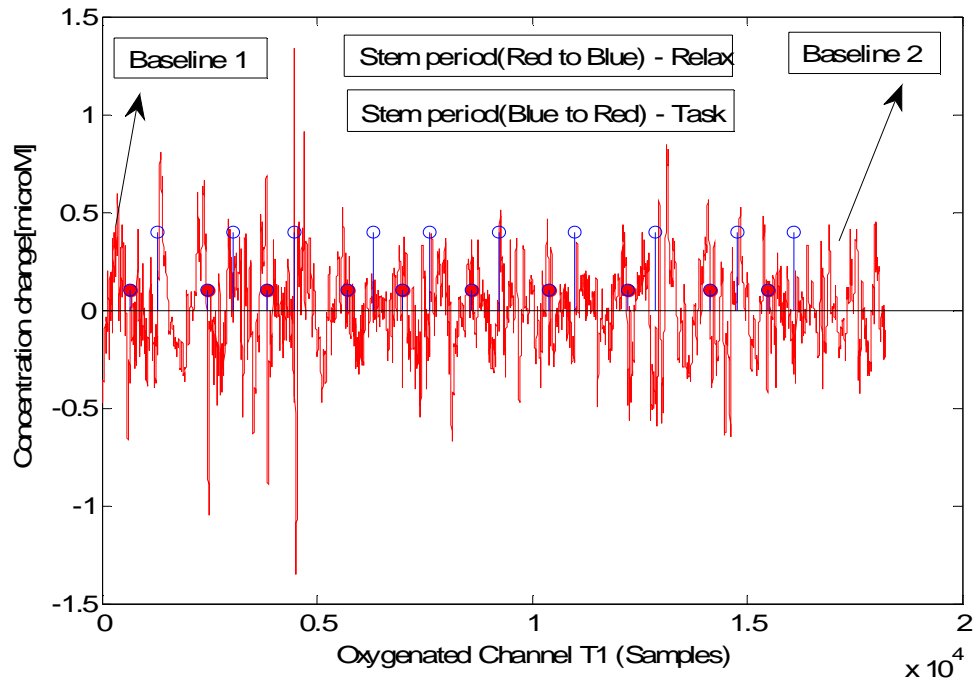
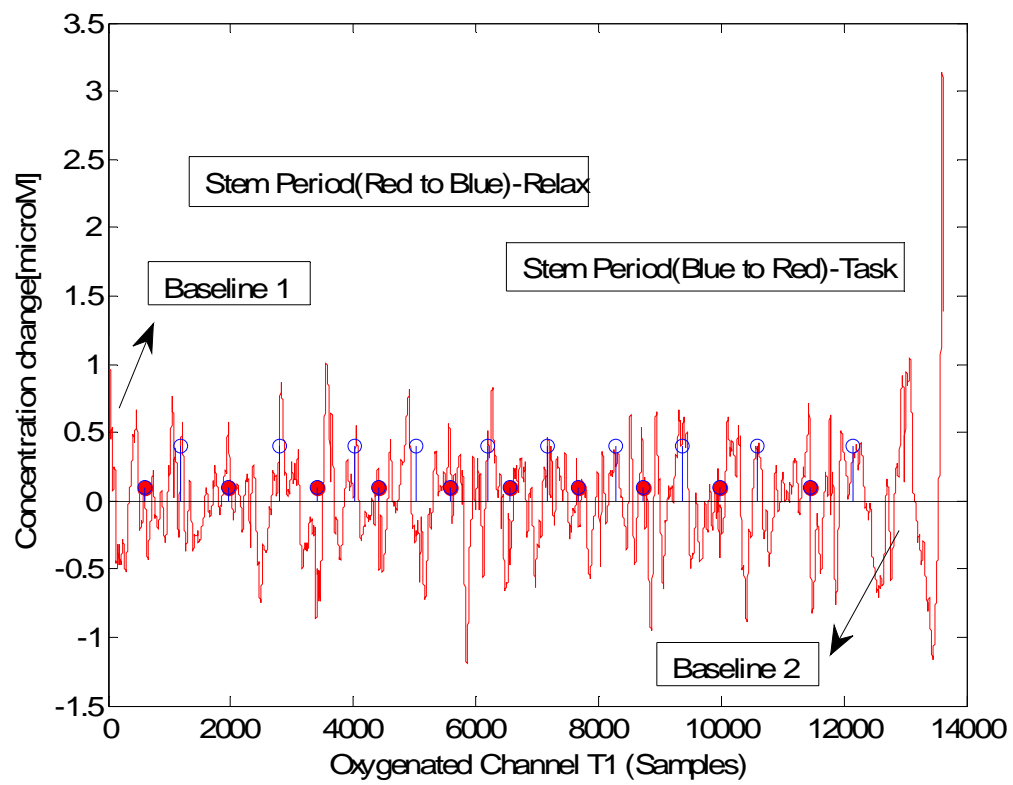Figure 3: NIRS signal during ten interleaved task and relaxation phases for participant 2.

Figure 4: NIRS signal during ten interleaved task and relaxation phases for participant 3.
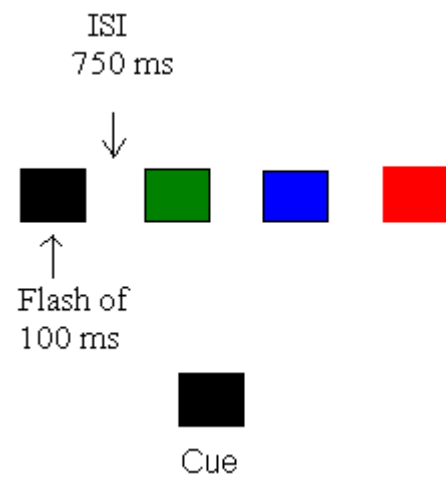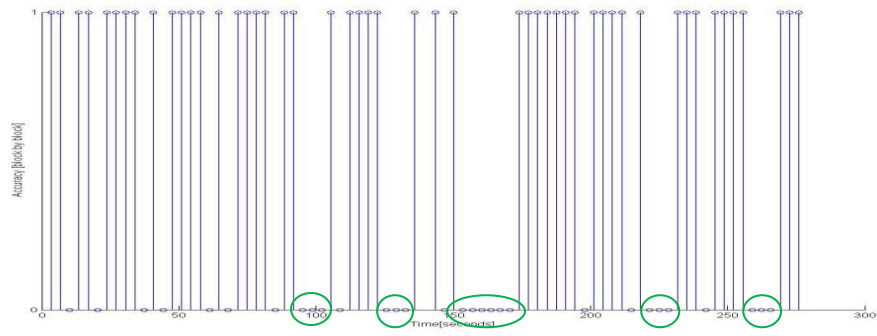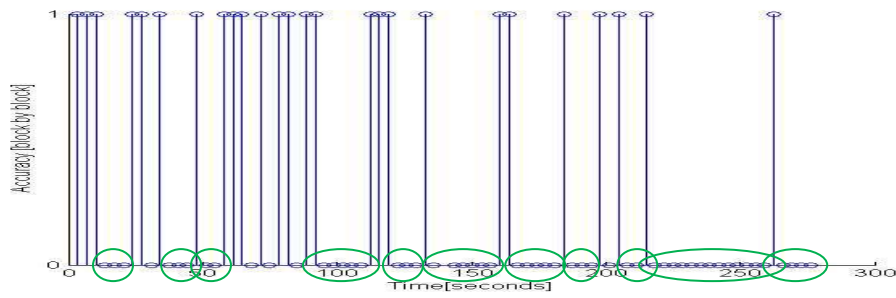
Figure 5: One colour block illustrating a sequence of flashes (total number blocks in each session was either 36 or 40). Note that only one block flashed on screen at a time. The cue was the target colour (either black or red).
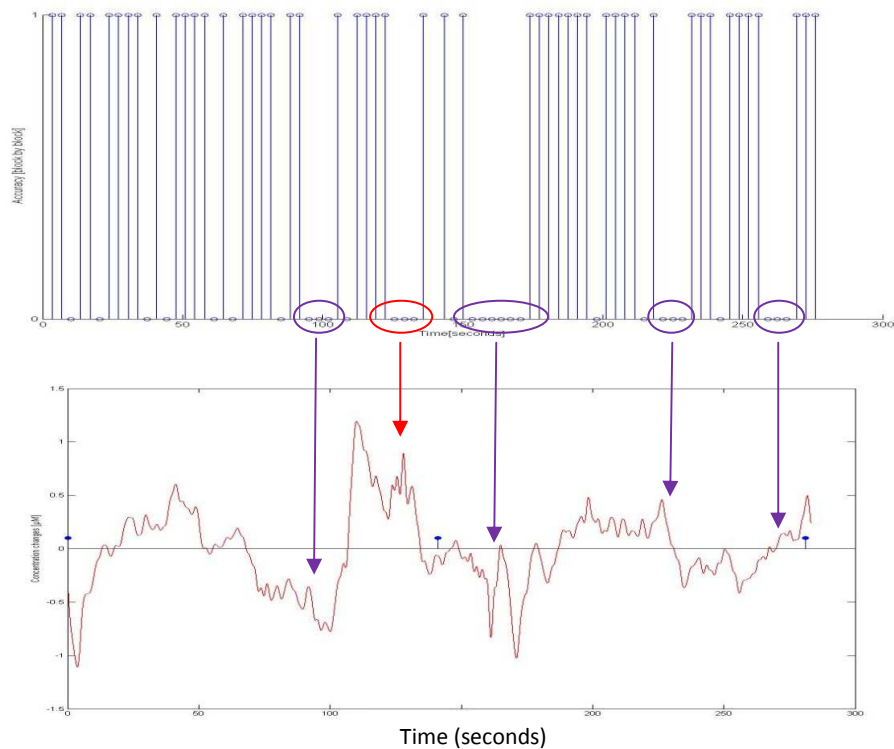
EEG classification block by block accuracy with S1-training dataset(concentrating), S2-testing dataset (concentrating)

EEG classification block by block accuracy with S3-training dataset(not concentrating), S2-testing dataset(concentrating)

a) Training dataset selection

Concurrent EEG-NIR analysis {for misclassifications in EEG blocks} and EEG classification with S1-training dataset (concentrating), S2-testing dataset (concentrating)

b) Participant concentration monitoring

Figure 6: Simultaneous EEG-NIR recording for one participant

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	$(138 - (-27)) - (121 + 42) + 21 = ?$

Table 2: Mean and standard deviation of the ten mathematical tasks and relaxation phases

Participant	Mean and std of task trials (Channel 1, HbO)	Mean and std of rest trials (Channel 1, HbO)
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)

Participant 1 (Channel 1, HbO)		Participant 2 (Channel 1, HbO)		Participant 3 (Channel 1, HbO)	
Mean of each task phase	Mean of each rest phase	Mean of each task phase	Mean of each rest phase	Mean of each task phase	Mean of each rest phase
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	

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

Participant	S1-Training Dataset (Concentrating), S2-Testing Dataset (Concentrating)	S3-Training Dataset, (No Concentration) S2-Testing Data (Concentrating)	S1-Training Dataset, (Concentrating) 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%

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

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