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A brain-computer interface based on functional transcranial doppler ultrasound using wavelet transform and support vector machines

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HIGHLIGHTS

- We investigated the feasibility of a 2-class and 3-class real-time BCI system.
- Three mental tasks that induce different blood flow velocities were employed.
- Statistical features for wavelet transform coefficients were calculated.
- Wilcoxon test and SVM were used for feature selection and classification.
- Bit rates exceeding 3 bits/min were achieved.

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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 s 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 s from the onset of the cognitive task. Furthermore, an average accuracy of 65.27% was obtained for the 3-class problem within 4.68 s.
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.

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

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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) (Weiskopf et al., 2004a), 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), (Weiskopf et al., 2004b). 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 (Vingerhoets and Stroobant, 1999a), (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 s 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 to 20 s (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 (Vingerhoets and Stroobant, 1999b). 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 min 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