6th Annual International IEEE EMBS Conference on Neural Engineering
San Diego, California, 6 - 8 November, 2013

A Comparison of Classification Performance among the Various Combinations of Motor Imagery Tasks for Brain-Computer Interface

Hyun Seok Kim, Min Hye Chang, Hong Ji Lee, and Kwang Suk Park, *Senior Member, IEEE*

Abstract— **Motor imagery brain-computer interface (BCI) is a system that sends commands from human to external devices using brain activity patterns of imagination of a motor action without an actual movement. In this paper, we compared classification performance among the various combinations of motor imagery tasks, toward the multi-dimensional control of motor imagery BCI. We used EEG motor imagery dataset of 99 subjects. Common spatial patterns (CSP) and linear discriminant analysis (LDA) were applied to extract features and to classify motor imagery tasks. 10x10 fold cross validation was used to evaluate classification accuracies through large dataset. For two-class discrimination, we compared the classification accuracy of the results between combinations: both feet and one hand, and both hand and one hand. From these results, using both feet motor imagery task showed 3% higher accuracy than using both hand motor imagery task (p<0.01). For four-class discrimination, the compared result of classification between left/right/both hand/rest and left/right/both feet/rest showed that there was no significant difference between above combinations.**

I. INTRODUCTION

Motor imagery based brain-computer interface (BCI) is a system that communicates between human and external devices using an imagination of a motor action without an actual movement [1]. Most commonly used motor imagery BCI systems are based on the electroencephalogram (EEG) to take advantage of noninvasiveness and practicality. Motor imagery BCI translates different brain activity patterns, which are due to topographical mapping between motor/somatosensory cortex region and the corresponding parts of body. However, there is a difficulty that limited number of different motor actions are recognizable due to a low spatial resolution of EEG. Most previous studies were used the imagination movement of left hand, right hand, foot and tongue as classes.

C. Guger *et al.* [2] investigated classification accuracies of right hand and feet movement imagery through ninety-nine healthy subjects and showed that 90% of the subjects were able to archive above 60% . B. Blankertz *et al.* [3] studied motor imagery performance of eighty subjects to predict BCI performances when performing motor imagery of left hand, right hand and feet . There were a smaller number of studies simultaneously classify left, right, both hand and both feet movement imagery tasks. Recently, A. J. Doud *et al.* [4] reported that three-dimensional control of a virtual helicopter was possible with over 85% accuracy using left/right arm, legs, tongue, and rest imaginations with three normal subjects, and Lafleur *et al.* [5] succeeded controlling a quadcopter in real three-dimensional space using left hand, right hand, both hand motor imagery with five subjects. There were below five subjects were participated in the experiments, further study is necessary to investigate the variation of motor imagery classification performance with many people.

The aim of this study was to find the best discriminable combinations of motor imagery tasks with a large number of subjects for binary and multi-class problem toward the multi-dimensional control of motor imagery BCI. We compared the classification performance among the various combinations of motor imagery tasks using common spatial patterns (CSP) and linear discriminant analysis (LDA).

II. METHODS

A. EEG Dataset

We used EEG motor movement/imagery dataset, which were recorded using BCI2000 system [6], provided by PhysioNet [7]. 64-channel EEG were recorded in accordance with the international 10-10 system at 160 Hz sampling rates as shown in Fig 1. (b), and 109 subjects performing a series of left hand, right hand, both fists and both feet movement/imagery tasks without feedback as shown in Fig 1. (a). In this study, we analyzed only motor imagery data of 99 subjects. First, a visual cue appeared on either the left or the right side of the screen, subjects perform either left or right hand movement imagery task until the target disappears (4 seconds) and relax. Second, a visual cue appeared on either the top or the bottom of the screen, subjects perform either

*This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. 2012R1A2A2A02010714) and by Public Welfare & Safety Research Program through the National Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (NRF-2010-0020808)

Hyun Seok Kim, Min Hye Chang and Hong Ji Lee are with the Interdisciplinary Program in Bioengineering, Seoul National University, Seoul, Republic of Korea (corresponding author to provide phone: +82-2-740-8585; fax: +82-2-744-7446; e-mail: khs0330kr@bmsil.snu.ac.kr; e-mail: binch007@bmsil.snu.ac.kr; e-mail: hongjidan@bmsil.snu.ac.kr).

Kwang Suk Park is with the Department of Biomedical Engineering, College of Medicine, Seoul National University, Seoul, Republic of Korea. (e-mail: pks@bmsil.snu.ac.kr)

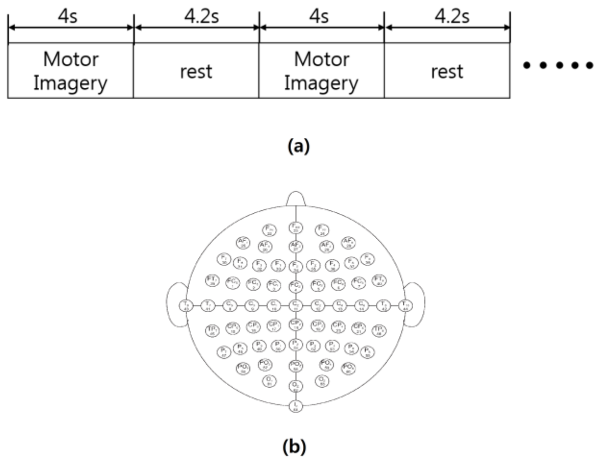

Figure 1. (a) Experimental paradigm. Each subject performs motor imagery task for 4 seconds and rests for 4.2 seconds. (b) Position of electrodes. The position of 64-channel electrodes following the international 10-10 system.

both fists or both feet movement imagery until the target disappears (4 seconds) and relax as in Fig 1. (a). Each subject performed total 90 trials.

B. Data Analysis

The EEG data were processed using EEGLAB, which is an open-source matlab toolbox [8]. The data were band-pass filtered between 6~30Hz using fifth-order Butterworth filter. CSP were used as a spatial filter that the variance of the spatially filtered signal is maximal for one class and minimal for the other class [9]. The number of used CSP patterns are three for each class. The log-variance of the spatially filtered signal was used as a feature and LDA was used as a classifier for two-class classification [10]. The LDA is a binary classifier, pair-wise approach [11] was applied for multi-class classification. 10 x 10 fold cross validation was used to evaluate the performance of classification of motor imagery tasks. To observe event-related desynchronization (ERD) and event-related synchronization (ERS) during motor imagery tasks, event-related spectral perturbation (ERSP) was obtained using the short-time Fourier transform (STFT) [12].

III. RESULTS

We evaluated the classification performance among multi-class motor imagery combinations. Table 1 shows that the classification accuracies of combinations of motor imagery tasks. For two-class discrimination, we compared classification accuracy among left/right hand (L-R), left/both hand (L-BH), right/both hand (R-BH), left/both feet(L-BF), right/both feet (R-BF) and both hand/both feet (BH-BF). For multi-class discrimination, we compared classification accuracy among the motor imagery of left/right/both feet (L-R-BF), left/right/both hand/both feet (L-R-BH-BF), left/right/both hand/rest (L-R-BH-Rt) and left/right/both feet/rest (L-R-BF-Rt). The classification accuracies between L-BH and R-BH had no significant differences. For two-class classification, using both feet motor imagery is 3% better than

TABLE I. CLASSIFICATION ACCURACIES(%) OF COMBINATIONS OF MOTOR IMAGERY TASKS

Class	*Mean*	*STD*	*Class*	*Mean*	*STD*
L-R	61.24	15.41	L-R-BH	57.38	13.01
L-BH	77.19	11.88	L-R-BF	61.05	14.04
R-BH	77.60	12.72	L-R-BH-BF	51.18	15.47
L-BF	80.93	11.81	L-R-BH-Rt	58.30	14.29
R-BF	81.96	11.69	L-R-BF-Rt	58.11	14.43
BH-BF	67.01	17.46	-	-	-

L = left hand; R = right hand; BH = both hand; BF = both feet; Rt = rest condition;

using both hand motor imagery when it is combined with one hand motor imagery ($p<0.01$). Classification result of BH-BF was 14.44% lower than L-BF/R-BF ($p<0.01$). For four class classification, there was no significant difference between L-R-BH-Rt and L-R-BF-Rt.

Fig. 2 shows that the boxplot of the classification performance of multi-class motor imagery combinations. For two-class classification, the classification accuracy of L-R was lowest among other combinations ($p<0.01$). When classifying L/R-BH and L/R-BF, using both feet motor imagery has higher 25% and 75% quantiles and median value than using both hand motor imagery. There was a significant difference between L-BH and L-BF, and between R-BH and R-BF ($p<0.01$). Three-class classification accuracies also show the same results as two-class cases. L-R-BF's accuracy is better than L-R-BH and has higher both side box edges, which indicates 25% and 75% quantiles. The results of four-class classification shows that L-R-BH-Rt and L-R-BF-Rt has no significant difference.

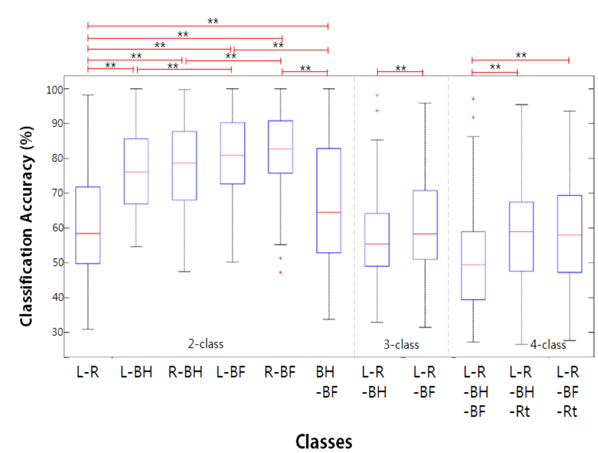

Figure 2. Boxplot of the performance of motor imagery classification between multi-class combinations. On each blue box, the red central mark is the median, the edges of the box are the 25th and 75th percentiles. A double asterisk (**) indicates P-value < 0.01. L = left hand; R = right hand; BH = both hand; BF = both feet; Rt = rest condition; e.g. L-R means that classification between left hand and right

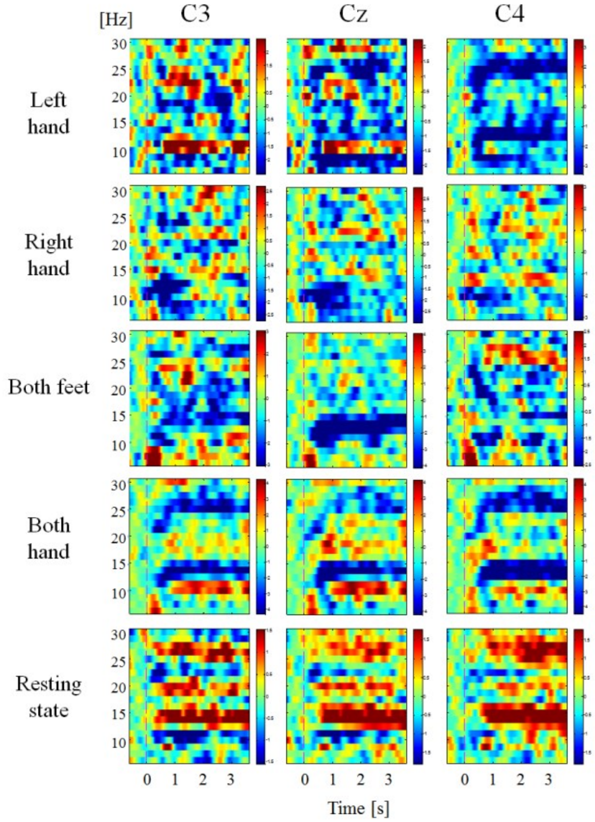

Figure 3. Event-related spectral perturbation (ERSP) obtained using short-time Fourier transform (STFT) for left hand, right hand, both feet, both hand motor imagery, and resting classes from subject 42 (mean accuracy over all cases = 94.2±3%). First, second, and third columns were obtained at electrodes position C3, Cz, and C4, respectively. Pink dash lines indicate the stimulus onset time at 0 s. Blue color represents event-related desynchronization (ERD) and red color represents event-related synchronization (ERS).

Fig. 3 shows that the ERSP obtained using the STFT from subject 42, who has 94.2±3% mean accuracy over all eleven cases. For left and right hand motor imagery, ERD and ERS map showed typical contralateral brain activity pattern. The strong ERD of both feet motor imagery distributed in *mu* band at Cz. When subject performed both hand motor imagery, ERD were observed in *beta* band at C3 and C4. Strong ERS was observed at C3, Cz, and C4 during resting state.

IV. Discussion

In this paper, we compared classification performances among the various combinations of motor imagery tasks. The results of two-class and three-class discrimination indicate that when we consider using either both hand or both feet motor imagery, using both feet motor imagery would be better than using both hand motor imagery. But if we consider four-class discrimination including resting state and one hand motor imagery, both tasks perform similarly.

The classification performance of L-R showed unexpected result that is lower than any other two-class cases. B. Blankertz *et al.* [3] studied classification performances of binary motor imagery tasks (left-right, left-foot, and foot-right) for 80 subject and results showed that accuracy was 74.4%±16.5%. Our result of the same combination of motor imagery tasks was 74.7%±16.1%. Although different dataset was used on each study, the results were almost same.

In this study, only CSP and LDA were used to classify motor imagery tasks along with other advanced methods. These simple methods were chosen to compare classification accuracies among the various multi-class motor imagery combinations with large dataset, not to compare advanced signal processing method's performances. If we use more advanced method as, common spatio-spectral pattern [13], multiclass CSP [14], filter bank CSP [15] and optimal spatio-spectral filter network [16], the performance of classification would be improved. There is no public EEG dataset recorded when performing motor imagery of left hand, right hand, both hand, both feet and tongue. So we couldn't evaluate the performance of 6 classes to find the number of person who has a feasibility of multi-dimensional motor imagery BCI system.

In a future study, we will apply previously identified signal processing methods and evaluate the performances of methods and investigate a strategy toward practical BCI system. Also we will investigate how the ERSP of each subject varies across all subjects, for example by clustering analysis.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clinical Neurophysiology,* vol. 113, pp. 767-791, Jun 2002.

[2] C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, and G. Pfurtscheller, "How many people are able to operate an EEG-based brain-computer interface (BCI)?," *Ieee Transactions on Neural Systems and Rehabilitation Engineering,* vol. 11, pp. 145-147, Jun 2003.

[3] B. Blankertz, C. Sannelli, S. Haider, E. M. Hammer, A. Kubler, K. R. Muller*, et al.*, "Neurophysiological predictor of SMR-based BCI performance," *Neuroimage,* vol. 51, pp. 1303-1309, Jul 15 2010.

[4] A. J. Doud, J. P. Lucas, M. T. Pisansky, and B. He, "Continuous Three-Dimensional Control of a Virtual Helicopter Using a Motor Imagery Based Brain-Computer Interface," *Plos One,* vol. 6, Oct 26 2011.

[5] K. Lafleur, K. Cassady, A. Doud, K. Shades, E. Rogin, and B. He, "Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain-computer interface," *J Neural Eng,* vol. 10, p. 046003, Jun 4 2013.

[6] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: a general-purpose brain-computer interface (BCI) system," *IEEE Trans Biomed Eng,* vol. 51, pp. 1034-43, Jun 2004.

[7] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark*, et al.*, "PhysioBank, PhysioToolkit, and PhysioNet - Components of a new research resource for complex physiologic signals," *Circulation,* vol. 101, pp. E215-E220, Jun 13 2000.

[8] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of Neuroscience Methods,* vol. 134, pp. 9-21, Mar 15 2004.

[9] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *Ieee Transactions on Rehabilitation Engineering,* vol. 8, pp. 441-446, Dec 2000.

[10] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern classification*: Wiley-interscience, 2012.

[11] J. Muller-Gerking, G. Pfurtscheller, and H. Flyvbjerg, "Designing optimal spatial filters for single-trial EEG classification in a movement task," *Clinical Neurophysiology,* vol. 110, pp. 787-798, May 1999.
[12] S. Makeig, "Auditory Event-Related Dynamics of the Eeg Spectrum and Effects of Exposure to Tones," *Electroencephalography and Clinical Neurophysiology,* vol. 86, pp. 283-293, Apr 1993.
[13] S. Lemm, B. Blankertz, G. Curio, and K. R. Muller, "Spatio-spectral filters for improving the classification of single trial EEG," *Ieee Transactions on Biomedical Engineering,* vol. 52, pp. 1541-1548, Sep 2005.
[14] M. Grosse-Wentrup and M. Buss, "Multiclass common spatial patterns and information theoretic feature extraction," *IEEE Trans Biomed Eng,* vol. 55, pp. 1991-2000, Aug 2008.
[15] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter Bank Common Spatial Pattern Algorithm on BCI Competition IV Datasets 2a and 2b," *Front Neurosci,* vol. 6, p. 39, 2012.
[16] H. Zhang, Z. Y. Chin, K. K. Ang, C. Guan, and C. Wang, "Optimum spatio-spectral filtering network for brain-computer interface," *IEEE Trans Neural Netw,* vol. 22, pp. 52-63, Jan 2011.