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A BRAIN-COMPUTER INTERFACE BASED ON FUNCTIONAL TRANSCRANIAL DOPPLER ULTRASOUND USING WAVELET TRANSFORM AND SUPPORT VECTOR MACHINES

Aya Khalaf, Matthew Sybeldon, Ervin Sejdic, Murat Akcakaya*

Electrical and Computer Engineering, University of Pittsburgh, 3700 O'Hara St, Pittsburgh, PA 15213, USA.

ABSTRACT

Background: Functional transcranial Doppler (fTCD) is an ultrasound based neuroimaging technique used to assess neural activation that occurs during a cognitive task through measuring velocity of cerebral blood flow.

New method: The objective of this paper is to investigate the feasibility of a 2-class and 3-class real-time BCI based on blood flow velocity in left and right middle cerebral arteries in response to mental rotation and word generation tasks. Statistical features based on a five-level wavelet decomposition were extracted from the fTCD signals. The Wilcoxon test and support vector machines (SVM), with a linear kernel, were employed for feature reduction and classification.

Results: The experimental results showed that within approximately 3 seconds of the onset of the cognitive task average accuracies of 80.29%, and 82.35% were obtained for the mental rotation versus resting state and the word generation versus resting state respectively. The mental rotation task versus word generation task achieved an average accuracy of 79.72% within 2.24 seconds from the onset of the cognitive task. Furthermore, an average accuracy of 65.27% was obtained for the 3-class problem within 4.68 seconds.

Comparison with Existing Methods: The results presented here provide significant improvement compared to the relevant fTCD-based systems presented in literature in terms of accuracy and speed. Specifically, the reported speed in this manuscript is at least 12 and 2.5 times faster than any existing binary and 3-class fTCD-based BCIs, respectively.

Conclusions: These results show fTCD as a promising and viable candidate to be used towards developing a real-time BCI.

Keywords—Neuroimaging, Functional transcranial Doppler, Brain computer interfaces, Wavelet Transform, Support Vector Machines.

1. INTRODUCTION

Brain computer interfaces (BCIs) process brain signals associated with mental activity to produce thought-controlled inference regimes that can be used to control external devices (Birbaumer, 2006). Typical BCI users lack the motor control or speech requirements necessary to operate more traditional computer devices(Nicolas-Alonso and Gomez-Gil, 2012) . BCIs have been extensively investigated in various applications such as neural prosthetics(Vidal et al., 2016) , rehabilitation engineering and virtual reality (Foldes et al., 2015), (Salisbury et al., 2016). It was shown that BCIs are attractive communication and control channels for individuals who suffer from neurological conditions such as stroke, Parkinson's disease, and amyotrophic lateral sclerosis (ALS) and have limited motor and speech abilities (Tai et al.,

2008a), ("Motor Impairment," 2012). Such conditions, when severe, can cause the individuals to lose control over all voluntary muscles leading to a disorder known as locked-in syndrome (LIS) (Laureys et al., 2005). Therefore, developing a BCI system that can assist such individuals to communicate with the outside world is one of the main concerns in the BCI field.

Several noninvasive modalities have been used to design BCI systems including electroencephalography (EEG) (Lotte et al., 2007), functional magnetic resonance imaging (fMRI) (N. Weiskopf et al., 2004), near-infrared spectroscopy (NIRS) (Coyle et al., 2004), and magnetoencephalography (MEG) (Mellinger et al., 2007a). Due to its portability, many advances in the EEG-based BCI development have been made (Müller-Putz et al., 2006). On the other hand, functional magnetic resonance imaging (fMRI) and near-infrared spectroscopy (NIRS) have also been proposed to introduce viable control signals for BCIs (Sitaram et al., 2007), (Nikolaus Weiskopf et al., 2004). However, most of the fMRI and NIRS-based BCI devices that have been developed are based on motor imagery detection (Abdelnour and Huppert, 2009), (Ayaz et al., 2009). Recently, MEG, which is a relatively new technology, has also been used in BCI applications (Mellinger et al., 2007b), (McClay et al., 2015) as well as neurofeedback-based rehabilitation therapy (Foldes et al., 2015). Even though these different modalities were shown to have potential benefits for BCI applications, they have disadvantages that prevent them from a reliable and consistent use especially outside the laboratory environments by the target population with severe speech and physical impairments. For example, EEG-based BCIs mainly suffer from electrical interference as well as certain physiological artifacts due to ocular and muscular activity (Tai et al., 2008b). On the other hand, fMRI and MEG based BCIs use expensive equipment without any portability and can perform well only in highly controlled environments (Allison et al., 2007). Moreover, current NIRS-based systems mainly investigate the slow hemodynamic response and lack the speed to be considered for real life applications (Zephaniah and Kim, 2014).

Considering the limitations mentioned above, other modalities that can produce more robust BCI control signals are currently investigated. One rather unexplored modality is functional transcranial Doppler ultrasound (fTCD) (Myrden et al., 2011) that measures blood flow velocity (Sloan et al., 2004). Changes in the fTCD signals have been associated with cognitive tasks, and it was shown that it is possible to develop a BCI based on the classification of cognitive tasks performed by the user (G. Vingerhoets and Stroobant, 1999), (Sejdic et al., 2013). fTCD has certain advantages to be considered for the development of a noninvasive BCI. Similar to EEG, fTCD is portable, but compared to EEG, it is more robust to nonstationarities from external electrical interferences and internal background brain activity (Wessels et al., 2006). Moreover, it is less expensive compared to fMRI and MEG (Szirmai et al., 2005). However, previous efforts to develop an fTCD-based BCI have been hampered by the fact that temporal resolution is low. In those studies, it was shown that each observation period required a length of 45 seconds in order to be classified in to a certain cognitive task with sufficient accuracy (Myrden et al., 2011). Towards making the fTCD-based BCIs more practical, recent studies achieved observation periods ranging from 15-20 seconds (Faress and Chau, 2013), (Aleem and Chau, 2013), (Lu et al., 2015). Later efforts were focused on increasing the data transmission rate by tuning the amount of potential classes and the observation period (Goyal et al., 2016), (Myrden et al., 2012). In these studies, bit rates of

1.08 and 1.2 bits/min were achieved. While these are pioneering significant contributions, more improvements are required in data rate to ultimately obtain a feasible BCI system that meets the speed and accuracy requirements for real-time end use.

In this paper, we propose feature selection techniques to build an fTCD-based BCI system that overcomes the speed limitations of previous fTCD-BCIs. Given the fact that fTCD detects different velocities of cerebral blood flow in response to different cognitive tasks, these tasks can be used as the selections in the development of the fTCD-based BCI if such cognitive tasks could be differentiated with sufficient accuracy and speed. In this manuscript, cognitive tasks including word generation and mental rotation as well as the resting state are considered for the development of the BCI. These cognitive tasks have already been explored in BCI design and it was shown that both mental rotation and word generation cause significant increase in cerebral blood flow velocity in right and left middle cerebral arteries (Guy Vingerhoets and Stroobant, 1999). However, the word generation task resulted in significantly stronger activation in the left middle cerebral arteries while the mental rotation task shows bilateral activation (Myrden et al., 2011) so it is expected that these tasks can be differentiated with a high accuracy if employed in a BCI application.

Four subject-specific classification schemes are formulated to study the feasibility of 2-class and 3-class real-time fTCD- based BCIs. The first and second classification schemes are formulated to distinguish each cognitive task from the resting state. The third scheme aims at classification of the word generation and mental rotation tasks against each other. Finally, in the fourth scheme, a 3-class classification problem combining mental rotation, word generation and the resting state is studied with the aim of increasing the number of possible selections for the BCI. For all these classification schemes, features derived from a five-level wavelet transform are used in a support vector machines (SVM) classifier that employs a linear kernel. To determine the classification accuracy as a function of data rate (speed), two methods for feature vector formulation are employed: (1) moving window (MW), and (2) incremental window (IW) methods. These feature vector formulation methods are presented in section 2.3. Finally, we show that with the proposed techniques we can achieve significant improvements in the data rate and hence the speed of operation, without compromising the accuracy.

2. MATERIALS AND METHODS

This section includes a description of the recruited participants, experimental procedure, and the proposed preprocessing, feature extraction, selection and classification methods.

2.1. Participants

All research procedures were approved by the local institutional review board at the University of Pittsburgh and all participants provided informed consent. Data was collected from 20 healthy participants including 10 males and 10 females with mean age of 21.5 ±1.86 years, mean weight of 67.9 ± 14.2 kg and mean height of 174 ± 9.69 cm (Li et al., 2014). None of the participants had a history of migraines, concussions, strokes, heart murmurs, or other brain related injuries. Participants were also subjected to the Edinburgh handedness tests (Oldfield, 1971) which showed 16 participants were right-handed, with a mean score of 64% ,3 participants were left-handed, with a mean score of 80%, and one was ambidextrous.

2.2. Experimental Procedure

Two 2 MHz transducers were fixed on the left-side and right-side transtemporal window located above the zygomatic arch (Alexandrov et al., 2007) . The depth of the TCD was set to 50 mm to approximate the depth of the mid-point of the middle cerebral arteries segment (Monsein et al., 1995). Since a previous TCD study (Nakagawa et al., 2007) reported that the maximum safe continuous exposure time to TCD is 30 minutes to avoid thermal damage to brain tissues, the data collection session was divided into 3 parts. In the first section, each participant was asked to take a rest so that the cerebral blood flow is stabilized while recording a 20-min baseline period. The next two sections were each 15-min trials with a 5-min break in between. Each of these trials included five-word generation tasks and five mental rotation tasks, in a random order. Within each trial, every task lasted 45 seconds (which we denote as an activation period for each task) with a 45 seconds resting period between consecutive tasks. In total, each participant underwent 20 cognitive tasks divided evenly into word generation and mental rotation.

2.2.1. Mental rotation task

Randomly selected pairs of images from a database of 3D shapes constructed from cubes (Peters and Battista, 2008) were displayed on the screen for a duration of 9 seconds. This means that for an activation period of 45 seconds, 5 different pairs of images were displayed. Each pair of images were displayed as either identical or symmetrically mirrored images. Participants were asked to decide if the displayed image pairs were identical or mirrored by mentally rotating these images as seen in Fig.2.

2.2.2. Word generation task

During the 45-second activation periods, a randomly chosen letter was displayed on the screen. The participants were asked to think of words starting with that displayed letter. This nonverbal action was chosen to avoid artifacts due to speech or intrathoracic pressure changes (R.R. Diehl, M. Sitzer, 1990).

2.3. Data Analysis

Two methods for classifying the cognitive tasks were tested; a moving window (MW) and an incremental window (IW). In the MW method, a window containing the first 0.5 seconds of the fTCD data was used for feature extraction. After taking the classification decision based on the data from that window, the window was shifted by 0.25 seconds and features were recalculated for that new window of data and a new classification decision was made. This procedure was repeated until the window reached 45 seconds, the length of a task. Note that in this approach the classification decision at a specific time was independent of all past windows.

As a second method, an incremental window was employed in which all the samples up to the time of classification were included. Initially, features were extracted from the first 0.5 seconds of data and a classification decision was made. Then, the size of the window was increased by 0.5 seconds, features were recalculated and a new decision was made. This incremental increase was then repeated until the length of the task was reached. One drawback of this method is that when the window size increases, fine changes in the signal, that might correspond to a specific task, might be dominated by the trend of the majority of the samples. The choice of the window size and the

amount of shift or increment for both methods was performed empirically. It was found that the smaller the window size, the better the performance accuracy.

Fig. 1 shows a flowchart for the main algorithm steps as well as the differences between these two windowing methods. Data transmission rate for both windowing methods was calculated according to equation (1).

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

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

2.3.1. Preprocessing

The data was approximately bandlimited to under 4 kHz. A 150th order low pass filter of 5 kHz corner frequency was applied for antialiasing purposes. The original data was sampled at 44.1 kHz, and it was downsampled by a factor of 5 to reduce computation requirements.

2.3.2. Feature Extraction

Five level wavelet decomposition (D. Valencia, 2010) was performed for each window defined by the IW, and MW methods using the Daubechies 4 mother wavelet. The choice of the number of decomposition levels was determined using visual inspection. First, approximate coefficients of the last level of each task were plotted to check if they show any difference between the 3 tasks. The number of decomposition levels was increased and approximate coefficients of the last level were plotted until no difference could be seen.

After performing the wavelet decomposition over each window of data, simple statistical features including mean, variance, skewness, and kurtosis were calculated for the wavelet coefficients. For each TCD channel, these 4 features were calculated for 6 wavelet bands resulting in a total of 24 statistical features for each channel (i.e., a total of 48 features), and these features were considered for feature selection. Both the skewness and kurtosis measure deviations from Gaussianity. Kurtosis (Decarlo, 1997) measures the peak of the curve compared to the Gaussian curve. The skewness also measures the asymmetry of a given probability distribution. A probability distribution with a heavier tail and higher peak than the Gaussian has a positive kurtosis while lighter tails with flatter peaks give a negative kurtosis. A positive skewness value reflects a distribution with the right side tail longer than the left side and with a mean that is greater than the mode; whereas, a distribution with a left side tail that is longer than the right side and a mean value less than the mode has a negative skewness (MacGillivray, 1981).

2.3.3. Feature Selection

Features were statistically assessed using the Wilcoxon test (Sidney Siegel, 1956), which is a nonparametric hypothesis test used to evaluate differences between two populations. One advantage of this test is that it does not restrict the data to follow any specific parametric distribution such as the Gaussianity assumption imposed by the Student-t test (Blair and Higgins, 1980). Briefly, for each feature, the difference between the two groups per sample is calculated. The higher the difference magnitude, the higher the rank assigned to that sample. Only ranks of positive differences are considered to estimate the Wilcoxon test statistic W while negative differences and zero-magnitude differences are excluded. The Wilcoxon test statistic W given by (2) is the sum of all the positive ranks.

$$W = \sum_{i=1}^{n'} R_i^{(+)} \qquad (2)$$

where $R_i^{(+)}$ is the rank of the ith positive difference and n' is the number of samples with positive rank. This means that $n' <= n$; that is, the number of positive differences is at most equal to the total number of available samples n.

When applying the Wilcoxon test, we chose a p-value of 0.05 to be used for the test and the features that satisfy such criteria were selected independently of each other. Therefore, the number of features can vary from person to person depending on the significance of each feature whether it satisfies the chosen p-value or not. For example, during cross-validation to predict the system performance, at each validation step, the number of features change based on the Wilcoxon test. As for the 3-class problem, considering the fact that the Wilcoxon test is a binary feature selection method, a one versus one approach (Chih-Wei Hsu and Chih-Jen Lin, 2002) was used to decompose the 3-class problem into 3 binary problems with a p-value of 0.05. The resulting 3 sets of selected features were used separately as inputs for 3 binary SVM classifiers as indicated in the next subsection.

2.3.4. Classification

Support vector machines (SVM) were used to perform the classification task (Chih-Wei Hsu and Chih-Jen Lin, 2002). Basic SVM is a linear classifier that formulates an optimization problem aimed at finding an optimal hyper plane that has the largest possible distance to the nearest data point in the training set regardless of the class that such point belongs to. Consequently, SVM achieves better generalization compared to the other linear classifiers such as linear discriminant analysis. Given the fact that the classes are not typically linearly separable, a kernel can be used to transform each observation into higher dimensional feature space in which the classes are linearly separable. Common kernels include linear, quadratic, Gaussian, and radial basis function kernels. In order to reduce the computational complexity, the linear kernel was employed in this paper. Four different classification schemes were formulated in this paper. In the first two schemes, two 2-class classifiers were developed to distinguish the word generation task from the resting state and mental rotation task from the resting state. In the third scheme, a 2-class classifier was developed to distinguish between the features corresponding to mental rotation and word generation. Finally, a 3-class classifier was developed to jointly distinguish among the mental rotation, word generation and resting state. A one versus one approach was used to convert the 3-class problem into 3 binary problems since the SVM is basically a binary classifier(Chih-Wei Hsu and Chih-Jen Lin, 2002). The majority vote obtained from the 3 classifiers was considered for the final decision.

To evaluate the robustness of the proposed system, for each participant, leave-one-out cross validation was used to assess the performance measures. MATLAB (R2015b) was used to run the experiments on a HP Z840 Workstation with Intel®, and Xeon® CPU, 2.2 GHz processor speed, and 128 GB RAM.

3. RESULTS

The proposed methodology was tested using fTCD data recorded from 20 participants. Three types of problems were analyzed including: 1) cognitive tasks versus resting state (two 2-class problems i.e., mental rotation task vs resting state and word generation task vs. resting

state), 2) mental rotation task versus word generation task (one 2-class problem) and 3) mental rotation versus word generation versus resting state (one 3-class problem). For each classification problem, MW and IW methods, as described in Section 2.3, were applied for feature extraction and performance measures (speed, sensitivity, specificity and accuracy of classification) were analyzed.

Tables 1 through 4 show the average of the maximum classification accuracy and corresponding sensitivity and specificity values achieved by each participant using IW and MW data analysis and feature extraction methods at different state durations. A state duration is defined as the period in which a mental activity takes place before it is assigned to a specific class. In other words, it is the time since the task onset till the time point at which a decision has to be made. In case of both MW and IW methods, for each state duration, all possible windows that are within that period (i.e. state duration) were considered, and the window achieving the maximum accuracy was selected to compute the average accuracy, sensitivity, specificity and time across participants. For example, in the MW method, a 5-s state duration means that the windows 0-0.5s, 0.25-0.75s, 0.5-1s, ……, and 4.5-5s are used for the analysis and the performance measures (accuracy, sensitivity, specificity and time) for the window that obtains the maximum accuracy are considered to calculate average performance measures across participants, while for the IW method, windows 0-0.5s, 0-1s, 0-1.5s,….., and 0-5s are analyzed and the average performance measures are computed in the same way described above for the MW method. Time column shown in these tables represents the average time at which the maximum accuracy was achieved for each participant within the corresponding state duration.

3.1. 2-class problems

As seen in Tables 1-2, the MW method achieved higher average accuracies, compared to the IW method, in a relatively short time of approximately 3 *s*, an average accuracy, sensitivity and specificity of 80.29%, 81.18%, and 79.41%, for the resting state versus mental rotation and 82.35%, 82.94%, and 81.76% for the resting state versus word generation. In addition, according to Tables 1 and 2, within approximately 3 s of the cognitive activity onset, an average accuracy, sensitivity, and specificity of 74.41%,72.94%, and 75.88% was achieved for the resting state versus mental rotation classification compared to 77.94% ,77.65%, and 78.24% for the resting state versus word generation problems using the IW method. Moreover, as seen in Table 3, using the MW method for the task versus task classification achieved 79.72%, 80.56%, and 78.89% average accuracy, sensitivity and specificity while IW method obtained average accuracy, sensitivity and specificity of 74.64%, 72.86%, and 76.43%. Both methods achieved such accuracies within approximately 3 s of the task onset.

Considering the maximum performance accuracy that could be achieved by each of the three binary classification problems, the MW method obtained the best possible accuracy compared to the IW method at each state duration. Using the MW method an average accuracy, sensitivity, and specificity of 94.41%, 95.29%, and 93.53% was achieved for the mental rotation versus resting state problem after 15.57 *s* from the task onset while the IW method obtained an average accuracy sensitivity, and specificity of 89.41%,89.41%, and 89.41% respectively in 20.38 s. On the other hand, word generation versus resting state problem obtained an average accuracy, sensitivity, and specificity 93.24%,94.70% and 91.76% respectively after 21.22 *s* from task onset using MW method while IW method achieved 88.53%, 86.47%, and

90.59% average accuracy, sensitivity, and specificity in 13.88 *s*. Considering the task versus task problem, the IW method achieved an average accuracy, sensitivity, and specificity of 88.93% ,90.00%, and 87.86% in 19 *s* while the MW method obtained 92.78%, 93.89%, and 91.67% accuracy, sensitivity, and specificity in 15.41 *s*.

3.2. 3-class problem

As shown in Table 4, the MW method shows better performance when compared to the IW method. Average accuracies of 66.12%, 68.26%, and 61.32% were achieved for mental rotation, word generation and resting state respectively with overall accuracy of 65.27% using the MW method within 5 *s* from the onset of the cognitive task (chance level is 33%). Using the IW method achieved accuracies of 57.70%, 69.71%, and 63.20% for mental rotation, word generation and resting state respectively with overall accuracy of 63.80% at the same 5-second period. Utilizing the whole observation period with the MW method, average accuracies of 72.19%, 75.93%, and 70.88% for mental rotation, word generation and resting state respectively with overall accuracy of 72.91% were obtained at average time of 11.27 *s*. Mental rotation, word generation and resting state accuracies of 70.10%, 77.86%, and, 67.04% were achieved in average time of 14.29 *s* with an overall accuracy of 71.57% using IW method.

3.3. Transmission Rate

The bit rate was calculated in bits/trial using equation (1) then divided by state duration in minutes to give bit rate in bits/min. Among the 3 binary problems described above, the bit rate calculated for the word generation versus resting state was the highest compared to the other binary problems. As seen in Fig. 3 using the IW method, a maximum bit rate of 3.95 and 2.28 bits per minute was achieved for the word generation vs resting state and the 3-class problem respectively. The MW method obtained a maximum bit rate of 3.83 and 3.09 bits per minute for the same problems. Moreover, maximum bit rates of 3.3, and 2.04 bits per min were achieved for mental rotation versus resting state and mental rotation versus word generation respectively using the MW method while IW method obtained bit rates of 1.30, and 1.63 bits per min for the same problems.

4. DISCUSSION

Considering the performance measures shown in Tables 1-3, among the 3 binary classification problems we addressed, the word generation versus baseline problem offered the highest accuracy within 3 *s* of the onset of the cognitive activity compared to the other binary problems. Therefore, it can be considered as the best candidate to build binary selection based BCIs. Additionally, according to Tables 1-3, it is clear that the MW method achieved the best accuracy. The main difference between the MW method IW method is that the MW method just accounts for the information belonging to the current window while IW method consider all the fTCD data up to the moment at which the decision is taken. One disadvantage of IW method is that the performance measures would be significantly degraded if the participant lost concentration at some point during the task; this means that nonstationaritys in the data would affect the future classification process.

Table 5 compares our method with the existing methods based on fTCD and NIRS. During comparison, both speed (observation period) and accuracy have been considered. For the proposed system, we include the accuracies for two different observation periods (3 s and 45 s). Although an observation period of 45 s is not practical for a real-time BCI, we computed the performance measures of the system with such observation period to ensure a fair comparison with the work proposed by Myrden et al. (2011) who used the same dataset employed in this work and achieved the reported accuracies for 45 s observation time. As seen in Table 5, the proposed MW method outperformed the other fTCD-based methods in the literature in terms of both accuracy and observation period. We achieved comparable accuracies to the Myrden et al. (2011) system with only 3 s observation period. On the other hand, NIRS is a portable and hemodynamic-based modality that, alike fTCD, is a promising tool to develop BCI applications. Recent NIRS-based BCIs proposed by Fazli et al., 2012 ,and Shin et al., 2016 showed promising results, shown in Table 5, that lead to development of a BCI that combines both fTCD and NIRS (Faress and Chau, 2013). However, the approach proposed in this paper outperformed these studies as it obtained average accuracies of 80.29% and 82.35% within approximately 3 *s* of the onset of the mental task for mental rotation vs resting state and word generation vs resting state classification problems respectively. Therefore, we believe that the presented results are promising and can be used to develop a real-time fTCD-based BCI application.

The proposed 3-class fTCD-based BCI achieved an average accuracy of 65.27% using the MW method within 5 s of the task onset as seen in Table 4. The studies suggested in (Goyal et al., 2016), (Myrden et al., 2012) reported accuracies of 62.40% within 15 s (Goyal et al., 2016) and 40% within 5 s(Myrden et al., 2012) of the onset of the cognitive task. Moreover, the maximum classification accuracy over the whole observation period obtained by our approach was 72.91% achieved in 11.27s compared to the previously reported 73.11% obtained in 24.90 s (Myrden et al., 2012).

A maximum bit rate of 3.83 and 3.09 bits per minute were achieved for the binary and the 3-class problems respectively using the moving window method, while the incremental window achieved maximum bit rates of 3.95 and 2.28 bits per minute. This is compared to 0.3 and 1.2 bits per minute previously reported for 2 and 3-class fTCD-based BCIs (Myrden et al., 2011),(Myrden et al., 2012). Being able to obtain reasonable classification accuracies within relatively short time period for the binary problems as well as the 3-class problem introduces the possibility of developing a real time fTCD-based BCI with acceptable data transmission rates. Applications of the proposed BCI include controlling assistive devices that can be used for communication and movement control through which the users can control prosthetic limbs or wheel chairs (Mak and Wolpaw, 2009). Another application of this technology is the environmental control such that the BCI users can adjust lights and temperature in their houses or control the TV, etc. (Cincotti et al., 2008). The BCI systems have the potential to enhance the quality of life for individuals with disabilities specially those who experience locked-in syndrome. Specifically, it would decrease their level of dependency to their caretakers and improve the individual's contact with society (Kübler et al., 2006). In addition, BCI has been recently shown to be a promising neurorehabilitation tool that can help individuals with disabilities to restore neuromuscular functions (Ramos-Murguialday et al., 2013).

5. CONCLUSION

In this study, we investigated the possibility of building 2-class and 3-class BCI systems using data acquired through bilateral fTCD measurements. To construct the BCI system, two different methodologies, incremental window(IW) and moving window (MW), were proposed. The main differences between these methods are the windowing and feature vector formulation. For each method, the raw data was analyzed using wavelet transform. Statistical features were calculated from the wavelet transform coefficients. These features were subjected to Wilcoxon test for feature selection followed by classification with SVM with linear kernel. With the proposed approach, we showed that within 3 s of the onset of the cognitive task, an accuracy of 80.29% was obtained for the mental rotation versus resting state problem while the word generation versus resting state achieved an accuracy of 82.35% using the MW. The MW method used for the task versus task problem achieved a mean classification accuracy of 79.72% within 3 s of the onset of cognitive activity. In addition, the MW method used for the 3-class problem obtained an average accuracy of 65.72% within 5 s of the onset of mental tasks. The presented results show significant improvement in the data rate without a compromise in the accuracy of cognitive task classification. Compared to the previous fTCD studies, the proposed method showed an increase of 12% and 9% accuracy for the 2-class and the 3-class BCIs respectively. In terms of speed, the proposed BCIs are at least 12 and 2.5 times faster than the 2-class and the 3-class systems proposed in previous fTCD studies. Such promising results support the real time implementation of a 2-class and 3-class fTCD-based BCIs. Moreover, the improvements in the data transmission rate reported in this paper imply that it would be feasible to utilize the fTCD in a multi-modal hybrid BCI. Such an approach to fuse information from multiple modalities to achieve a certain task simultaneously will likely improve the system performance compared to a single modality BCI. For example, a hybrid system that employs both EEG and fTCD may be able to achieve higher performance by utilizing both sources of information simultaneously. Such a hybrid BCI will be the subject of our future research.

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Figure 1: A flowchart for the algorithm used for data analysis using moving window(MW) and incremental window(IW) methods.

Figure 2: Sample of the mental rotation task. The participant was asked to decide if the pair of images are identical by mentally rotating one of the two images.

Figure 3: Transmission rate in bits/min for binary and 3-class problems using a) IW method b) MW method.

Table

Table 1: Average maximum accuracy and the corresponding sensitivity, specificity, and time at different state durations for the word generation task versus resting state using MW and IW methods.

	State Duration (S)	Time(s)	Sensitivity (%)	Specificity (%)	Accuracy (%)
MW Method	5.0	2.84	82.94%±09.19%	81.76%±09.51%	82.35%±06.87%
	7.5	4.41	88.82%±09.28%	85.88%±07.12%	87.35%±05.89%
	10.0	4.93	90.00%±08.66%	86.47%±07.02%	88.24%±05.29%
	12.5	4.93	90.00%±08.66%	86.47%±07.02%	88.24%±05.29%
	15.0	6.10	90.59%±08.99%	87.65%±06.64%	89.12%±05.07%
	17.5	6.63	91.18%±09.27%	87.65%±06.64%	89.41%±05.29%
	20.0	8.62	91.76%±08.09%	88.24%±06.36%	90.00%±05.00%
	22.5	8.62	91.76%±08.09%	88.24%±06.36%	90.00%±05.00%
	45	21.22	94.701%±07.17%	91.76%±07.28%	93.24%±04.31%
IW Method	5.0	2.50	77.65%±13.93%	78.24%±13.80%	77.94%±11.73%
	7.5	3.17	80.00%±12.25%	80.59%±13.91%	80.29%±10.96%
	10.0	3.65	80.59%±11.97%	81.76%±12.37%	81.18%±09.93%
	12.5	4.79	82.94%±07.72%	82.35%±12.51%	82.65%±08.31%
	15.0	5.82	83.53%±08.62%	83.53%±11.69%	83.53%±08.06%
	17.5	6.65	83.53%±08.62%	84.12%±12.28%	83.82%±08.39%
	20.0	7.32	84.12%±09.39%	84.12%±12.28%	84.12%±08.88%
	22.5	7.88	84.71%±09.43%	84.12%±12.28%	84.41%±08.82%
	45	13.88	86.47%±09.31%	90.59%±12.49%	88.53%±08.62%

Table 2: Average maximum accuracy and the corresponding sensitivity, specificity, and time at different state durations for the mental rotation task versus resting state using MW and IW methods.

	State Duration (S)	Time(s)	Sensitivity (%)	Specificity (%)	Accuracy (%)
MW Method	5.0	2.04	81.18%±09.28%	79.41%±13.45%	80.29%±09.27%
	7.5	4.19	84.12%±12.28%	84.12%±10.64%	84.12%±08.52%
	10.0	5.78	87.65%±09.03%	86.47%±10.57%	87.06%±06.86%
	12.5	5.96	88.82%±09.28%	87.06%±10.47%	87.94%±06.86%
	15.0	7.82	90.59%±08.27%	88.82%±09.93%	89.71%±05.44%
	17.5	10.34	90.59%±09.66%	93.53%±07.02%	92.06%±04.70%
	20.0	11.19	92.35%±08.31%	93.53%±07.02%	92.94%±04.70%
	22.5	11.19	92.35%±08.31%	93.53%±07.02%	92.94%±04.70%
	45	15.57	95.29%±06.24%	93.53%±07.02%	94.41%±03.91%
IW Method	5.0	2.59	72.94%±17.95%	75.88%±16.61%	74.41%±14.35%
	7.5	3.47	77.06%±14.04%	78.24%±17.04%	77.65%±13.36%
	10.0	4.59	81.18%±13.17%	77.65%±17.51%	79.41%±12.36%
	12.5	4.88	82.94%±12.13%	79.41%±14.78%	81.18%±09.77%
	15.0	6.06	83.53%±11.15%	81.76%±15.09%	82.65%±10.33%
	17.5	7.29	83.53%±11.15%	83.53%±13.67%	83.53%±09.81%
	20.0	8.41	84.71%±11.79%	83.53%±13.67%	84.12%±10.19%
	22.5	9.97	85.29%±12.31%	84.12%±12.78%	84.71%±09.60%
	45	20.38	89.41%±09.66%	89.41%±11.44%	89.41%±07.05%

Table 3: Average maximum accuracy and the corresponding sensitivity, specificity, and time at different state durations for the mental rotation versus word generation using MW and IW methods.

	State Duration (S)	Time(s)	Sensitivity (%)	Specificity (%)	Accuracy (%)
MW Method	5.0	2.24	80.56%±11.62%	78.89%±10.23%	79.72%±06.75%
	7.5	3.18	83.33%±12.37%	81.11%±11.32%	82.22%±07.90%
	10.0	3.87	85.00%±11.50%	81.11%±11.32%	83.06%±07.89%
	12.5	5.93	87.78%±08.78%	84.44%±09.84%	86.11%±07.58%
	15.0	7.22	91.11%±08.32%	86.11%±09.16%	88.61%±06.14%
	17.5	9.01	92.78%±08.26%	87.22%±09.58%	90.00%±05.94%
	20.0	10.78	92.22%±09.43%	89.44%±08.73%	90.83%±04.62%
	22.5	11.28	91.67%±09.24%	91.11%±07.58%	91.39%±04.47%
	45	15.41	93.89%±07.78%	91.67%±07.86%	92.78%±03.52%
IW Method	5.0	2.50	72.86%±13.26%	76.43%±11.51%	74.64%±07.71%
	7.5	3.73	78.57%±09.49%	79.29%±13.28%	78.93%±05.94%
	10.0	4.80	79.29%±09.97%	82.14%±11.88%	80.71%±07.03%
	12.5	6.87	80.71%±09.97%	85.00%±10.92%	82.86%±06.99%
	15.0	6.87	80.71%±09.97%	85.00%±10.92%	82.86%±06.99%
	17.5	7.17	82.14%±11.21%	85.00%±10.92%	83.57%±07.70%
	20.0	7.17	82.14%±11.21%	85.00%±10.92%	83.57%±07.70%
	22.5	10.93	83.57%±10.08%	86.43%±11.51%	85.00%±07.34%
	45	19.00	90.00%±09.61%	87.86%±11.88%	88.93%±07.12%

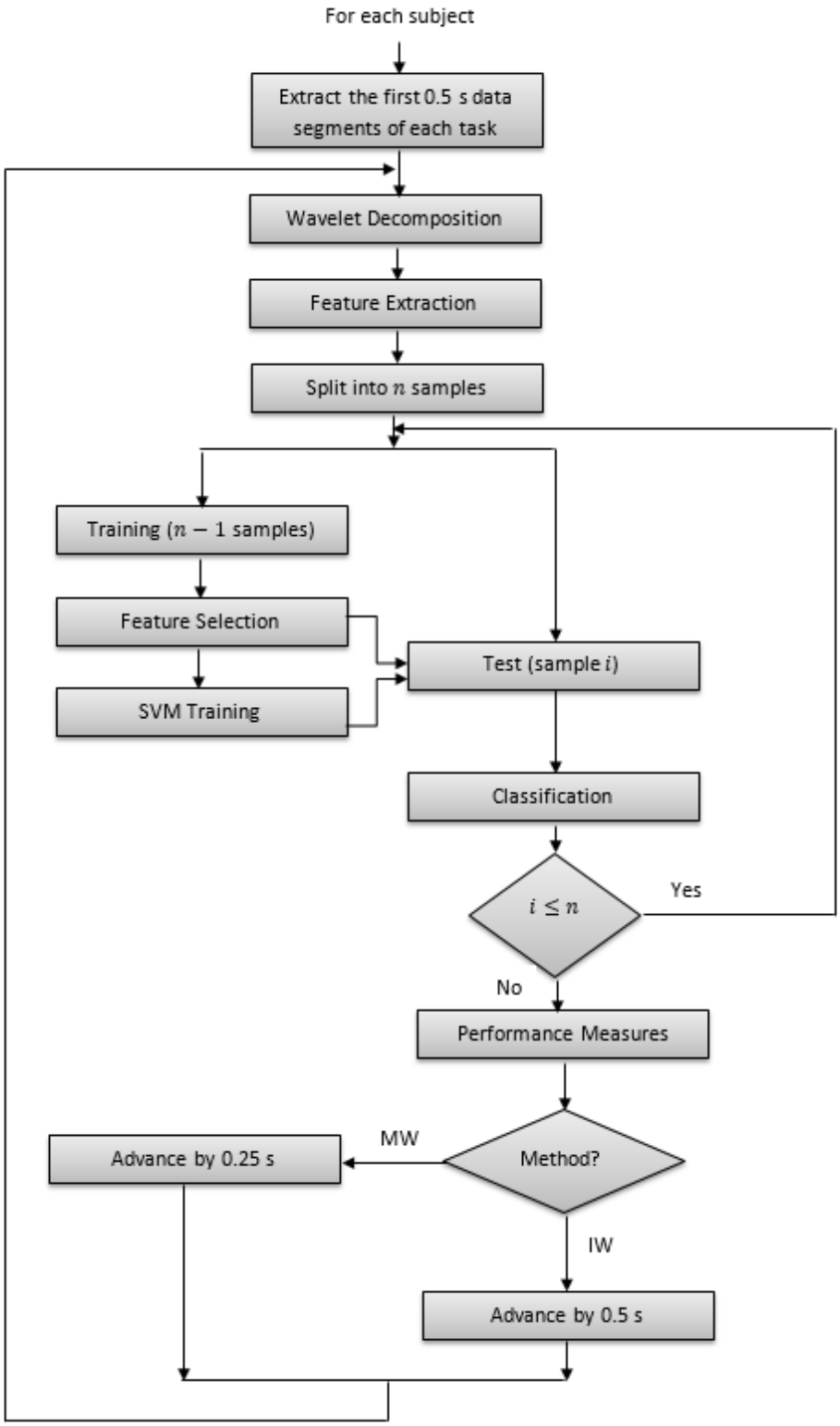
Table 4: Average maximum accuracy and the corresponding sensitivity, specificity, and time at different state durations for the 3-class (mental rotation (MR), word generation (WG), and resting state problem using MW and IW methods.

	State Duration (S)	Time(s)	MR Sensitivity (%)	WG Sensitivity (%)	Specificity (%)	Accuracy (%)
MW Method	5.0	3.35	59.20%±11.97%	70.43%±06.67%	51.90%±22.34%	60.23%±08.89%
	7.5	4.05	63.02%±04.83%	69.10%±07.37%	55.76%±22.73%	62.33%±08.47%
	10.0	4.68	66.12%±09.66%	68.26%±09.19%	61.32%±16.63%	65.27%±09.06%
	12.5	5.75	68.00%±10.33%	71.00%±11.01%	65.00%±18.41%	68.00%±10.80%
	15.0	6.13	70.20%±10.54%	73.65%±08.23%	62.15%±25.73%	68.36%±10.09%
	17.5	7.63	68.78%±12.29%	76.92%±06.99%	67.76%±14.18%	70.83%±08.08%
	20.0	9.45	68.17%±12.29%	76.20%±06.99%	68.91%±13.98%	70.67%±07.98%
	22.5	9.45	68.17%±12.29%	76.20%±06.99%	68.91%±13.98%	70.67%±07.98%
	45	11.27	72.19%±11.01%	75.93%±07.07%	70.88%±14.14%	72.91%±07.73%
IW Method	5.0	2.53	50.00%±18.26%	65.00%±10.80%	47.00%±29.46%	54.00%±11.84%
	7.5	3.41	58.23%±13.17%	68.01%±12.29%	48.42%±30.47%	58.21%±11.35%
	10.0	3.97	54.07%±23.19%	69.23%±12.87%	58.70%±17.29%	60.67%±08.86%
	12.5	4.59	55.00%±22.73%	69.33%±12.87%	63.67%±10.59%	62.33%±06.49%
	15.0	4.94	57.70%±23.12%	69.71%±12.87%	63.20%±10.59%	63.80%±07.28%
	17.5	4.94	57.70%±23.12%	69.71%±12.87%	63.20%±10.59%	63.80%±07.28%
	20.0	5.94	65.00%±10.80%	68.96%±14.49%	57.04%±22.63%	63.67%±06.37%
	22.5	9.59	68.00%±13.17%	70.48%±12.87%	61.52%±25.58%	66.64%±08.46%
	45	14.29	70.10%±15.63%	77.86%±13.17%	67.04%±29.08%	71.57%±12.59%

Table 5: Comparison between the proposed MW method and the state of the art methods for binary BCIs.

Method	BCI Type	Accuracy	Observation Period (s)
Myrden et al., 2011	fTCD	82.90%	45
Myrden et al., 2011	fTCD	85.70%	45
Aleem and Chau, 2013	fTCD	80.00%	20
Lu et al., 2015	fTCD	79.69%	15
Fazli et al., 2012	NIRS	73.30%	7
Shin et al., 2016	NIRS	77.00%	10
Faress and Chau, 2013	fTCD-NIRS	76.10%	20
Proposed method (MR/rest)	fTCD	80.29%	3
Proposed method (WG/rest)	fTCD	82.35%	3
Proposed method (MR/rest)	fTCD	93.24%	45
Proposed method (WG/rest)	fTCD	94.41%	45

Figure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Feature Extraction
Split into n samples
Training ($n-1$ samples)
Feature Selection
SVM Training
Test (sample i)
Classification
$i \leq n$
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No
Performance Measures
Method?
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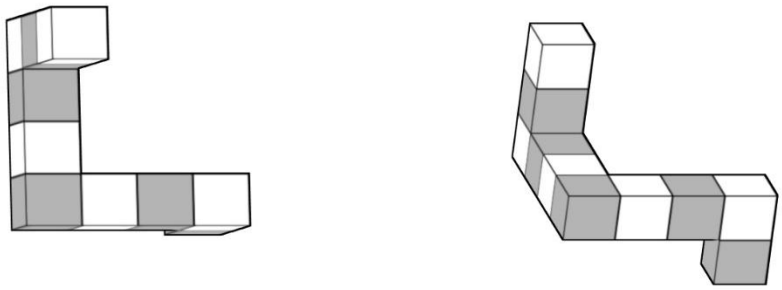
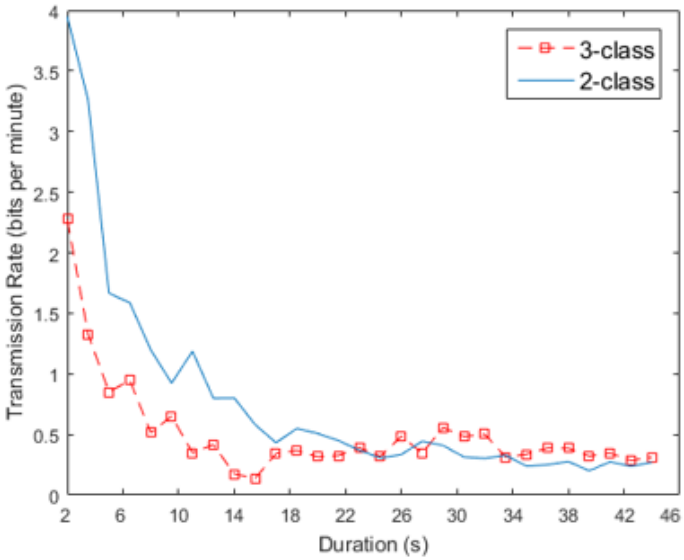
Advance by 0.25 s
IW
Advance by 0.5 s

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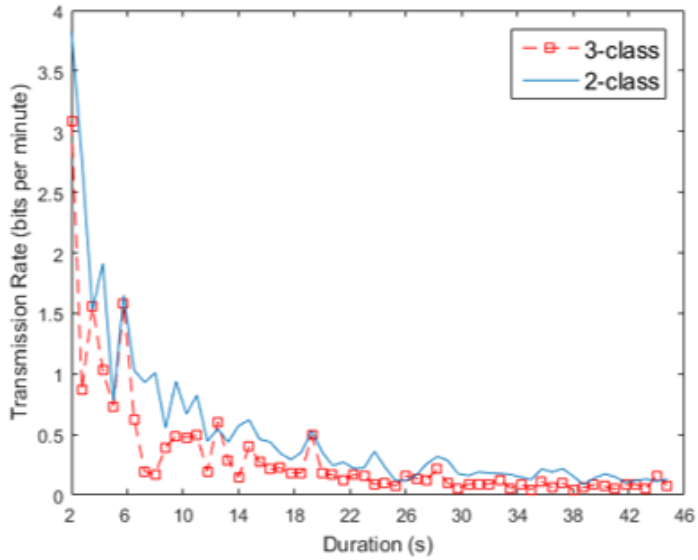
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