Transcranial Doppler Ultrasonography-Driven Online Augmentative and Alternative Communication Aid

J. Lu[1,2], T. Chau[1,2]

[1]Bloorview Research Institute, Toronto, Canada; [2]University of Tronto, Toronto, Canada

Correspondence: J. Lu, Bloorview Research Institute, 150 Kilgour Road, M4G 1R8, Toronto, Canada. E-mail: jielucy.lu@mail.utoronto.ca

Abstract. Transcranial Doppler Ultrasonography (TCD) has been shown to be a promising brain-computer interface (BCI) modality that could accurately differentiate between two mental tasks. However, the success of TCD as an online BCI has yet to be demonstrated. Within this study, TCD is implemented as an online BCI modality for the control of a communication system (scanning keyboard) through the use of two mental tasks: repetitive mental spelling and visual tracking of the TCD signal feedback. Data is classified using Naïve Bayes and a set of time-domain user-dependent features. The preliminary results have shown that the overall training validation accuracy is 79.54 ± 3.42% and the online testing accuracy is 80.32 ± 7.32%. These results are very encouraging and provide the first step towards an online TCD-BCI system.

Keywords: TCD, Online BCI, Mental Task, CBFV Lateralization, AAC

1. Introduction

Individuals who are cognitively aware but have severe motor disorders such as muscular dystrophy, spinal cord injuries or locked-in syndrome often have difficulty interacting with their surroundings. Out of the available technologies that attempt to shorten this communication gap, brain-computer interfaces (BCIs) have been particularly promising, as they allow the users to manipulate output devices through mental activities alone [Tai et al., 2008]. Within the recent developments, transcranial Doppler ultrasonography (TCD) has sparked great interest as a BCI modality because it is affordable and robust against environmental noises [Myrden et al., 2011].

TCD is a non-invasive ultrasound technology that exploits the changes in cerebral blood flow velocity (CBFV). Within the recent years, TCD has been utilized as a functional brain imaging tool to examine the effects of mental tasks on the CBFV, especially the middle cerebral arteries (MCAs) [Lohmann et al., 2006]. Using mental task elicited CBFV changes, previous offline BCI study has achieved over 70% accuracy [Myrden et al., 2011]. In this study, we further explore the possibility of TCD-BCI by designing and implementing an online TCD-BCI system.

2. Material and Methods

2.1. Participants and Instrumentation

Twelve able-bodied participants with normal or corrected-to-normal eyesight are recruited for this study. The participants are all right-handed and have no history of neurological, metabolic, respiratory, cardiovascular, or drug/alcohol-related conditions. The MultiDop X-4 TCD (Compumedics Germany) and the accompanying bilateral headgear with fixed 2 MHz ultrasonic transducer are used to acquire the Doppler spectra of blood flow through the left and right MCAs. The probes are positioned over the transtemporal insonation window as in accordance with the established insonation procedure [Alexandrov et al., 2007].

2.2. Experimental Protocol

Each participant completes three sessions, with three blocks per session. For session one, the first two blocks are for training with the last block for testing. For sessions two and three, the first block is for training while the last two blocks are testing. A one minute baseline level is established prior to each block, which is then used to normalize all ensuing data collected from that same block. A five minute resting period is allowed in-between each block.

For each training block, participants perform a total of 20 mental spelling tasks (activation task) and 20 visual tracking tasks (rest task) that are randomly ordered. A 10 second recovery period is applied after each activation task to allow the participants' CBFV to return to baseline levels. For each mental task, task appropriate cue (Fig. 1) is presented to the participants through the whole task duration.

Figure 1. *Cues for activation mental task and rest mental task from left to right respectively.*

For each testing block, participants are asked to perform the activation mental task when the target letter is shown on the screen and to perform the rest mental task otherwise. A trained classifier based on the session's training data is used to differentiate participants' intentions and select the appropriate letter.

2.3. Data Processing and Classification

For the first session, 40 activation and 40 rest data segments are collected to train a user-specific classifier. The second and third sessions each has 60 activation and 60 rest data. Each data segment is 15 seconds in duration, from which 44 unilateral and bilateral features are extracted [Myrden et al., 2011].

For the training data, a 10-fold cross-validation is performed on feature vectors selected through a weighted sequential forward search (WSFS) method. In each cross-validation fold, the training data set is randomly split 90-10 for training and validation. The WSFS method was developed as an improvement of the sequential forward selection [Devijer et al., 1982]. Instead of selecting the feature combination with the highest accuracy, the best feature combination for each fold was considered and the feature are regroup according to their contributions across the 10 folds. The feature group with the best performance is the final group used to train the Naïve Bayes classifier.

3. Results and Discussion

The preliminary results from 8 participants are summarized in Table 1 and Table 2, which shows the classification accuracies for offline and online settings respectively. The average accuracy across all participants was 79.54 ± 3.42% for the offline data and 80.32 ± 7.32% for the online data. Both the online and offline accuracies were well above chance levels of 60%, indicating that the repetitive spelling activation mental task and signal tracking rest mental task can be differentiated at above chance level.

Table 1. *Training set validation accuracy*

Participant Number	*SPE (%)*	*SEN (%)*	*ACC (%)*
1	72.50	90.00	81.25
2	83.75	75.00	79.38
3	76.25	70.00	73.13
4	80.00	81.25	80.63
5	75.00	77.50	76.25
6	82.50	86.25	84.38
7	82.50	78.75	80.63
8	73.75	87.50	80.63
Average	78.28	80.78	79.54

Table 2. *Testing set average accuracy*

Participant Number	*SPE (%)*	*SEN (%)*	*ACC (%)*
1	77.46	80.60	78.33
2	82.72	81.08	82.20
3	76.35	70.18	73.17
4	77.64	90.91	81.93
5	79.77	81.82	80.33
6	92.09	76.19	87.50
7	87.36	87.69	87.45
8	86.14	89.04	86.67
Average	79.93	81.11	80.32

The overall online accuracies have improved from the offline accuracies, which could be due to an increase in concentration and additional encouragement from the online feedback.

In this study, the potential benefits of practice were not examined. Despite this, acceptable classification accuracies were obtained. It is possible that participants could achieve an even higher accuracy as they gained further proficiency with the mental tasks. However, it is also possible that further practice could lead to habituation.

References

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