An EEG and fTCD based BCI for Control

Aya Khalaf[1], Matthew Sybeldon[1], Ervin Sejdic[1,2], and Murat Akcakaya[1]
[1]Electrical and Computer Engineering Department, University of Pittsburgh, Pittsburgh, PA 15213, USA
[2]Bioengineering Department, University of Pittsburgh, Pittsburgh, PA 15213, USA

***Abstract*— Brain-computer interfaces (BCIs) promise to promote a novel access channel for functional independence for individuals with severe speech and physical impairment (SSPI) that can occur as a result of numerous neurological diseases and injuries. Current BCI systems lack the robustness and accuracy to allow individuals with SSPI to complete tasks required for independent living (e.g. communication or navigation). We aim to develop a noninvasive hybrid BCI relying on two imaging modalities: Electroencephalography (EEG) and functional transcranial Doppler sonography (fTCD). Such hybrid BCI is expected to be sufficiently robust and accurate to be operated in a real-life environment.**

Keywords— Brain-computer interfaces; Electroencephalography; Functional transcranial Doppler sonography; Canonical correlation analysis; Learn. ++ NSE; Transfer learning; Wavelet transform; Support vector machines.

I. Introduction

Brain Computer Interfaces (BCIs) are newly evolving technology that acquire and process mental activity to carry out thought-controlled actions [1]. Typical BCI users suffer from motor and/or speech impairment that occur due to different neurological conditions such as stroke, Parkinson's disease and amyotrophic lateral sclerosis (ALS) [2], therefore a BCI system can assist such individuals to communicate with the outside world.

Several modalities have been introduced to design BCI systems including electroencephalography (EEG) [3], functional magnetic resonance imaging (fMRI) [4], functional transcranial Doppler ultrasound (fTCD) [5], near-infrared spectroscopy(NIRS) [6] and magnetoencephalography (MEG) [7]. Although these modalities have been used for BCI applications [8][9][7], most of them suffer from certain drawbacks that prevents them from being reliably and consistently used in real-life environments by individuals with severe speech and motor impairments. For example, fMRI and MEG based BCIs employ bulky equipment with expensive running costs. Such equipment can perform well only in highly controlled environments [10]. Moreover, current NIRS-based systems study the slow hemodynamic response and lack the speed necessary to be considered for real-life applications [11]

Great strides in BCI development have been made using EEG as the input modality. Steady state visual evoked potentials (SSVEPs) are a type of EEG-based BCI control signals elicited by the use of flickering stimuli [12]. The power spectrum of the EEG in case of SSVEP BCI shows increased power at stimuli frequencies and their harmonics. Recently, functional transcranial Doppler ultrasound (fTCD) has been introduced as an input modality for BCI systems. It measures the cerebral blood flow velocity[5]. Changes in the fTCD signal are associated with mental tasks, and it was shown that it is possible to design BCI based on fTCD using certain mental tasks [13], [14].

Considering the limitations mentioned earlier, EEG as well as fTCD provide promising sensing methods that have low setup complexity and relatively fast response times. The basic idea is to combine both modalities in a BCI system that can afford a decision with higher accuracy and speed compared to single modality based BCI. In this paper, we design two different binary BCI systems based on EEG and fTCD input modalities. To examine the possibility of integrating both systems, we evaluated each system separately to check if they showed comparable performance in terms of accuracy and speed. If their performance is comparable, the possibility of using both of them to build a hybrid BCI is more likely to afford a system with higher performance measures. In addition, we proposed a presentation scheme for the hybrid system with mental tasks that could be differentiated through both EEG and fTCD. Moreover, the hybrid system we introduced was extended to include 3 classes.

For the EEG based BCI, an ensemble learning technique named as Learn++.NSE which deals with nonstationarity in data is used. To reduce the calibration requirements, transfer learning is utilized to allow including data sets of other users with the data set of the current user by using mutual information for data set selection purposes. To investigate the feasibility of 2-class fTCD based BCI, three classification problems were studied. Statistical features for the wavelet coefficients derived from a five level wavelet transform were extracted. The nonparametric Wilcoxon test was used for feature selection while support vector machines (SVM) classifier with a linear kernel was used for classification.

II. Materials and Methods

A. EEG-based BCI

1) System Description

We designed an SSVEP-based BCI with two flickering checkerboards at frequencies of 6 and 20 Hz . The stimulus presentation was implemented in MATLAB 2015a using Psychtoolbox which is an online free toolbox for designing time-accurate stimuli. All the experiments were conducted using a Lenovo ThinkPad W541 laptop with 64-bit Windows 7.

2) Participants

In this study, we recruited 10 healthy participants including 2 females and 8 males. None of the participants were less than 18 years old or have a history of epilepsy.

3) Experimental Procedure

At each trail, the participants were asked to focus their attention randomly on one of the two checkerboards. Each trial contained a 5-second flickering checkerboard with total of 100 trails per session. For each participant, four data collection sessions were held including 3 calibration sessions as well as 1 test session. In both the calibration and the testing phase, the chosen checkerboard was selected using an arrow that pointed randomly to one of the checkerboards.

4) Data Analysis

The EEG data was sampled at 256 Hz and filtered using a 150th order FIR filter with corner frequencies of 2, and 45 Hz. To analyze the preprocessed data, we employed two methods including canonical correlation analysis (CCA) as well as an ensemble learning based approach.

a) Canonical Correlation Analysis (CCA)

Canonical correlation analysis is a technique that suits healthy users who are able to control and focus their attention towards all the available stimuli[15][16]. CCA gets the correlation scores between the EEG signal and artificial reference signals that are generated based on frequencies of the shown stimuli. Each reference signal corresponds to a specific stimulus and contains sinusoids with frequencies same as stimulus harmonics. Determination of the stimulus that possess participant's attention is based on the maximum correlation score. For simple CCA application in which different stimuli have different frequencies, no training is needed as the decision is made based on the maximum correlation at each trail.

b) Ensemble Learning

For a BCI to be used by patients with disabilities, a machine learning approach may achieve better results compared to CCA [16]. Challenges in such approach include EEG nonstationarity and high calibration requirements[17]. For classification purposes, we employed Learn++.NSE ensemble which is an algorithm used for nonstationary learning. It detects nonstationarity and generates a new classifier for new data originating from the statistically changing environment[18].

To reduce the length of calibration sessions, we apply transfer learning to make use of data sets for other users with the current user. In general, transfer learning is a type of machine learning that is used to improve the performance of a learner by applying knowledge from one domain to another. In this case, the objective is to use data sets of previous users with the current user to enhance the accuracy of the system. To identify the data sets that will help in classifying current EEG data, we employed an information theoretic approach by utilizing mutual information.

Mutual information [19] is a measure of the amount of information that one random variable can provide about another random variable. In this paper, mutual information was used to find previous data sets best represented the current data set. After, the mutual information between previous data sets and the current data set was calculated, the data sets with the highest mutual information were selected to train the Learn++.NSE.

A 4-dimensional feature vector was formulated using the power spectral density estimate at the first two harmonics of the stimuli frequencies. Such estimate was obtained using Welch's method [20].

A linear discriminant classifier (LDA) was used as the base learner in the Learn++.NSE ensemble to reduce computational complexity. For every participant, ensembles were formulated using groups of three individual classifiers. The first group contained Learn++.NSE ensembles (LPP-MI) that are based on the mutual information. The first 3 data sets with the highest mutual information were added to the Learn++.NSE. The data set with second most mutual information was added first then the data set with the most mutual information, and finally the latest user's data set. The second group consisted of the standard Learn++.NSE ensembles (LPP-S) that did not employ the transfer learning. For every participant, LPP-S was formulated using the three data sets collected during the calibration sessions.

B. fTCD-based BCI

1) System Description

Data was collected using two 2 MHz transducers placed on the right and left-side transtemporal window positioned above the zygomatic arch [21] with 50 mm TCD depth to match the depth of the mid-point of the middle cerebral arteries [22].

2) Participants

Twenty healthy participants including 10 males and 10 females were enrolled in this study. All the participants didn't have a history of concussions, migraines, strokes, or any other neurological injury.

3) Experimental Procedure

The data collection session was divided into 3 parts: 1) 20-min baseline period during which each participant was asked to take a rest to stabilize the cerebral blood flow. 2) two 15-min tasks separated by a 5-min break. Each task included randomly alternating five mental rotation tasks and five word generation tasks. The duration of each task was 45 seconds with 45 seconds resting period separating consecutive tasks.

Considering the mental rotation task, a 3D shapes database constructed from cubes [23] was used to extract randomly selected pairs of images to be displayed on the screen. Participants were asked to decide if the displayed image pairs were identical or mirrored by rotating the images mentally as seen in Fig.1.

During the 45 seconds of every word generation task, each participant was asked to think of words starting with a randomly chosen letter that is displayed on the screen. Such nonverbal action was selected to avoid artifacts due to speech or changes in intrathoracic pressure [24].

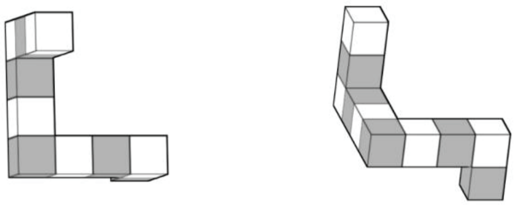

Figure 1: Random pair of images that each participant was asked to mentally rotate to decide whether they are identical.

4) Data Analysis

We used the moving window (MW) method to classify the cognitive tasks. We started with a window containing the first 0.5 seconds of the data. This window was used for feature extraction, then a decision based on the data from that window was made. After that, the window was shifted by 0.25 seconds and features were calculated again for that new window of data leading to a new classification decision. This procedure was repeated until the window reached 45 seconds which is the length of each task. Note that in this scheme, classification decision at a certain time was independent of the past samples.

a) Preprocessing

The data was sampled at 44.1 kHz. A 150th order low pass filter with corner frequency of 5 kHz was used for antialiasing purposes. The data was downsampled by a factor of 5 to decrease computation expenses.

b) Feature Extraction

Five level wavelet decomposition [25] employing Daubechies 4 mother wavelet was applied to each window . Statistical features were computed for approximation and detail coefficients at each decomposition level. Forty-eight statistical features were used for feature selection.

After applying the wavelet decomposition for each window of data, statistical features including mean, variance skewness[26], and kurtosis [27] were calculated for the wavelet coefficients. Skewness and kurtosis measure deviations from Gaussianity. Specifically, kurtosis measures the peak of the curve in comparison with the Gaussian while the skewness measures the asymmetry of a given probability distribution.

c) Feature Selection

Features were evaluated using the nonparametric Wilcoxon test [28], which is basically a hypothesis test used to assess differences between two groups. The main advantage of this test compared to Student-t test [29] is that it does not assume that the data follows any parametric distribution. We formulated 3 binary problems to be assessed using Wilcoxon test with a p value of 0.05 including mental rotation versus resting state, word generation versus resting state, and mental rotation versus word generation.

d) Classification

Support vector machines (SVM) [30] with linear kernel was employed for classification purposes. In this paper, three different binary classification problems were formulated. In the first two binary problems, two linear SVM classifiers were used to distinguish the word generation task from the resting state and mental rotation task from the resting state respectively. In the third binary problem, one linear SVM classifier was used to distinguish between the mental rotation and word generation tasks.

C. Hybrid BCI

To combine both binary BCI systems, we employ the same mental tasks used for the fTCD based system. To generate SSEVPs necessary for EEG subsystem, a checkerboard texture is added to the stimuli as seen in Fig.2 and these stimuli flickered with frequencies of 6, and 20 Hz. In addition, the system will be extended to include a third class which is a fixation cross that resembles the resting state. During each trial, an arrow will point randomly to one of the 3 tasks for duration of 9 seconds. A total of 150 trials will be presented per session. Each participant will attend one calibration and one test session.

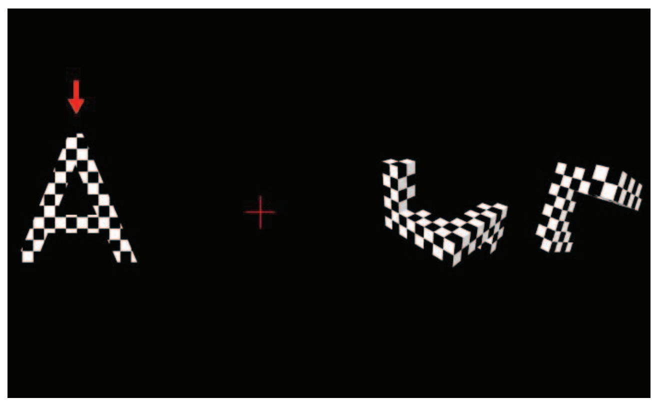

Figure 2: Stimulus presentation for the hybrid BCI system.

III. Results and Discussion

A. EEG-based BCI

Table 1 shows the accuracies for the 3 different approaches. Performance of standard Learn++.NSE ensemble (LPP-S) and Learn++.NSE ensemble based on mutual information (LPP-MI) is compared to show if the mutual information boosts the performance of the classification. The third method is standard CCA in which the reference signals are sinusoidal signals with frequencies corresponding to the first two harmonics of the two presentation stimuli.

LPP-MI outperformed LPP-S in terms of performance accuracy as seen in Table 1. However, CCA showed the best performance. The participants enrolled in this study consisted of healthy users who were able to focus their attention on the targeted checkerboards. For this reason, the success of CCA compared to ensemble based methods is expected given its current reputation as state of the art for SSVEP BCIs.

Table 1: Average accuracy for each tested method.

Method	LPP-S	LPP-MI	CCA
Accuracy	62.30%	75.80%	83.90%

B. fTCD-based BCI

Tables 2, and 3 show the average of the maximum classification accuracy for each participant and the corresponding time at different state durations. A state duration is the period during which a mental activity occurs before it is assigned to a certain class. Time column shown in Tables 2, and 3 represents the average time at which the maximum accuracy was achieved for each participant within the corresponding state duration. Such time is a direct measure for speed of classification.

Table 2: Average maximum accuracy and the corresponding time at different state durations for the word generation task versus resting state and the mental rotation task versus resting state.

State Duration (S)	Time(s)	Accuracy (%)	Time(s)	Accuracy (%)
5.0	2.84	82.35%	2.04	80.29%
7.5	4.41	87.35%	4.19	84.12%
10.0	4.93	88.24%	5.78	87.06%
12.5	4.93	88.24%	5.96	87.94%
15.0	6.10	89.12%	7.82	89.71%
17.5	6.63	89.41%	10.34	92.06%
20.0	8.62	90.00%	11.19	92.94%
22.5	8.62	90.00%	11.19	92.94%
45	21.22	93.24%	15.57	94.41%

Table 3: Average maximum accuracy and the corresponding time at different state durations for the word generation versus mental rotation.

State Duration (S)	Time(s)	Accuracy (%)
5.0	2.24	79.72%
7.5	3.18	82.22%
10.0	3.87	83.06%
12.5	5.93	86.11%
15.0	7.22	88.61%
17.5	9.01	90.00%
20.0	10.78	90.83%
22.5	11.28	91.39%
45	15.41	92.78%

As seen in Tables 2, and 3, classification of resting state versus mental rotation as well as resting state versus word generation using MW method achieved high average accuracy in a relatively short time of approximately 3 s with average accuracy of 80.29%, and 82.35% respectively. In addition, the MW method when used for the task versus task problem, achieved 79.72% accuracy within 2.24 s of the onset of the cognitive task.

Maximum accuracy of 94.41% was achieved for the mental rotation versus resting state problem after the onset of the task by 15.57 s. On the other hand, word generation versus resting state problem obtained maximum accuracy of 93.24% after the onset of the task by 21.22 s. Considering the mental rotation versus word generation problem, the MW method obtained 92.78% accuracy in 15.41 s.

The system introduced in [31] obtained average maximum accuracy of 82.90% and 85.70% for mental rotation and word generation respectively using observation period of 45 seconds while the proposed system got average maximum accuracy of 93.24% and 94.41% for the same tasks within the same observation period. Moreover, the system we introduced in this paper achieved accuracy of 80.29% and 82.35% within around 3 s of the onset of the mental activity for mental rotation versus resting state and word generation versus resting state respectively as seen in Tables 2. Therefore, such system can be utilized in a real-time BCI application.

IV. Conclusion

In this paper, we designed two different BCI systems based on EEG and fTCD modalities. These systems were assessed independently of each other so that in case they showed comparable performance in terms of accuracy and speed, the possibility of achieving higher performance measures in case of combining them in a hybrid system is increased. In addition, we designed a presentation scheme for the hybrid system that employs both EEG and fTCD. The mental tasks used for the hybrid systems were designed so that they could be differentiated through both modalities. Our future work will focus on recruiting healthy participants to test the hybrid system.

V. References

[1] L. F. Nicolas-Alonso and J. Gomez-Gil, “Brain computer interfaces, a review.,” *Sensors (Basel).*, vol. 12, no. 2, pp. 1211–79, 2012.

[2] K. Tai, S. Blain, and T. Chau, “A review of emerging access technologies for individuals with severe motor impairments.,” *Assist. Technol.*, vol. 20, no. 4, pp. 204–19; quiz 220–1, 2008.

[3] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, “A review of classification algorithms for EEG-based brain–computer interfaces,” *J. Neural Eng.*, vol. 4, no. 2, pp. R1–R13, Jun. 2007.

[4] N. Weiskopf, K. Mathiak, S. W. Bock, F. Scharnowski, R. Veit, W. Grodd, R. Goebel, and N. Birbaumer, “Principles of a Brain-Computer Interface (BCI) Based on Real-Time Functional Magnetic Resonance Imaging (fMRI),” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 966–970, Jun. 2004.

[5] M. A. Sloan, A. V. Alexandrov, C. H. Tegeler, M. P. Spencer, L. R. Caplan, E. Feldmann, L. R. Wechsler, D. W. Newell, C. R. Gomez, V. L. Babikian, D. Lefkowitz, R. S. Goldman, C. Armon, C. Y. Hsu, and D. S. Goodin, “Assessment: Transcranial Doppler ultrasonography: Report of the Therapeutics and Technology Assessment Subcommittee of the American Academy of Neurology,” *Neurology*, vol. 62, no. 9, pp. 1468–1481, 2004.

[6] S. Coyle, T. Ward, C. Markham, and G. McDarby, “On the suitability of near-infrared (NIR) systems for next-generation brain–computer interfaces,” *Physiol. Meas.*, vol. 25, no. 4, pp. 815–822, Aug. 2004.

[7] J. Mellinger, G. Schalk, C. Braun, H. Preissl, W. Rosenstiel, N. Birbaumer, and A. Kübler, “An MEG-based brain–computer interface (BCI),” *Neuroimage*, vol. 36, no. 3, pp. 581–593, 2007.

[8] G. R. Müller-Putz, R. Scherer, and G. Pfurtscheller, “Motor imagery and EEG-based control of spelling devices and neuroprostheses,” *Prog. Brain Res.*, vol. 159, pp. 393–409, 2006.

[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. 133–143, 2009.

[10] B. Z. Allison, E. W. Wolpaw, and J. R. Wolpaw, “Brain-computer interface systems: progress and prospects.,” *Expert Rev. Med. Devices*, vol. 4, no. 4, pp. 463–74, Jul. 2007.

[11] P. V. Zephaniah and J. G. Kim, “Recent functional near infrared spectroscopy based brain computer interface systems: Developments, applications and challenges,” *Biomed. Eng. Lett.*, vol. 4, no. 3, pp. 223–230, Sep. 2014.

[12] S. Amiri, A. Rabbi, L. Azinfar, and R. Fazel-Rezai, “A Review of P300, SSVEP, and Hybrid P300/SSVEP Brain- Computer Interface Systems,” in *Brain-Computer Interface Systems - Recent Progress and Future Prospects*, InTech, 2013.

[13] G. Vingerhoets and N. Stroobant, “Lateralization of Cerebral Blood Flow Velocity Changes During Cognitive Tasks : A Simultaneous Bilateral Transcranial Doppler Study,” *Stroke*, vol. 30, pp. 2152–2158, 1999.

[14] E. Sejdic, D. Kalika, and N. Czarnek, “An Analysis of Resting-State Functional Transcranial Doppler Recordings from Middle Cerebral Arteries,” *PLoS One*, vol. 8, no. 2, 2013.

[15] C. Chuan Jia, X. Xiaorong Gao, B. Bo Hong, and S. Shangkai Gao, “Frequency and Phase Mixed Coding in SSVEP-Based Brain--Computer Interface,” *IEEE Trans. Biomed. Eng.*, vol. 58, no. 1, pp. 200–206, Jan. 2011.

[16] B. Allison, T. Luth, D. Valbuena, A. Teymourian, I. Volosyak, and A. Graser, “BCI Demographics: How Many (and What Kinds of) People Can Use an SSVEP BCI?,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 2, pp. 107–116, Apr. 2010.

[17] M. Akcakaya, B. Peters, M. Moghadamfalahi, A. R. Mooney, U. Orhan, B. Oken, D. Erdogmus, and M. Fried-Oken, “Noninvasive Brain-Computer Interfaces for Augmentative and Alternative Communication,” *IEEE Rev. Biomed. Eng.*, vol. 7, pp. 31–49, 2014.

[18] R. Elwell and R. Polikar, “Incremental Learning of Concept Drift in Nonstationary Environments,” *IEEE Trans. Neural Networks*, vol. 22, no. 10, pp. 1517–1531, Oct. 2011.

[19] E. T. Jaynes, “Information Theory and Statistical Mechanics,” *Phys. Rev.*, vol. 106, no. 4, pp. 620–630, May 1957.

[20] P. D. Welch and P. D., “The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms,” *IEEE Trans. Audio Electroacoust., Vol. AU-15, p. 70-73*, vol. 15, pp. 70–73, 1967.

[21] A. V. Alexandrov, M. A. Sloan, L. K. S. Wong, C. Douville, A. Y. Razumovsky, W. J. Koroshetz, M. Kaps, and C. H. Tegeler, “Practice Standards for Transcranial Doppler Ultrasound: Part I-Test Performance,” *J. Neuroimaging*, vol. 17, no. 1, pp. 11–18, Jan. 2007.

[22] L. H. Monsein, A. Y. Razumovsky, S. J. Ackerman, H. J. W. Nauta, and D. F. Hanley, “Validation of transcranial Doppler ultrasound with a stereotactic neurosurgical technique,” *J. Neurosurg.*, vol. 82, no. 6, pp. 972–975, Jun. 1995.

[23] M. Peters and C. Battista, “Applications of mental rotation figures of the Shepard and Metzler type and description of a mental rotation stimulus library,” *Brain Cogn.*, vol. 66, no. 3, pp. 260–264, 2008.

[24] M. H. R.R. Diehl, M. Sitzer, “Changes of cerebral blood flow velocity during cognitive activity,” *Stroke*, vol. 21, no. 8, pp. 1236–1237, 1990.

[25] D. Valencia, “Discrete Wavelet Transform Filter Bank Implementation.” [Online]. Available: https://www.dsprelated.com/showarticle/115.php.

[26] H. L. MacGillivray, “The Mean, Median, Mode Inequality and Skewness for a Class of Densities,” *Aust. J. Stat.*, vol. 23, no. 2, pp. 247–250, Jun. 1981.

[27] L. T. Decarlo, “On the meaning and use of kurtosis,” *Psychological Methods*. .

[28] Sidney Siegel, *Nonparametric statistics for the behavioral sciences ebook « Mara’s life*. New York: McGraw-Hill, 1956.

[29] R. C. Blair and J. J. Higgins, “A Comparison of the Power of Wilcoxon’s Rank-Sum Statistic to That of Student's t Statistic under Various Nonnormal Distributions,” *J. Educ. Stat.*, vol. 5, no. 4, p. 309, 1980.

[30] C.-W. Chih-Wei Hsu and C.-J. Chih-Jen Lin, “A comparison of methods for multiclass support vector machines,” *IEEE Trans. Neural Networks*, vol. 13, no. 2, pp. 415–425, Mar. 2002.

[31] A. J. B. Myrden, A. Kushki, E. Sejdic, A.-M. Guerguerian, and T. Chau, “A Brain-Computer Interface Based on Bilateral Transcranial Doppler Ultrasound,” *PLoS One*, vol. 6, no. 9, 2011.