

# Classification of Various Mental Task Combinations for NIRS-Based Brain-Computer Interface (BCI)

H. J. Hwang<sup>1</sup>, J. H. Lim<sup>1</sup>, D. W. Kim<sup>1</sup>, C. H. Im<sup>1</sup>  
<sup>1</sup>Hanyang University, Seoul, Republic of Korea

Correspondence: Chang-Hwan Im, Department of Biomedical Engineering, Hanyang University, 222 Wangsimni-ro, Seongdong-gu, Seoul, 133-791, Republic of Korea. E-mail: ich@hanyang.ac.kr

**Abstract.** The goal of this study was to investigate the most suitable feature type and combinations of mental tasks for the development of practical NIRS-based brain-computer interface (BCI) systems. To this end, we recorded concentration changes of oxygenated [oxy-Hb] and deoxygenated [deoxy-Hb] hemoglobins while eight participants were performing eight different mental tasks. Four different feature sets were extracted from the recorded NIRS signals ([oxy-Hb], [deoxy-Hb], [total-Hb], and a combination of [oxy-Hb] and [deoxy-Hb]), and classification accuracies were estimated for all possible pairs of the eight mental tasks. As a result, the numbers of mental task pairs showing accuracy high enough for practical communication ( $> 70\%$ ) were 5.5 for [oxy-Hb], 4.86 for [deoxy-Hb], 6.75 for [total-Hb], and 6 for [oxy-Hb] + [deoxy-Hb] on average, among 28 mental task pairs ( $= {}_8C_2$ ). In addition, five mental task combinations commonly showed high classification accuracy over 70% in more than half of the participants (none for [oxy-Hb]; two combinations for [deoxy-Hb]; two combinations for [total-Hb]; one combination for [oxy-Hb] + [deoxy-Hb]). In particular, a combination of right hand motor imagery and mental rotation task only showed high classification accuracy over 70% on average, when using the feature set of [total-Hb]. From the results, it was confirmed that the features extracted from [total-Hb] showed best performance in classifying various mental tasks, and the combination of right hand motor imagery and mental rotation task can be a promising candidate task for a practical NIRS-based BCI system.

**Keywords:** Various Mental Tasks, Single-Trial Classification, Near-Infrared Spectroscopy (NIRS), Brain-Computer Interface (BCI)

## 1. Introduction

Brain-computer interface (BCI) has been actively studied using a variety of neuroimaging modalities, such as electroencephalography (EEG), near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI), electrocorticography (ECoG) and magnetoencephalography (MEG). Among them, EEG has been most widely used and a number of mental tasks have been investigated to realize practical EEG-based BCI systems. Recently, NIRS has attracted BCI researchers' attention [Coyle et al., 2007] because it is portable and non-invasive similarly to EEG. Most importantly, unlike EEG, NIRS is less susceptible to electrophysiological artifacts caused by eye blinks, eyeball movements, muscle activity, and so on. Despite of the above mentioned advantages of NIRS for development of practical BCI systems, investigations on optimal mental task combinations and feature types have been rarely conducted in NIRS-based BCI studies. Therefore, in this study, we investigated which feature type and mental task combination are more appropriate to develop NIRS-based BCI systems.

## 2. Methods

Eight participants took part in this study, and performed eight different mental tasks: A) left hand motor imagery, B) right hand motor imagery, C) foot motor imagery, D) mental singing, E) mental subtraction, F) mental multiplication, G) mental rotation, and H) mental writing. Each mental task was carried out 20 times for 15 s each.

For the data acquisition, we used a multi-channel NIRS imaging system (FOIRE-3000, Shimadzu Co. Ltd., Kyoto, Japan). Fifty channels broadly placed on the participants' scalps were used to measure the task-related concentration changes of [oxy-Hb] and [deoxy-Hb]. To extract features relevant to each mental task, we used three different window sizes of 5, 10 and 15 s, and consequently making six time windows, i.e., 0–5 s, 0–10 s, 0–15 s, 5–10 s, 5–15 s, and 10–15 s. The features were extracted by averaging hemodynamic responses in each time window, and four different feature sets were constructed, i.e., [oxy-Hb], [deoxy-Hb], [total-Hb], and a combination of [oxy-Hb] and [deoxy-Hb]. For the feature selection or reduction, the sequential floating forward selection (SFFS) was used, and the selected best feature subsets were classified with linear discriminant analysis (LDA) algorithm. To

evaluate the classification accuracy, we used a leave-one-out cross validation (LOOCV) method. The classification accuracy was estimated for all possible combinations of two mental tasks using the four different feature sets.

### 3. Results

Since the classification accuracy should be at least over 70% for practical communications [Perelmouter et al., 2000], we counted the number of combinations showing classification accuracy over 70%, and calculated their average classification accuracy. Table 1 shows how many combinations of binary mental tasks can be used for practical communication (over 70% classification accuracy). The selected numbers of the mental task combinations were 5.5 for [oxy-Hb], 4.86 [deoxy-Hb], 6.75 for [total-Hb], and 6 for [oxy-Hb] + [deoxy-Hb]. Among the selected mental task combinations, five mental task combinations commonly showed the classification accuracy over 70% in half of eight participants: combination of tasks E and F for [deoxy-Hb], combinations of tasks B/D and G for [total-Hb], and combinations of tasks A and B/E for [oxy-Hb] + [deoxy-Hb]. In particular, the mental task combination of B (right hand motor imagery) and G (mental rotation) commonly showed the average classification accuracy over 70% when the [total-Hb] feature set was used.

**Table 1.** The numbers of mental task combinations showing the classification accuracy over 70 %, and their averaged classification accuracies. Num and CA represent the number of mental task pairs and classification accuracy, respectively.

Participant	[oxy-Hb]		[deoxy-Hb]		[total-Hb]		[oxy-Hb] + [deoxy-Hb]	
	Num.	CA	Num.	CA	Num.	CA	Num.	CA
P1	12	75.42 %	13	78.12 %	12	77.72 %	12	78.64 %
P2	3	75.00 %	7	75.00 %	3	75.83 %	4	76.88 %
P3	3	75.00 %	5	78.50 %	8	75.00 %	7	78.57 %
P4	10	79.25 %	4	76.25 %	11	80.23 %	7	80.36 %
P5	4	80.00 %	3	81.66 %	8	75.31 %	6	78.33 %
P6	5	76.00 %	5	77.00 %	3	78.33 %	6	77.92 %
P7	5	81.50 %	1	75.00 %	7	75.00 %	5	78.50 %
P8	2	75.00 %	1	75.00 %	2	73.75 %	1	72.50 %
Mean	5.50	77.93 %	4.86	77.07 %	6.75	76.40 %	6.00	77.71 %

### 4. Discussion

Recently, some BCI studies demonstrated that NIRS can be one of the promising alternatives to EEG. However, there are a number of issues to be investigated in order to develop a practical NIRS-based BCI system. One of the issues might be to find optimal feature extraction methods and mental task combinations. In the present study, we investigated the most suitable feature type and mental task combination among eight different mental tasks, and confirmed that [total-Hb] can be the best feature type for classification of various mental tasks. Also, the mental task pair of right hand motor imagery and mental rotation might be the optimal mental task combination for NIRS-based BCI systems. Besides the concentration values of [oxy-Hb] and [deoxy-Hb], we will continue testing other feature types introduced in previous NIRS-based BCI studies, e.g., slope, laterality and variance of NIRS signals, to provide a useful reference for the selection of optimal feature extraction methods and mental task combinations.

### Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. 2012R1A2A2A03045395).

### References

Coyles S, Ward TE, Markham CM. Brain-computer interface using a simplified functional near-infrared spectroscopy system. *J Neural Eng*, 4(3):219-226, 2007.

Perelmouter J, Birbaumer N. A binray spelling interface with random errors. *IEEE Trans Rehabil Eng*, 8:227-32, 2000.

Luu S, Chau T. Decoding subjective preference from single-trial near-infrared spectroscopy signals. *J Neural Eng*, 6(1):016003, 2009.