# A Multimodal 2D Brain Computer Interface*

Rand K. Almajidy, Yacine Boudria, Walter Besio, Ulrich G. Hofmann and Kunal Mankodiya

***Abstract*— In this work we used multimodal, non-invasive brain signal recording systems, namely Near Infrared Spectroscopy (NIRS), disc electrode electroencephalography (EEG) and tripolar concentric ring electrodes (TCRE) electroencephalography (tEEG). 7 healthy subjects participated in our experiments to control a 2 D Brain Computer Interface (BCI). Four motor imagery task were performed, imagery motion of the left hand, the right hand, both hands and both feet. The signal Slope (SS) of the change in oxygenated hemoglobin concentration measured by NIRS was used for feature extraction while the power spectrum density (PSD) of both EEG and tEEG in the frequency band (8-30Hz) was used for feature extraction. Linear Discriminant Analysis (LDA) was used to classify different combinations of the aforementioned features. The highest classification accuracy (85.4) was achieved by using features from all the three brain signals recording props. The improvement in classification accuracy was highly significant (p= 0.0033) when using the multimodal signals features compared to the EEG features.**

***Index Terms*—Near Infrared Spectroscopy, multimodal Brain Computer Interface, tripolar concentric ring electrodes (TCRE).**

## I. Introduction

Many attempts have been made recently to combine electroencephalography (EEG) and Near Infrared Spectroscopy (NIRS) as two noninvasive brain signals recording modules [1]. Those efforts can facilitate creating a robust, noninvasive, low cost and mobile Brain Computer Interface system [2][3]. The main hurdle in the way of this achievement is the quality of the brain signals that are acquired by noninvasive modules [4]. Various approaches are envisaged by researchers that include optimizing the design of the signal acquisition modules whether EEG [5] or NRS [6][7], applying sophisticated signal processing techniques for noise reduction, feature extraction, feature selection and classification[8][9].

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## II. Methods

### A. Subjects

7 healthy right handed subjects (5 males and 2 females) age 20 -36 participated in the experiments. Five subjects were naive to BCI experiments. All subjects were informed about the experiment prior to its start and signed a consent form.

### B. Data Acquisition

The experiments were carried out in a dim lighted room. The subjects were seated on a comfortable chair with arms resting on their legs; the chair was 1.5m from the screen. Subjects were encouraged to minimize their motion to reduce motion artifact.

During the experiments EEG and NIRS signals were acquired simultaneously. We used an 8 sources and 8 detectors NIRS system (NIRScout, NIRx Medizintechnik GmbH, Germany). Each source has 850 nm and 760 nm wavelengths. The source- detectors arrangement we used as depicted in Fig.1 formed 20 measurement's channels. The sampling frequency was 6.25 Hz.

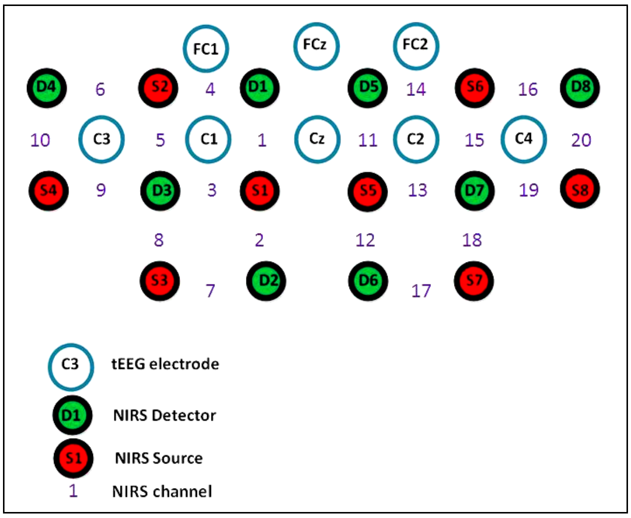


Figure 1. tEEG electrodes and NIRS optodes channels numbering according to 10-20 international system.

Figure 2. Disc EEG, tEEG electrodes and NIRS source and detector (from left to right)

EEG signals were acquired with a gUSB amplifier (g.tec GmgH, Schiedlberg, Austria). Eight tripolar concentric ring electrodes (TCRE) were used to record TCRE Laplacian electroencephalography (tEEG) and disc electrode electroencephalograph (EEG) at the same time and location. The TCRE electrodes (see Fig.2) are described elsewhere [5][10].

We recorded signals from C3, C1, Cz, C2, C4, FC1, FCz and FC2 according to the international 10–20 system. The reference and ground electrodes were placed on the right and left mastoid respectively. Skin-to-electrode impedances were kept below 5 k Ohm. The sampling frequency was 256 Hz. Signals were Notch filtered at 60Hz and band pass filtered between 0.1 and 70 Hz.

NIRS cap was used to secure both tEEG electrodes and NIRS probes in their prospective locations on the motor cortex area of the head as depicted in Fig.3. We designed rings for the TCRE electrodes. Eight NIRS cap rings were replaced with TCRE electrodes rings. The NIRS inter-optode distances were around 3 cm.

### C. Experimental Paradigm

The real-time feedback experiments were tEEG based using the BCI2000[11]software. The NIRS signals were included in the classifiers only during the offline analysis.

During the experiment the subject performed four motor imagery tasks: left hand movements, right hand movements, both hands movements, both feet movements.

The experiment paradigm is depicted in Fig. 4 A baseline period of 10 sec proceeded each session during which the subject performed no task. A 10 sec motor imagery task then 10 sec rest period between tasks. During the task period, an arrow appeared on the screen pointing left, right, up or down as a visual cue for the aforementioned tasks respectively.

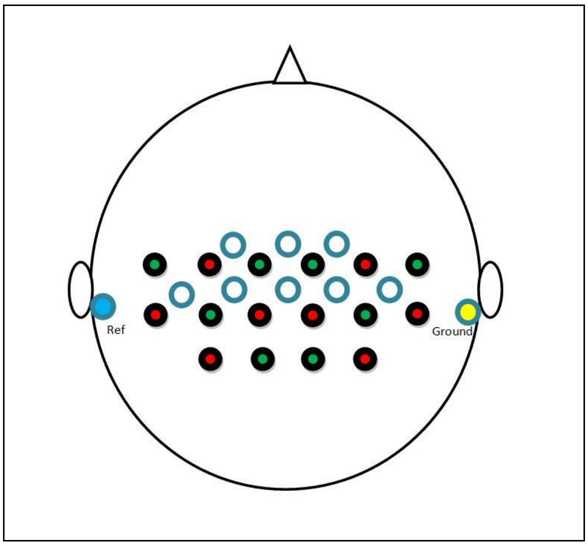



Figure 3. tEEG electrodes and NIRS optode placement on the motor cortex area.

10 runs were recorded with 20 trails per run totaling 200 trails. EEG and tEEG were recorded for the first five runs then NIRS, EEG and tEEG were recorded for the remaining runs.

### D. Signal processing

16 Electroencephalography channels (8 tEEG and 8 EEG) and 20 NIRS channels signals were preprocessed, feature extracted then classified.

We used nirsLAB (v2014.05 by NITRC) to preprocess the NIRS measurements. They were band pass filtered between 0.01 and 0.5 Hz then converted to oxygenated (HbO) and deoxygenated hemoglobin (HbR) concentration changes, using the modified Beer-Lambert law as depicated in Fig.5[12].

The NIRS channels were visually examined and the noisy channels were excluded. Signals were segmented then HbO Signal Slope (SS) was calculated as a feature [13].

The tEEG and EEG signals were band pass filter (8-30 Hz) using $10^{th}$ order Butterworth filter. The power spectrum density (PSD) was chosen for EEG and tEEG feature extraction. It was computed using Welch method with 1sec window and 50% overlap [14].

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Rest 10 sec | Motor imagery Left hand 10 sec | Rest 10 sec | Motor imagery Right hand 10 sec | Rest 10 sec | Motor imagery Both hands 10 sec | Rest 10 sec | Motor imagery Both feet 10 sec |

Figure 4. The BCI experimental paradigm.

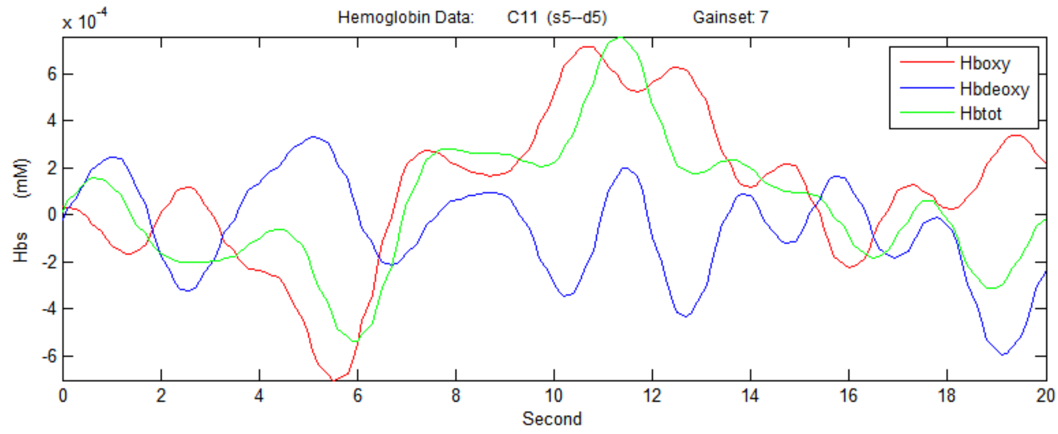


Figure 5. 0-20 sec section of HbO and HbR concentration changes for subject 5.

Linear discriminant analysis (LDA) was used to classify both NIRS and EEG features. The classifiers used different combinations of features HbO Signal Slope [15], tEEG and EEG power spectrum[16][17].

# I. RESULTS

Fig. 6. shows the four classes when using tEEG PSD and NIRS SS. In Table I the classification accuracy using different modularity combinations are shown. The paired t-test between EEG and dual module classification (tEEG+NIRS) result p= 0.0165 and p= 0.0033 (tEEG+ EEG+NIRS)

# II. DISCUSSION

The classification accuracy for dual modality classification was higher than those for EEG or tEEG. The increase in accuracy is more obvious when compared with EEG results. The classification accuracy was highest when both tEEG and EEG plus the NIRS signals features were used.

TABLE I. LDA CLASSIFICATION ACCURACY

| Subject | EEG | tEEG | EEG+NIRS | tEEG+ NIRS | tEEG+ EEG+NIRS |
|---|---|---|---|---|---|
| 1 | 57.1 | 67.0 | 67.2 | 73.2 | 82.1 |
| 2 | 83.2 | 87.0 | 91.3 | 95.4 | 100 |
| 3 | 51.0 | 57.2 | 63.1 | 64.0 | 67.4 |
| 4 | 72.4 | 82.4 | 86.0 | 87.8 | 89.2 |
| 5 | 60.5 | 71.0 | 74.1 | 80.3 | 84. 7 |
| 6 | 64.0 | 80.5 | 81.4 | 86.0 | 90.6 |
| 7 | 67.9 | 70.0 | 75.6 | 78.3 | 83.0 |
| mean | 65.2 | 73.6 | 77.0 | 80.7 | 85.4 |

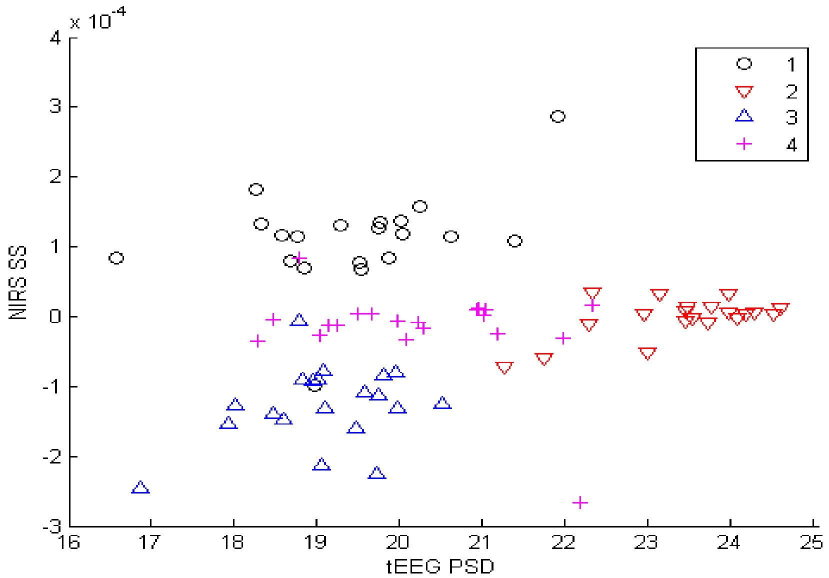


Figure 6. Scatter plot of tEEG and NIRS features for the four classes(subject 1) .

## I. CONCLUSION

Our work emphasis the improvement of BCI performance by using multimodal which is been investigated by researchers [18]. Our novel work use tEEG in combination with NIRS and compare its performance at the same instance with EEG-NIRS. It shows the superiority of tEEG-NIRS BCI accuracy, especially when compared with the plain EEG. Our work also shows that improved in the classification was highly significant (p= 0.0033) when using the three brain signals (EEG, tEEG and NIRS) compared to EEG.

The results can be improved by optimizing the feature selection for the three brain signals. Our novel multi modal can be extended to a real time feedback BCI, since there are various attempts in this direction. The overall performance can also be improved by training the subject for multiple sessions.

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