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Mutual Information for Transfer Learning in SSVEP Hybrid EEG-fTCD Brain-Computer Interfaces

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Abstract—**Brain-computer interfaces (BCIs) allow individuals with limited speech and physical abilities to communicate with the surrounding environment. Such BCIs require calibration sessions which is burdensome for such individuals. We introduce a transfer learning approach for our novel hybrid BCI in which brain electrical activity and cerebral blood velocity are recorded simultaneously using Electroencephalography (EEG) and functional transcranial Doppler ultrasound (fTCD) respectively in response to flickering mental rotation (MR) and word generation (WG) tasks. With the aim of reducing the calibration requirements, for each BCI user, we used mutual information to identify the top similar datasets collected from other users. Using these datasets and the dataset of the current user, features derived from power spectrum of EEG and fTCD signals were calculated. Mutual information and support vector machines were used for feature selection and classification. Using the hybrid combination, an average accuracy of 93.04% was achieved for MR versus baseline whereas WG versus baseline yielded average accuracy of 90.94%. As for MR versus WG, an average accuracy of 92.64% was obtained by hybrid combination compared to 88.14% obtained by EEG only. Average bit rates of 11.45, 17.24, and 19.72 bits/min were achieved for MR versus WG, MR versus baseline, and WG versus baseline respectively. The proposed system outperforms the state of the art EEG-fNIRS BCIs in terms of accuracy and/or bit rate.**

I. Introduction

With the aim of improving the generalization performance of existing prediction models, transfer learning has been exploited recently so that such models can use previously acquired data to efficiently train a classifier such that the model can perform well on unknown datasets [1]. Transfer learning methods, when used in BCI applications, can significantly enhance the classification performance of the BCI for a certain individual when a short calibration session is available for system training through employing similar datasets collected from other BCI users [2].

BCIs measure mental activity and convert it into signals that can control assistive devices such as prosthetic limbs and wheel chairs [3]. Therefore, BCIs can help individuals with motor or speech impairments to communicate with the surrounding environment [4]. Moreover, BCIs aid disabled individuals to restore lost communication or motor functionalities through development of rehabilitation cost-effective programs that can be administered at home [5].

BCIs exploit either invasive or non-invasive modalities to measure brain activity. Electroencephalography (EEG) is widely used to design non-invasive BCIs since it is portable, cost-effective, and has high temporal resolution [4]. Several approaches for designing EEG-based BCIs have been extensively investigated especially those based on steady state visual evoked potentials (SSVEPs) [6] due to their high SNR [7].

Recent studies suggested enhancing the performance of EEG BCIs through using a secondary brain sensing modality simultaneously with EEG such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG) and functional near-infrared spectroscopy (fNIRS). Since fNIRS is portable and cost-effective modality compared to fMRI and MEG, it was extensively studied to be used with EEG for development of hybrid BCIs. However, functional transcranial Doppler ultrasound (fTCD) was shown to be a viable candidate for development of real-time BCIs that has higher temporal resolution and less setup complexity compared to fNIRS [8]. Therefore, we have designed a hybrid BCI that utilizes both EEG and fTCD [9]. In such BCI, EEG and fTCD simultaneously measure electrical brain activity and cerebral blood velocity respectively in response to flickering mental rotation (MR) and word generation (WG) tasks. We have shown that this hybrid BCI improves both the accuracy and information transfer rate of the system compared to the case of using EEG or fTCD only for BCI design.

In this paper, we extend our hybrid system through developing a transfer learning approach to investigate the feasibility of reducing the calibration requirements for each user. In particular, the proposed transfer learning method uses mutual information (MI) to identify the top similar datasets collected from other users to increase the size of the calibration dataset for the current user. Three binary selection problems were formulated to test the proposed approach. The first problem aimed at distinguishing flickering MR versus flickering WG tasks while the other two problems aimed at differentiating MR/WG against the baseline.

II. Materials and Methods

A. Simultaneous Data Acquisition

A g.tec EEG system was used to record data from 16 different electrodes positioned over frontal, central, and parietal lobes. A SONARA TCD system was used to record fTCD signals using two 2 MHz transducers placed on the left and right sides of the transtemporal window located above the zygomatic arch. fTCD depth was set to the depth of middle cerebral arteries (MCAs) which is 50 mm since they contribute approximately 80% of the brain blood supply [10].

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B. *Visual Presentation Design*

To design an efficient hybrid BCI, the cognitive tasks introduced to the user have to induce differences in signals recorded using both brain sensing modalities. In terms of fTCD, it was shown that MR tasks introduce bilateral activation while WG tasks result in higher blood flow velocity in left MCAs [11]. Moreover, in literature, the most efficient fTCD-based BCI in terms of accuracy and bit rate employed MR and WG tasks [8]. However, in terms of EEG, these tasks are not differentiable. If such tasks are intended to be used for designing EEG-fTCD hybrid system, they have to be modified such that the introduced modification induces the minimum possible cognitive load for the participant who will be already performing WG and MR tasks. Therefore, the visual stimuli representing WG and MR tasks were textured with a flickering checkerboard pattern, as seen in Fig.1, to induce SSVEPs in EEG corresponding to the flickering frequency of each task [9]. The WG and MR stimuli flickered with frequencies of 7, and 17 Hz. A fixation cross that represents the baseline was shown also on the screen.

In each session, a total of 150 trials were presented. Within each trial, a vertical arrow pointed randomly to one of the 3 icons on the screen for duration of 10 s. During this time, the user is asked to perform the mental task specified by the arrow. For instance, in flickering WG task, a random letter flickers on the screen and the user has to silently generate words starting with that letter. On the other hand, a pair of flickering 3D similar shapes rotated with different angles represents the flickering MR task and the user is required to decide if they are identical or mirrored by mentally rotating them.

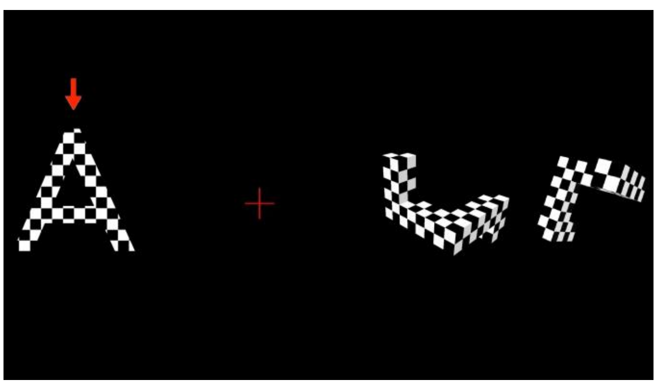

Fig. 1. Stimulus presentation for the proposed hybrid BCI system.

C. *Participants*

All research procedures employed in this study were approved by the local institutional review board (IRB) at the University of Pittsburgh. Eleven healthy participants (3 females and 8 males) with ages ranging from 25 to 32 years old (mean and standard deviation: 27.64±1.96). were recruited for the study and signed informed consents. Each participant attended one session. None of them had a history of strokes, heart murmurs, migraines, concussions or any brain related injury.

D. *Transfer Learning*

MI was used to find the top similar 3 datasets to the dataset under test. Assuming x, and y are gaussian distributed multivariate random variables, MI between x and y can be calculated as:

$$MI = \frac{1}{2} log_2 \left(\frac{\det(\sigma_x)\det(\sigma_y)}{\det(\sigma)} \right) \quad (1)$$

where σ_x, and σ_y are covariance matrices of x and y while σ is the full covariance matrix obtained through concatenating x and y. In this paper, when calculating MI between 2 datasets corresponding to 2 different subjects, x and y represent the multi-channel raw trial data coming from these two subjects.

After identifying the top similar 3 datasets, features were extracted separately from each dataset as well as the dataset of the current user. To further reduce signal variability across subjects, for each dataset, the mean values of features extracted from the baseline trials were subtracted from the corresponding features of WG and MR trials.

E. *Feature Extraction and Fusion*

EEG and fTCD data corresponding to each 10-s trial were segmented. Features were extracted from the Welch power spectral estimate [12] of each segment. Instead of using all the power spectrum values as features, average power values over each consecutive 2 Hz were computed for the EEG power spectrum and considered as features whereas the fTCD features were the average power values over each consecutive 50 Hz of the fTCD power spectrum since the fTCD signals has higher bandwidth (≈2.5 KHz) compared to the EEG signals (≈40 Hz). EEG feature vector was formed by concatenating the features from the 16 EEG channels while the fTCD vector included the features obtained from the 2 fTCD channels. For each trial, the EEG and fTCD feature vectors were concatenated to form one single feature vector representing that trial.

F. *Feature Selection and Classification*

MI was used to measure the contribution of each feature within the EEG-fTCD feature vector towards making a correct decision. For details of using MI for feature selection, we refer the reader to [9], [13]. The cumulative distribution function (CDF) was calculated for the MI scores to determine the number of selected features. Specifically, CDF thresholds corresponding to probabilities ranging from 0.5 to 0.95 with 0.05 step were selected. For each threshold, the features with scores greater than or equal that CDF threshold were selected. The performance measures corresponding to each CDF threshold were computed.

Support vector machine (SVM) was used for classification [14] since it has better generalization compared to the other linear classifiers. Instead of using non-linear kernels, linear SVM was used since the proposed BCI will be employed in real-time applications with a possibility that there will be an online update for the classifier parameters. Performance measures including accuracy, and information transfer rate given by (2) were computed.

$$B = log_2(N) + Plog_2(P) + (1-P)log_2\left(\frac{1-P}{N-1}\right) \quad (2)$$

where N is the number of classes, P is the classification accuracy and B is the information transfer rate per trial.

G. Significance of Hybrid System

To assess the significance of EEG-fTCD combination compared to EEG only and fTCD only, Wilcoxon signed rank test [15] was used to statistically compare the EEG-fTCD accuracy vector comprising accuracies for the 11 participants with the corresponding EEG only and fTCD only accuracy vectors for the same 11 participants.

III. Results and Discussion

The dataset corresponding to each participant as well as the top 3 similar datasets were analyzed using an incremental window of 1 s initial width and increment size of 1 s. The top 3 similar sessions were considered for classifier training only while the dataset under test was divided into training and testing using 10-fold cross validation. For each participant, accuracy of EEG-fTCD combination was evaluated at each increment up to 10 s which is the trial length. Since we have 10 different CDF thresholds corresponding to probabilities ranging from 0.5 to 0.95 with 0.05 step, 10 different profiles for the accuracy across time were obtained per person. The maximum possible EEG-fTCD accuracy for each participant across all CDF thresholds was considered and the average of the maximum accuracy across all participants was obtained. Table 1 shows average accuracies obtained using EEG only, fTCD only, and EEG-fTCD combination for MR versus baseline, WG versus baseline, and MR versus WG. For each participant, the accuracies of EEG only and fTCD only were calculated at the time yielding the maximum possible EEG-fTCD accuracy. Bit rates were also calculated for EEG only, fTCD only, and their combination as seen in Table 2.

As seen in Table 1, hybrid combination achieved average accuracy of 93.07% for MR versus baseline problem compared to 90.82% achieved using EEG only. In terms of bit rates, as shown in Table 2, the combination obtained 17.24 bits/min while EEG only obtained 15.52 bits/min. As for WG versus baseline problem, the combination yielded 90.94% average accuracy and bit rate of 19.72 bits/min whereas EEG only obtained 88.22% accuracy and bit rate of 17.29 bits/min. Considering MR versus WG problem, as seen in Table 1, the hybrid system outperformed EEG only as it obtained average accuracy of 92.64% compared to 88.14% obtained using EEG only with average accuracy difference of 4.50%. Moreover, the EEG-fTCD combination achieved higher bit rates than EEG only as seen in Table 2.

TABLE 1
Average accuracies obtained using EEG only, fTCD only, and hybrid combination for the three binary selection problems.

Modalitiy	MR vs Baseline	WG vs Baseline	MR vs WG
Hybrid	93.07%±04.13%*	90.94%±03.40%*	92.64%±03.27%*
EEG	90.82%±04.80%	88.22%±05.60%	88.14%±03.75%
fTCD	64.76%±11.109%	61.22%±07.79%	58.00%±09.75%

*P-value <0.03

TABLE 2
Average bit rates obtained using EEG only, fTCD only, and hybrid combination for the three binary selection problems.

Modality	MR vs Baseline	WG vs Baseline	MR vs WG
Hybrid	17.24	19.72	11.45
EEG	15.52	17.29	8.82
fTCD	4.66	1.61	1.06

On the other hand, statistical significance testing performed between EEG-fTCD and EEG/fTCD accuracy vectors showed that the combination is significant with p-values <0.03 for the 3 problems. The highest significance of the EEG-fTCD combination compared to EEG only was obtained for WG versus MR problem (p-value=0.002).

As seen in Tables 1, and 2, accuracies and bit rates obtained using fTCD only were very low. However, fTCD was able to boost the performance of the hybrid system when it was combined with the EEG. Such fTCD performance measures contradicts with a previous fTCD study [8] in which we obtained around 80% average accuracy within 3 s of the task onset. However, there are 3 major differences between the work presented here and our previous fTCD study. First, in that fTCD study, the objective was to find the maximum possible fTCD accuracy for each participant whereas in the system proposed here, the objective is to find the maximum EEG-fTCD accuracy which does not necessarily correspond to the maximum possible fTCD accuracy. Moreover, in the current study, the flickering negatively affected the concentration of each subject on the mental tasks to be performed. Finally, the experimental design in the previous study allowed adding baseline and resting periods to stabilize the cerebral blood flow before performing the tasks. Specifically, fTCD signals were recorded during a baseline period of 15 min before stating the tasks. Moreover, a resting period of 45 s was

TABLE 3
Comparison between the proposed hybrid system and the state of the art hybrid BCIs.

Method	BCI Type	Accuracy	Trial length (s)	
			Task	Baseline/rest
[16] Fazli et al., 2012	EEG+fNIRS	83.20%	15	6/0
[17] Blokland et al., 2014	EEG+fNIRS	79.00%	15	0/30±3
[18] Yin et al., 2015	EEG+fNIRS	89.00%	10	0/21±1
[19] Koo et al. 2015	EEG+fNIRS	88.00%	15	0/60
[20] Buccino et al., 2016	EEG+fNIRS	72.20%	6	6/0
[21] Buccino et al., 2016	EEG+fNIRS	94.20%	6	6/0
[22] Shin et al., 2017	EEG+fNIRS	88.20%	10	0/16±1
Proposed method (MR/baseline)	EEG+fTCD	**93.07%**	10	NA
Proposed method (WG/baseline)	EEG+fTCD	**90.94%**	10	NA
Proposed method (MR/WG)	EEG+fTCD	**92.64%**	10	NA

*NA: Not applicable

included between consecutive tasks. In the current study, to ensure high bit rates, no baseline/ resting periods were included before/after each task. In fact, the baseline cross was shown at random times since the aim behind having it was not to stabilize the blood flow, but it was considered as a task that resembles the case when the BCI user does not intend to issue any command.

To show the significance of using transfer learning for the proposed BCI, within-subject analysis was employed to calculate EEG-fTCD performance measures. Such measures were compared with those obtained using transfer learning. In particular, average accuracies of 89.11%, 80.88%, and 92.32% were obtained for MR versus baseline, WG versus baseline, and MR versus WG respectively [9]. Moreover, average bit rates of 4.39, 3.92, and 5.60 bits/min were achieved. Compared to accuracies and bit rates listed in Tables 1, and 2, it can be concluded that the transfer learning not only can enable shorter calibration sessions, but also ensures faster and more accurate performance.

As seen in table 3, compared to the state of the art EEG-fNIRS hybrid BCIs [16], [17], [18], [19], [20], [21] , the proposed BCI has the shortest trial length of 10 s. Moreover, the proposed BCI requires no baseline/rest period before/after each task. In terms of accuracy, the proposed hybrid BCI outperforms all BCIs in comparison except for the system introduced in [20] that achieved higher accuracy (94.20%). However, that system [20] is slower since it requires a 6-s baseline period before starting each task.

IV. Conclusion

We propose a novel hybrid BCI that uses EEG and fTCD to measure brain electrical activity and cerebral blood velocity respectively. Flickering MR and WG cognitive tasks as well as a baseline cross were used in designing the system. Three binary selection problems were formulated and solved using a transfer learning approach that exploits mutual information. These problems included MR versus baseline, WG versus baseline, and MR versus WG. MR and WG versus baseline problems obtained average accuracy of 93.07%, and 90.94% respectively while accuracy of 92.64% was achieved for MR versus WG. Bit rates of 11.45, 17.24, and 19.72 bits/min were obtained for MR versus WG, MR versus baseline, and WG versus baseline respectively. Such promising results show that the transfer learning approach we used increased both accuracy and bit rates for the proposed system compared to within-subject classification.

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