

Evaluating a Four-Class Motor-Imagery-Based Optical Brain-Computer Interface*

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Abstract—This work investigates the potential of a four-class motor-imagery-based brain-computer interface (BCI) using functional near-infrared spectroscopy (fNIRS). Four motor imagery tasks (right hand, left hand, right foot, and left foot tapping) were executed while motor cortex activity was recorded via fNIRS. Preliminary results from three participants suggest that this could be a viable BCI interface, with two subjects achieving 50% accuracy. fNIRS is a noninvasive, safe, portable, and affordable optical brain imaging technique used to monitor cortical hemodynamic changes. Because of its portability and ease of use, fNIRS is amenable to deployment in more natural settings. Electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) BCIs have already been used with up to four motor-imagery-based commands. While fNIRS-based BCIs are relatively new, success with EEG and fMRI systems, as well as signal characteristics similar to fMRI and complementary to EEG, suggest that fNIRS could serve to build or augment future BCIs.

I. INTRODUCTION

A brain-computer interface (BCI) is a system that records and classifies human brain signals into commands to control a computer. Recording brain signals directly allows the BCI to bypass the neuromuscular system, making them a promising research area for restoring communication or movement in patients suffering from neuromuscular diseases [1]. Additionally, such a system could serve as a secondary control method for healthy individuals, freeing the user's hands for performing other tasks while ideally incurring minimal mental strain.

A. fNIRS BCI

Functional near infrared spectroscopy (fNIRS) is a non-invasive optical brain imaging technique that has shown promise for future BCI applications [2]–[6], including the detection of motor movements [7]–[9]. It has also been used alongside bio-signals [10] and to augment existing EEG BCIs [11]. fNIRS uses near infrared light to measure blood oxygenation changes in the brain, which are correlated with functional activity such as cognitive tasks and motor activity [12], [13]. The devices are low-cost, wearable, and can be used wirelessly [14]. This allows them to be used in more natural settings, such as sitting at a desk, rather than an artificial lab environment. While fNIRS has a time delay due to the slow hemodynamic response, it has good spatial

resolution and is free from most muscle artifacts, such as eye blinks.

B. Motor-Imagery-Based BCI

Motor imagery is an imagined movement of the body, typically performed in preparation for motor execution (or actual movement), during which the muscles remain inactive. The hemodynamic response produced is similar to that of motor execution, but with a smaller increase in blood flow and slight delay in activation time [15]. Motor imagery could provide an intuitive mapping for BCI commands, since the required tasks would be closely related to naturally produced muscle movement commands. Natural and intuitive mappings for commands increase the usability of a BCI system while decreasing the mental strain required for operation.

Several EEG- or fMRI-based studies have used motor imagery as the sole input method with two [16], three [17], or four [18] motor imagery classes. The primary motor imagery classes are left hand vs. right hand, with a few studies using both feet together as a third class and tongue motor imagery as a fourth class. Other groups have used motor imagery as one of several control methods (e.g. motor imagery and P300 signal) in a “hybrid BCI” [19].

While most motor imagery (or motor execution) fNIRS BCI studies have focused on left vs. right hand classification, Kaiser et al. have looked at detecting right hand vs. both feet motor imagery [20] and Abibullaev et al. studied directional movements of the forearm [21]. Ito et al. developed a four-class BCI to differentiate right arm movement, left arm movement, lower leg movement, and rest [22].

The objective of this paper is to assess the potential of a four-class motor imagery fNIRS BCI using left hand, right hand, left foot, and right foot tapping. The BCI accuracy is evaluated individually for each subject in an offline analysis.

II. METHODS

A. Participants

Three healthy subjects participated in the experiment, which was approved by the Drexel University institutional review board. Subjects were aged 18-35, right-handed, English speaking, and with vision correctable to 20/20. No subjects reported any physical or neurological disorders, or were on medication. Subjects were informed of the experimental procedure and provided written consent prior to participating.

B. fNIRS Recording

Twenty-four channels of fNIRS data were recorded using a Hitachi ETG-4000 optical topography system. Each channel

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recorded oxygenated and deoxygenated hemoglobin levels sampled at 10 Hz. Fig. 1 shows the sensor arrangement with reference to Cz (according to the international 10/20 system).

C. Experiment Protocol

Subjects attended two training sessions. Each subject sat in front of a computer screen with both feet flat on the floor and hands in his or her lap or on chair arm rests with palms facing upwards. The training sessions were split into two runs as shown in Fig. 2. The first run had 16 trials of motor execution, and the second run had 40 trials of motor imagery. Each run had an equal number of the four tasks in a randomized order. Motor execution was performed before motor imagery in order to improve the subject’s ability to imagine performing the task.

In each trial, subjects performed one of four tasks: right hand, left hand, right foot, or left foot tapping. During motor execution tasks, subjects were instructed to tap their fingers against their palm (for hand tasks) or tap their foot and toes on the floor while keeping their heel on the ground (for foot tasks). During motor imagery tasks, subjects were instructed to imagine performing these tasks, but refrain from any muscle movement. Subjects self-paced the movements or motor imagery at approximately one per second.

D. Trial Protocol

The training session trial timing diagram is shown in Fig. 3. During the six seconds of rest a cross cue was displayed and subjects were instructed to relax their mind and refrain from any movement. Immediately after the rest period, the cue for the next task (left hand, right foot, etc.) was displayed in the middle of the screen for three seconds. Subjects were instructed not to perform motor execution or imagery during this display, but to wait until the feedback display was shown (Fig. 4). The feedback display showed the probability of selecting each class with the real-time classifier, in order to

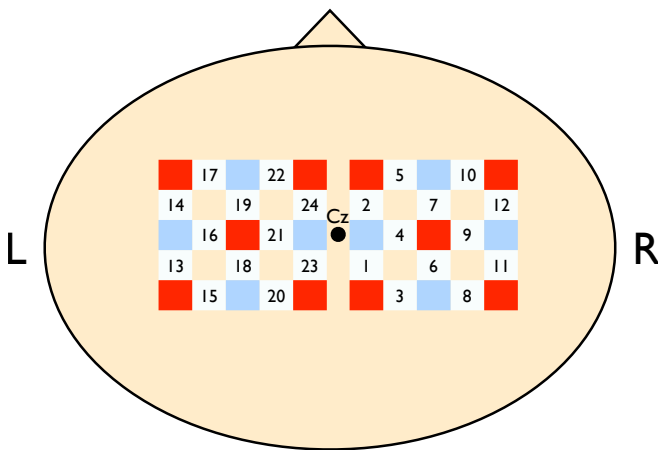


Fig. 1: The fNIRS sensor layout. Channels are numbered 1-24, light sources are shown as red squares and detectors are blue squares. The spacing between an adjacent source and detector is 3 cm.

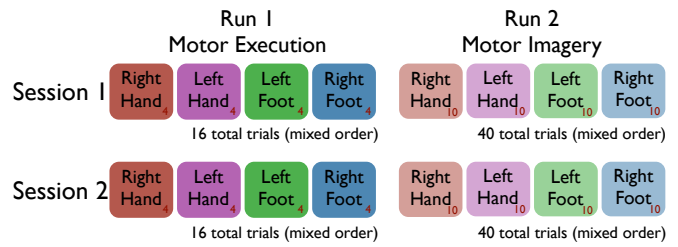


Fig. 2: Trial organization for the two sessions. Tasks are separated into motor execution or motor imagery.

help the subject improve his or her performance [23]. After each 30-second task period, a results screen showing the final prediction probabilities for each task was displayed for six seconds. Each trial lasted 45 seconds, and was followed immediately by the next trial.

III. DATA ANALYSIS

A total of 32 (8 per task) motor execution and 80 (20 per task) motor imagery trials were collected from each participant. Each trial had 30 seconds of both oxygenated hemoglobin (oxyHb) and deoxygenated hemoglobin (deoxyHb) data from each of the 24 channels, totaling 48 data sequences per trial. An additional 24 sequences of total hemoglobin (totalHb) data were created by adding the oxyHb and deoxyHb sequences together for each channel. The data were recorded at 10 Hz and low-pass filtered at 0.1 Hz. Trials were classified by a support vector machine (SVM) [24].

A. Online Analysis

During the experiment, SVM classification probabilities for each class were shown to the subject as feedback, updated twice per second. The first set of measurements for each trial

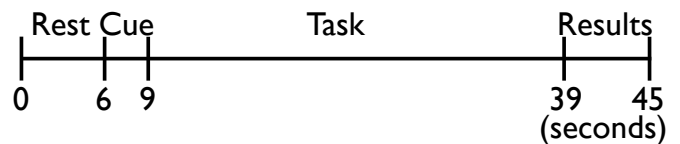


Fig. 3: Diagram of individual trial timing.

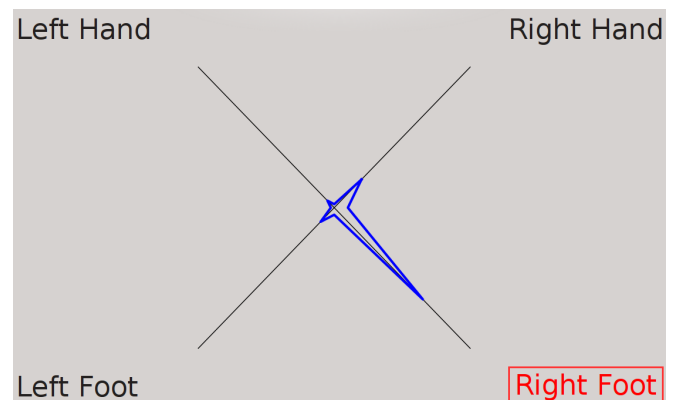


Fig. 4: Subject feedback display during right foot task. The length of each point is proportional to the class’s probability.

was used as the baseline and subtracted from all following data values for that trial. The first five seconds of each trial were not used and no feedback was shown to the subject due to the slow hemodynamic response. The online classifier was trained on preliminary data for the first session, and retrained on the subject’s own data for the second session.

B. Offline Analysis

The recorded data were inspected for signal quality. Artifacts (such as spikes or sudden baseline shifts) were removed, as well as any channels that had a low signal-to-noise ratio or became saturated [25]. Data for a trial were completely removed if more than 70% of the data was rejected from the baseline data (first five seconds of the trial) or the analysis data (last 25 seconds of the trial).

C. Features

For offline analysis, the individual channels were combined into six groups by physical location, resulting in three groups on each half of the brain. The channels belonging to each group were averaged to create a single time series, using the channel groupings shown in Table I. This reduced the likelihood of over-fitting the classifier by reducing the number of calculated features, ideally replacing a larger feature set with a smaller group of more informative features.

TABLE I: Channels assigned to each group and their relative location in the sensor array.

Group	Location	Channels
1	Right Top	1,2,3,4,5
2	Right Middle	4,6,7,9
3	Right Bottom	8,9,10,11,12
4	Left Bottom	13,14,15,16,17
5	Left Middle	16,18,19,21
6	Left Top	20,21,22,23,24

For each trial, the data were baseline corrected using the average of the first five seconds of the task, and features were calculated on the remaining 25 seconds.

Four types of features were calculated: the mean, median, range (difference between maximum and minimum value) and slope of the line of best fit. Each feature was calculated separately for oxyHb, deoxyHb, and totalHb on the data series from each of the six groups. Feature sets were created for oxyHb, totalHb, and the concatenation of oxyHb and deoxyHb features. Additionally, the set of all feature types concatenated together was examined for each of the three hemoglobin combinations, for 15 total feature sets.

D. Classifier Training

The data were divided into a testing set of 24 trials, evenly distributed between the four classes, and a training set consisting of the remaining trials. If no trials were removed due to artifacts, the training set had 56 examples, or 70% of the total dataset. A classifier was selected using a grid search and 7-fold cross-validation to determine the best performing features and kernel, linear or radial basis function (RBF), on

the training set. The best performing classifier and feature set were then evaluated on the testing set.

IV. RESULTS

Motor imagery classification was performed using a four-class one-vs-all SVM. Table II shows the accuracy for each subject, along with the kernel and feature type selected on the validation set. All three subjects performed better than chance (25%) and two subjects achieved 50% accuracy. All subjects achieved their best results using totalHb, as opposed to oxyHb or combining oxyHb and deoxyHb features. Two subjects performed best with a RBF kernel and the slope feature, while one subject used a linear kernel and the mean feature.

TABLE II: Classification accuracy of motor imagery task data for each subject, chance level is 25%.

	Subject 1	Subject 2	Subject 3
Accuracy	54%	50%	33%
Features	Mean	Slope	Slope
Hb Type	totalHb	totalHb	totalHb
Kernel	Linear	RBF	RBF

Fig. 5 shows a confusion matrix for the best and worst performing subjects (subject 1 and subject 3, respectively) on the testing set. The confusion matrix for subject 1 shows high classification percentages on the diagonal, corresponding to higher accuracy. The most problematic task was right foot, which was most frequently misclassified as left hand. Subject 3 shows a much weaker diagonal on the confusion matrix, indicating frequent task misclassification. In particular, right hand was often mistakenly classified as left hand or left foot. Misclassifications for subject 1 appear to be more common between tasks involving the same side of the brain (e.g. left hand and left foot), while subject 3 does not appear to follow this pattern as strongly.

V. CONCLUSIONS

This preliminary study shows that fNIRS may prove useful in developing a four-class motor imagery BCI, with results

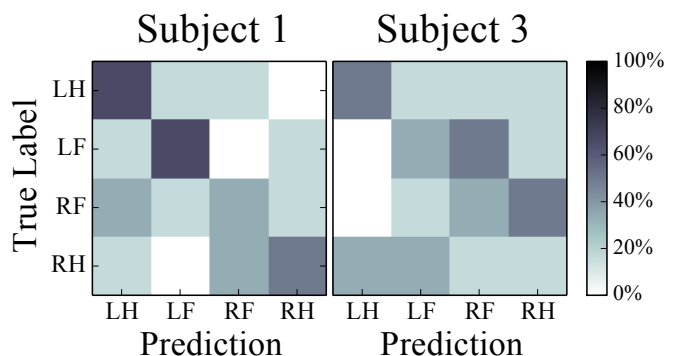


Fig. 5: Classifier confusion matrices for subjects 1 and 3. Classes are left hand (LH), left foot (LF), right foot (RF), and right hand (RH), and the colors correspond to frequency of classification (percent) for each task.

showing above-chance levels for all subjects. Future analysis could improve performance by utilizing more informative features and classifiers, particularly if they model the time-course of the channels rather than computing single-number feature values (e.g. mean).

The confusion matrices show that misclassifications are not necessarily between adjacent areas of the brain (e.g. confusing left hand and left foot). A closer study of the activation patterns may yield insights into improving classification by making better use of spatial information, such as subject-specific channel groupings or features that incorporate spatial information. Motor execution data could prove useful in choosing channels or groupings to use for individual subjects.

Better selection of motor tasks could potentially improve performance, such as combining both feet into a single class as is often done with EEG. Additionally, one subject self-reported difficulty imagining movements, which may have hampered the BCI accuracy. Further training might be required for improved performance. Finally, future analysis should examine the minimum task time required for accurate predictions in order to reduce the trial time and improve the utility of the BCI.

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, no. 6, pp. 767–791, Jun. 2002.
- [2] S. D. Power, A. Kushki, and T. Chau, "Towards a system-paced near-infrared spectroscopy braincomputer interface: differentiating prefrontal activity due to mental arithmetic and mental singing from the no-control state," *Journal of Neural Engineering*, vol. 8, no. 6, p. 66004, 2011.
- [3] H. Ayaz, P. A. Shewokis, S. Bunce, and B. Onaral, "An Optical Brain Computer Interface for Environmental Control," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Boston, MA, 2011, pp. 6327–6330.
- [4] 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, Feb. 2007.
- [5] S. M. Coyle, T. E. Ward, and C. M. Markham, "Brain-computer interface using a simplified functional near-infrared spectroscopy system," *Journal of Neural Engineering*, vol. 4, no. 3, p. 219, 2007.
- [6] H. Ayaz, P. A. Shewokis, S. Bunce, M. Schultheis, and B. Onaral, "Assessment of Cognitive Neural Correlates for a Functional Near Infrared-Based Brain Computer Interface System," in *Foundations of Augmented Cognition. Neuroergonomics and Operational Neuroscience SE - 79*, ser. Lecture Notes in Computer Science, D. Schmorow, I. Estabrooke, and M. Grootjen, Eds. Springer Berlin Heidelberg, 2009, vol. 5638, pp. 699–708.
- [7] N. Naseer and K.-S. Hong, "Classification of functional near-infrared spectroscopy signals corresponding to the right- and left-wrist motor imagery for development of a braincomputer interface," *Neuroscience Letters*, vol. 553, no. 0, pp. 84–89, Aug. 2013.
- [8] H. T. Nguyen, C. Q. Ngo, K. Truong Quang Dang, and V. T. Vo, "Temporal Hemodynamic Classification of Two Hands Tapping Using Functional Near - Infrared Spectroscopy," *Frontiers in Human Neuroscience*, vol. 7, no. 516, 2013.
- [9] A. F. Abdelnour and T. Huppert, "Real-time imaging of human brain function by near-infrared spectroscopy using an adaptive general linear model," *NeuroImage*, vol. 46, no. 1, pp. 133–43, May 2009.
- [10] R. Zimmermann, L. Marchal-Crespo, J. Edelmann, O. Lambercy, M.-C. Fluet, R. Riener, M. Wolf, and R. Gassert, "Detection of motor execution using a hybrid fNIRS-biosignal BCI: a feasibility study," *Journal of NeuroEngineering and Rehabilitation*, vol. 10, no. 1, p. 4, 2013.
- [11] Y. Liu, H. Ayaz, A. Curtin, B. Onaral, and P. A. Shewokis, "Towards a Hybrid P300-Based BCI Using Simultaneous fNIR and EEG," in *Foundations of Augmented Cognition*, ser. Lecture Notes in Computer Science, D. Schmorow and C. Fidopiastis, Eds. Springer Berlin Heidelberg, 2013, vol. 8027, pp. 335–344.
- [12] H. Ayaz, P. A. Shewokis, S. Bunce, K. Izzetoglu, B. Willems, and B. Onaral, "Optical brain monitoring for operator training and mental workload assessment," *NeuroImage*, vol. 59, no. 1, pp. 36–47, Jan. 2012.
- [13] A. H. Rodrigo, S. I. D. Domenico, H. Ayaz, S. Gulrajani, J. Lam, and A. C. Ruocco, "Differentiating functions of the lateral and medial prefrontal cortex in motor response inhibition," *NeuroImage*, vol. 85, Part 1, no. 0, pp. 423–431, Jan. 2014.
- [14] H. Ayaz, B. Onaral, K. Izzetoglu, P. A. Shewokis, R. McKendrick, and R. Parasuraman, "Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic research: Empirical examples and a technological development," *Frontiers in Human Neuroscience*, vol. 7, no. 871, 2013.
- [15] S. C. Wriessnegger, J. Kurzmann, and C. Neuper, "Spatio-temporal differences in brain oxygenation between movement execution and imagery: A multichannel near-infrared spectroscopy study," *International Journal of Psychophysiology*, vol. 67, no. 1, pp. 54–63, Jan. 2008.
- [16] 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 braincomputer interface," *Journal of Neural Engineering*, vol. 10, no. 4, p. 46003, 2013.
- [17] Y. Chae, J. Jeong, and S. Jo, "Toward Brain-Actuated Humanoid Robots: Asynchronous Direct Control Using an EEG-Based BCI," *IEEE Transactions on Robotics*, vol. 28, no. 5, pp. 1131–1144, 2012.
- [18] 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, no. 10, p. e26322, 2011.
- [19] B. Choi and S. Jo, "A Low-Cost EEG System-Based Hybrid Brain-Computer Interface for Humanoid Robot Navigation and Recognition," *PLoS ONE*, vol. 8, no. 9, p. e74583, 2013.
- [20] V. Kaiser, G. Bauernfeind, A. Kreiling, T. Kaufmann, A. Kübler, C. Neuper, and G. R. Müller-Putz, "Cortical effects of user training in a motor imagery based brain-computer interface measured by fNIRS and EEG," *NeuroImage*, 2014.
- [21] B. Abibullaev, J. An, S.-H. Jin, and J. I. Moon, "Classification of brain hemodynamic signals arising from visual action observation tasks for brain-computer interfaces: A functional near-infrared spectroscopy study," *Measurement*, vol. 49, pp. 320–328, Mar. 2014.
- [22] T. Ito, H. Akiyama, and T. Hirano, "Brain Machine Interface using Portable Near-InfraRed Spectroscopy - Improvement of Classification Performance based on ICA analysis and Self-proliferating LVQ," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Tokyo, Japan, Nov. 2013, pp. 851–858.
- [23] S. E. Kober, G. Wood, J. Kurzmann, E. V. C. Friedrich, M. Stangl, T. Wippl, A. Våljamäe, and C. Neuper, "Near-infrared spectroscopy based neurofeedback training increases specific motor imagery related cortical activation compared to sham feedback," *Biological psychology*, vol. 95, pp. 21–30, Jan. 2014.
- [24] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
- [25] H. Ayaz, P. A. Shewokis, A. Curtin, M. Izzetoglu, K. Izzetoglu, and B. Onaral, "Using MazeSuite and Functional Near Infrared Spectroscopy to Study Learning in Spatial Navigation," *Journal of Visualized Experiments*, no. 56, p. e3443, 2011.